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Enabling technologies and business models for energy communities

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Enabling technologies and business models for energy communities

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Table of contents

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Editorial: Enabling technologies and business models for energy communities

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This Research Topic on "*Enabling Technologies and Business Models for Energy Communities*" presents a comprehensive exploration of critical facets in the realm of sustainable energy transitions. The Research Topic encompasses diverse topics, ranging from smart energy frameworks for urban communities and off-grid renewable energy deployment in Mexico to the impact of institutional support on the coalbed methane industry. It further investigates complex grid investment decisions, solar-based irrigation adoption in water-scarce regions, and risk management in power supply projects. Additionally, the Research Topic delves into financial aspects, exploring the pricing of Public-Private Partnership (PPP) project Asset-backed Securities (ABS) products, the impact of managerial competence on corporate carbon performance, and equity-based predictions for the energy industry. The influence of innovation on fossil fuel abandonment in low and middle-income countries and the significance of climate risk for green innovation in heavy-polluting industries are also examined. A regional perspective is provided on the technological convergence of hydrogen energy, and the interplay between renewable energy, Gross Domestic Product (GDP), and CO_2 emissions in highly-globalized countries is scrutinized. Lastly, the effects of green credit policy on the risk of stocks prices crash are investigated. Together, these contributions offer a holistic understanding of the challenges and opportunities in enabling technologies and business models for energy communities, contributing valuable insights for researchers, policymakers, and industry stakeholders striving for a sustainable energy future.

KEYWORDS

energy communities, electricity markets, best practices, business models, consumers engagement, flexsumers, ITC

Editorial on the Research Topic
Enabling technologies and business models for energy communities

1 Introduction

In the pursuit of sustainable and resilient energy systems, the Research Topic on "*Enabling Technologies and Business Models for Energy Communities*" serves as a pivotal platform for exploring the intersection of technology and innovative business models. This Research Topic delves into the challenges and opportunities inherent in the dynamic landscape of energy transitions. From smart energy solutions to renewable energy deployment, institutional support, and corporate sustainability, each paper contributes valuable knowledge to shape the future of energy communities.

2 Research published in Research Topic

The first paper, titled "*Accelerating the Change to Smart Societies—a Strategic Knowledge-Based Framework for Smart Energy Transition of Urban Communities*," (Zaidan et al.) offers a strategic framework to expedite smart energy transitions in urban settings. It emphasizes the need for a cohesive approach to create smart societies and sustainable urban energy landscapes. Moving to Mexico, the second paper explores the "*Deployment of Sustainable Off-Grid Marine Renewable Energy Systems*" (Gorr-Pozzi et al.). This research investigates the challenges and opportunities associated with implementing off-grid marine renewable energy systems, contributing valuable insights to the discourse on decentralized energy generation. The third paper, titled "*How Does Institutional Support Affect the Coalbed Methane Industry?*" (Wei and Niu) delves into the coalbed methane sector, examining the impact of institutional support. This analysis sheds light on the critical relationship between institutions and the development of the coalbed methane industry. Addressing the complexities of grid investment decisions, the fourth paper introduces a method that considers source-grid-load-storage integration. Titled "*A Complex Grid Investment Decision Method Considering Source-Grid-Load-Storage Integration*," (Zhang et al.) this research provides a comprehensive approach to guide investment decisions in the energy system.

Shifting focus to Bangladesh, the fifth paper explores the "*Adoption Impact of Solar-Based Irrigation Facility by Water-Scarce Northwestern Areas Farmers*" (Sunny et al.). Through panel data analysis, the study evaluates the effectiveness of solar-powered irrigation in enhancing agricultural practices and water management in water-scarce regions. The sixth paper, "*Research on Construction Schedule Risk Management of Power Supply and Distribution Projects Based on MCS-AHP Model*," (Xinfa et al.) presents a risk management model for the construction schedule of power supply and distribution projects. The integration of Monte Carlo Simulation (MCS) and Analytical Hierarchy Process (AHP) provides a systematic approach to address construction schedule uncertainties. For Public-Private Partnership (PPP) projects, the seventh paper explores the "*Research on the Pricing of PPP Project ABS Products Based on the Right of Income of Heating*" (Duan and Zhang). This research investigates the pricing of Asset-Backed Securities (ABS) products based on heating income rights, contributing to the financial understanding of PPP projects in the energy sector. The eighth paper investigates "*The Impact of Managerial Competence on Corporate Carbon Performance*," (Zhao and Wang) focusing on Chinese heavy polluters. Through empirical research, the study examines how managerial competence influences corporate carbon performance, contributing valuable insights to the sustainability efforts of heavy-polluting industries.

The ninth paper proposes a method for predicting the return on equity in the energy industry based on equity characteristics. Titled "*Prediction of Return on Equity of the Energy Industry Based on Equity Characteristics*," (Yang and Wang) this research aims to enhance financial forecasting in the energy sector, providing valuable insights for investors and industry stakeholders. In the 10th paper, the research explores "*The Impact of Product and Process Innovation on Abandoning Fossil Fuel Energy Consumption in Low and Middle-Income Countries*" (Taqqadus et al.). This study investigates how innovation influences the abandonment of fossil fuel energy in less economically developed countries, contributing to the discourse on achieving carbon neutrality. The 11th paper investigates "*How Does Climate Risk Matter for Corporate Green Innovation? Empirical Evidence from Heavy-Polluting Listed Companies in China*" (Ling and Gao). Focusing on climate risk, this empirical study explores its significance for corporate green innovation strategies, particularly in industries with high environmental impact.

Taking a regional perspective, the 12th paper explores "*What Can Accelerate Technological Convergence of Hydrogen Energy*" (Lee). This research identifies factors that can accelerate the technological convergence of hydrogen energy, providing insights into fostering collaboration and innovation in the hydrogen energy sector from a regional standpoint. Examining the interplay between renewable energy adoption, GDP, and CO_2 emissions in high-globalized countries, the 13th paper "*Renewable energy, GDP and CO_2 emissions in high-globalized countries*" (Mirziyoyeva and Salahodjaev) provides valuable insights into the complex relationship between economic development, environmental sustainability, and energy choices. Finally, the 14th paper investigates the "*Effects of Green Credit Policy on the Risk of Stock Price Crash*" (Liu et al.) Focusing on the financial aspects of green policies, this research explores the effects of green credit policy on the risk of stock price crash, contributing to the understanding of sustainable finance initiatives' impact on stock markets.

3 Conclusion

In conclusion, this Research Topic synthesizes a diverse array of research papers, each offering unique perspectives and insights into the intricate challenges and opportunities in the realm of enabling technologies and business models for energy

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communities. Collectively, these contributions advance our understanding of the pathways to a sustainable and resilient energy future. While diverse in focus, a general trend across the submissions underscores a growing emphasis on renewable energy adoption, innovative technological solutions, and the critical role of institutional support in shaping sustainable energy landscapes globally.

Author contributions

AB: Writing–original draft, Writing–review and editing. MJ: Writing–original draft, Writing–review and editing. ZL: Writing–original draft, Writing–review and editing.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Accelerating the Change to Smart Societies- a Strategic Knowledge-Based Framework for Smart Energy Transition of Urban Communities

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Urban communities differ in their social, economic, and environmental characteristics, as well as in the approach to energy use. Dynamic energy use and available on-site resources allow interaction with the surroundings and contribute to the key performance indicators of smart cities. This study aimed at proposing systematically a strategic framework for smart cities development by gradually transforming urban communities into smart-energy systems. This framework is based on multidisciplinary practices regarding the staged planning of smart communities and develops smart transformation concepts to enhance capacities toward the preservation, revitalization, livability, and sustainability of a community. In this study, we focused on the concept of smart and zero-carbon communities by using technology and infrastructure. We also considered the premise of the "community" and the related social, technological, and economic aspects. The decision constructs are explained from the perspective of a bottom-up approach ranging from preliminary inspections to economic investment planning. The study proposed a set of decision constructs aimed at allowing planners, engineers, and investors to have different alternatives at their disposal and select a feasible set of practical solutions for smart transformations accordingly.

Keywords: smart cites, community synergy, zero-carbon transition, strategic planning, smart communities, decision-making

1 INTRODUCTION

The energy sector has undergone a technology-driven transformation aimed at achieving smart and zero-carbon ecosystems initiated by the governments through intensive investments in Information and Communication Technologies (ICT)-based infrastructures. The end goal is to develop smart cities using efficient solutions and to reshape urban development through megaprojects and centralized master planning. This global and modernist approach is, however, controversial, which can be seen in the literature. In the last decades, the concept of a smart city has gained popularity owing to an emerging critical role of technology in cities' urban sustainability plans, especially following the smart growth movement of the late 1990s (Susanti et al., 2016) (Harrison and Donnelly, 2011). The smart city concept refers to the implementation of cutting-edge technologies aimed at social development and economic growth. Cities use intelligent technologies and innovative design to offer high-quality services to citizens and reconstruct urban spaces to enhance life quality. Currently, more than 1,000 smart cities have been developed worldwide, mostly in Asia, Europe, and North America (Zheng et al., 2020). Yet, the definition of this concept in both academia and industry is lacking.

The performance metrics of smart cities consist of the following pillars: smart people, smart economy, smart environment, smart mobility, smart living, and smart governance (Zheng et al., 2020)– (Elessawy and Zaidan, 2014). Accordingly, traditional urban development theories are connected with modernization in sustainable development to provide a comprehensive definition of a smart city (Giffinger et al., 2007). This definition focuses on actors, technologies, and outcomes aimed at improving the city's quality (Cocchia et al., 2014). The inclusion of those pillars of a smart city contributes to the effectiveness and efficiency of necessary and useful city activities, processes, and services. A city represents a smart system when investments are in line with human and social capital, advanced energy and mobility, and ICT infrastructure. Accordingly, participatory governance and the careful management of natural resources contribute to the sustainable development of the economy and enhance life quality.

There are three main approaches toward the concept of smart cities. The first is a techno-centered approach that assigns a critical role to ICT and it focuses on advanced technologies, hardware, and digital infrastructure. For example, Harrison et al. (Harrison, 2010) defined smart cities as a concept that integrates real data in real-time into a computing platform to offer services by implementing practices such as modeling, visualization, information processing, and optimization. Hancke et al. (Hancke and Silva, 2012) argue that a smart city operates in a sustainable and intelligent environment based on intelligent devices for monitoring and control. Moreover, its infrastructure and citizen services are cohesively integrated. Today, smart city technologies are used to improve urban life quality on daily basis in different fields such as society and economy (i.e., cultural heritage management, human capital management, digital education, innovation, and entrepreneurship), government (i.e., transparency, e-democracy, and e-governance), daily life (i.e., management of public spaces, culture, welfare and social inclusion, health, public security, pollution control, hospitality, and entertainment), smart buildings (i.e., housing quality, construction services, and facilities management), transport and mobility (i.e., services related to district information models, citizens mobility, mobility information, and city logistics), and natural resources and energy (i.e., food and agriculture, waste management, renewable energies, smart street lighting, and smart grids) [(Sousa et al., 2012; Barthel and Isendahl, 2013; Gomes et al., 2014; Perera et al., 2014; Kingston et al., 2015; Chamoso and De La Prieta, 2016; De Paz et al., 2016; González-Briones et al., 2018; Abulibdeh, 2020a)]. Digital broadband technologies contribute to intra-community and inter-community interactions and they can enhance social inclusion, local prosperity, and competitiveness in the urban context. Moreover, these technologies can provide a communication platform for informed citizens to enhance further the development potential of the community (Albert et al., 2009). Numerous urban environments focused on providing sufficient digital infrastructure development for local stakeholders and citizens considering that digital broadband technology can transform current interaction patterns and communications increase efficiency in social, economic, and environmental urban processes.

The second is a human-centered approach and it emphasizes the role of social and human capital in the smart city. Different authors highlight the role of human capital and education in urban development and sustainability. The definition of the smart community proposed by Coe et al. (Coe et al., 2001) emphasizes the importance of social and environmental capital in urban development. Therefore, participation in community affairs, social inclusion, and decision-making processes are critical for reaching social and environmental objectives. Some studies investigated, the relation between the educated labor force and smart cities (Berry and Glaeser, 2005). This relation is critical for employment growth, economic development, and technology (Eger, 2009). However, intense debates are focused on social innovation and the role of the human factors and communities. The communities are regarded as key elements of the regeneration of urban areas using innovation. Accordingly, the concept of a smart community is based on the synergy using technology and infrastructure that is technically feasible and relevant for any region. Nevertheless, when the concept of the "community" is discussed, it is necessary to consider its critical aspects such as affordability, acceptability, privacy, and coherence. Moreover, the smart community is the concept encompassing advanced technologies and infrastructures aimed at sustainable development. Consequently, smart communities allow governance and infrastructural and technological drivers to generate social innovation. In turn, those innovations can engage local actors such as associations, businesses, and citizens, and accordingly respond to the challenges related to life quality, inclusion, and growth. Networking and information technology research and development (NITRD) offered a framework for smart and connected communities defined as "communities in all settings and at all scales that have access to advanced cyber-physical systems/Internet of Things [IoT] technologies and services to enhance the sustainability and quality of life and improve health and safety and economic prosperity for their residents" (Sun et al., 2014). The generation of smart communities is aimed at their preservation, revitalization, livability, and sustainability.

The third is an integrated approach arguing that human and social capital and technology create jointly adequate conditions for a continual process of growth and innovation (Bencardino and Greco, 2014). A smart city integrates human capabilities, knowledge-intensive activities, institutional mechanisms for social cooperation toward knowledge, and innovation development and digital infrastructure (i.e., ICT infrastructure, tools, and applications). Accordingly, the smart city represents an environment that can combine sustainability and competitiveness by integrating different dimensions of development (i.e., social, economic, environment, and living,

TABLE 1 | Climate Change Performance Index 2022—Rating table.

Clusters	Characteristic	Countries	Rank		Score	
			Min	Max	Min	Max
Alpha	High commitment to smart and zero-carbon transition, GHG Emissions, renewable energy and climate policy	Denmark, Sweden, Norway, United Kingdom, Morocco, Chile, India, Lithuania, Malta, Germany, Finland, Switzerland, Portugal, France, Luxembourg, Netherlands, Ukraine, Egypt, European Union (27), Philippines, Greece, Colombia, Latvia, Indonesia, Mexico, Croatia, Italy, Thailand, Estonia, Brazil	4	33	54.86	76.67
Beta	Medium commitment to Smart and zero-carbon transition	Spain, New Zealand, Romania, Austria, China, South Africa, Slovak Republic, Turkey, Cyprus, Vietnam, Bulgaria, Japan, Ireland, *Argentina*, Belarus, Belgium	34	49	45.90	54.35
Gamma	Low commitment to smart and zero-carbon transition, GHG emissions, renewable energy and energy use	Slovenia, Czech Republic, Poland, Hungary, Algeria, United States, Russian Federation, Malaysia, Chinese Taipei, Australia, Korea, Canada, Islamic Republic of Iran, Saudi Arabia, Kazakhstan	50	64	19.23	43.28

and governance, people, and mobility). The focus is on ICT drivers and how they influence urban development. All definitions of smart communities, share three common concepts: the process (networking of various actors); communication means (ICT, technology, and network infrastructure); and the goal pursued (public involvement or other).

The Climate Change Performance Index (CCPI) (‘Climate Change Performan, 2022a) is one of the significant metrics that can evaluate the commitment of governments supporting the transformation toward a zero-carbon energy system and technological developments. The CCPI is calculated using 14 indicators classified into four categories (‘Climate Change Performan, 2022b): 1) Greenhouse gas emissions 2) Renewable energy sources 3) Energy consumption 6) Climate policy. Based on Climate Change Performance Index 2022 results (Jan et al., 2022), countries can be classified the into three main clusters, “Alpha”, “Beta”, and “Gamma”, as displayed in **Table 1**.

- “Alpha” or “High commitment to smart and zero-carbon transition, GHG Emissions, renewable energy and climate policy”. This cluster is primarily composed of northern European nations that able to perform in the CCPI. They are all targeting a zero-carbon future, reducing GHG emissions, and contributing to the Green Climate Fund (‘Green Climate Fund’.2022, 2022), while also participating actively and constructively in climate legislation. Sweden exemplifies the hypothesis that the more industrialized countries are more environmentally friendly (Yesiloglu et al., 2019), having committed to producing 100 percent renewable electricity by 2040 and imposing the world’s highest carbon tax (delclima, 2019). Despite these encouraging findings, there is still room for improvement in terms of energy efficiency (Sweden and Norway) (‘Nordic Energy Technology, 2013) or carbon reduction in the transportation, building, and agriculture sectors (Denmark) ((2022). Denmark: foc, 2022). As a result, none of them achieves the maximum CCPI pillar score.

- “Beta” or “Medium commitment to Smart and zero-carbon transition”. This group is primarily formed of eastern European states, but also includes nine other nations from different continents. These are countries whose commitment to combating climate change should be bolstered by more effective measures targeted at lowering GHG emissions and increasing the use of renewable energy; in other words, they require stronger environmental legislation. Romania and Bulgaria, in particular, lack a strategy for coal phase-out and rely significantly on fossil fuels for energy (Zlateva et al., 2020). Typically, these are countries with significant economic resources to accelerate the shift to cleaner technology. Nonetheless, there is a need for increased awareness and action on the part of the competent agencies.
- “Gamma” or “Low commitment to smart and zero-carbon transition, GHG emissions, renewable energy and energy use”: This category is consisting mostly of eight Asian countries, United States, Australia and Canada, all of which are ranked at the bottom of the CCPI. Globally, the poor climate performance is a result of high per capita GHG emissions, particularly in Canada, which ranks first among the most active emitters (Davis et al., 2018), a lack of commitment to renewable energy implementation, and a lack of long-term energy planning. Specifically, Hungary and Poland’s lackluster activities are impeding the EU’s 2030 Climate Target Plan (Poland (2022). Hungary th, 2022). Saudi Arabia is particularly deserving of consideration. This country is highly reliant on fossil fuels and has substantial challenges in transitioning to renewable energy. Similarly, approximately 80% of Iran’s electricity producing sector’s energy demand is satisfied by fossil fuels (Shahsavari and Akbari, 2018).

The concept of smart communities has been developed as a result of competitiveness gains and community development aimed towards new network opportunities. Revolutionary network developments and technologies offer access to knowledge, resources, and tools for connection, and accordingly, they have a considerable impact on the interactions of individuals, local governments, institutions, and businesses. Smart communities are, thus, clusters that can establish alliances and partnerships via electronic networks and the internet, leading to novel economic and social values (anadian Federal Gove, 2002). In particular, it is critical to invest in human and social capital along with the network deployment (transport and ICTs) to reach objectives of the sustainable community and enhance life. To achieve this, social participation, as well as user-specific technologies and community-building applications, should be fostered (Komninos, 2009).

2. KNOWLEDGE GAPS

Despite improvements in smart cities and communities, certain gaps regarding the integration of the multi-dimensional domain knowledge of this transition to create a meaningful roadmap remain. This integration is highly complex considering that smart transition involves human, technological, economic, policy, and environmental factors. The integration is a prerequisite for complex large-scale projects because such projects must respond to and incorporate gradual, but constant changes of communities. However, it is still not investigated how this incorporation can occur. Moreover, up to date, the convergence of regional projects aimed at achieving high-level sustainability objectives has not been explored.

Accordingly, further research is needed to develop a multistage and multidisciplinary transition plan that will incorporate all aforementioned factors into the transformation of an existing urban community into a smart system to achieve high-level sustainability goals. As argued by Israilidis et al. (Israilidis et al., 2021) studies conducted on smart city projects so far have not been systematic enough to conduct efficiently future smart city policies and practices. The reason is that both academic studies and policies have been primarily focused on addressing solely technical issues and accordingly, further research is urgently needed to address non-technical aspects. Our study intends to overcome this gap. Accordingly, the transition plan must take into account social, economic, environmental, and technological factors and constraints based on both local and regional contexts. We particularly focus on local and regional context, considering that efficient engagement and cooperation of different stakeholders (e.g., private, public, and civic) is critical. Furthermore, Walker et al. (Walker and Devine-Wright, 2008) proposed the assessment of energy and environmental projects at the neighborhood level, as opposed to the approach focused on single buildings. However, we assume that the convergence of neighborhood policies is needed to achieve sustainability policies at the higher levels, following the argument by Kim et al. that energy management at the city level remains unsatisfactory. However, drawing upon Walker et al. (Walker and Devine-Wright, 2008) and Kim et al. (Kim et al., 2021), we devised a bottom-up approach to energy transition of smart communities and their convergence by particularly focusing on non-technical aspects. Thus, the purpose of this study is to propose a strategic knowledge-based framework based using a systems approach that incorporates all of these factors emphasizing social and energy dimensions. The objective is to develop a set of simple-to-use decision constructs for investors, engineers, and planners to allow them exploring various alternatives and identifying a feasible set of practical solutions for a smart transformation.

3 THE PROPOSED FRAMEWORK

3.1 From Connected Communities to a Connected World

The transition from a community's targets and plans to those at the city level is highly challenging considering an exponential increase in complexities, particularly owing to the inevitable inclusion of social and policy factors at the greater scale. Thus, the transition at the city level should be conducted in two ways—distributed and incremental to achieve the transformation of a connected network of smart communities into large-scale smart cities. The communities assumed as capable of a smart and sustainable transformation have the following common characteristics: public participation, asset ownership and management, available resources, heterogeneous and flexible energy demands, and scale. Consequently, it is possible to establish a knowledgeable resource-driven system that includes individuals residing in it. The transition involving underprivileged communities is an excellent showcase of economic and social benefits resulting from the transition at the community and city levels. Furthermore, certain areas have a considerable footprint and are highly vulnerable in an environmental sense, namely major commercial areas, transportation hubs, and ports.

From an energy perspective, the continual advancement of smart technologies regarding energy systems, advanced automation, IoT, and ICT has enabled the connection of a distributed network of smart communities. Energy consumers, such as assets, buildings, and mobility, and energy providers within the community should operate in synchronization to achieve optimization in terms of energy conservation and energy efficiency. Smart technologies and data (e.g., waste, water, and electricity tracking, energy use optimization, and air quality monitoring) can be used to considerably enhance life quality for the citizens, increase their opportunities, and ensure a sustainable future. The use of these technologies will lead to considerable saving of water and less solid waste per person annually, interception of pollutants, and fewer GHG emissions. However, to meet the objectives of a smart city, it is necessary to combine community- and facility-level actions. The incremental transition takes the form of the establishment of systems-aware community clusters to achieve the broader impacts of all sub-systems in high-level logistics. Accordingly, smart cities are reinforced, and a smart economy, smart society, and smart governance are enhanced. Such a holistic system is accessible and inclusive, and consequently, the life quality, in general, is improved. Furthermore, it is important to note that environmental impacts are not limited to GHG emissions. Moreover, the synergy should be established within a connected system. This connected architecture allows the communities to operate in a connected world and exchange their resources in an energy transition roadmap. More precisely, the transactive energy exchange between communities can be envisioned although costs and benefits have not been specified yet. Furthermore, community-to-community offerings could have particular financial parameters. This connected network will allow optimal management to expand sustainability and efficiency. Various measures can be used to define communities and collaborating entities in a connected energy world. Concepts that can serve as a baseline for the incremental transition to a smart city are nanogrids (NG), microgrids (MG), and community energy.

3.1.1 Community Energy and Zero-Carbon Communities

Community energy (CE) is a potential concept to be applied to a multistage transition to a connected energy world ('Climate Change Performan, 2022a). Through CE, communities can be transformed into zero-carbon energy systems by prioritizing the participation of local community members. Worldwide, this strategy has attracted considerable attention, particularly in Denmark, the United Kingdom, Germany, Australia, and the United States (MacArthur, 2017). CE can provide alternative energy initiatives aimed at local people and conducted by local people, in contrast to traditional energy systems (Walker and Devine-Wright, 2008), (Hoffman and High-Pippert, 2005), (Abulibdeh, 2021a). Led by people residing in the community, those communities can significantly benefit through CE projects (Rogers et al., 2008). Various assumptions on the processes such as increased local support for renewable energy, socio-economic regeneration, energy literacy and environmental lifestyles, knowledge and skill development, community empowerment, improved social capital, access to affordable energy, ownership, participation, and decision-making are critical for the outcomes of CE (Berka and Creamer, 2018)– (Abulibdeh, 2021b). However, there is no strong evidence supporting the theoretical assumptions of benefits to the local community (Berka and Creamer, 2018). Accordingly, it is necessary to investigate those benefits systematically, comparatively, and empirically (Wyse and Hoicka, 2019). The studies should explore technological, economic, and social factors that impact the sustainable transition to zero-carbon, in addition to the factors impacting uptake and successful implementation.

CE is primarily defined by the way communities participate in energy developments. Through CE, citizens actively participate in policy perceptions, and energy production, delivery, and consumption, in contrast to traditional energy systems (Ceglia et al., 2020) (Wyse and Hoicka, 2019). CE consists of open participatory practices based on the participation of community members. This allows gathering comprehensive evidence-based data based on a variety of local perspectives (Abulibdeh, 2021a), (Wyse and Hoicka, 2019), (Groves et al., 2013), (Hoffman et al., 2013). The new approaches and practices of CE systems primarily focus on community participation and resemble bottom-up approaches (citizen involvement and a variety of community actors) in opposition to top-down approaches (institutionally-driven traditional systems) (Wyse and Hoicka, 2019), (Groves et al., 2013)– (Devine-Wright and Wiersma, 2013). Therefore, community members' participation is critical for the efficient adoption of non-carbon energy sources and emission reduction. Accordingly, it is necessary to investigate and determine related socio-economic factors. As a result, residents participate in the process impacting their lives. Moreover, a high level of place attachment and related positive emotional bonds between people and the environment can have a considerable impact on either opposing or supporting the transformation toward a zero-carbon energy system and technological developments (Wyse and Hoicka, 2019). The opposition or support depend on the perceptions of new technologies, which can be regarded as a threat or an opportunity to the local community. Thus, the concept of a "community" is useful for investigating how new technologies and new technological activities such as the transformation toward zero-carbon energy systems and technologies and their associated risks are related to people's feelings about their community (Jin, 2015).

3.1.2 Microgrid and Nanogrid Concepts

Distributed energy resources (DERs) have been widely adopted in power systems, and their use is continually increasing. Therefore, it is necessary to revise current business models and infrastructure behind the grid operations to make them more environmentally friendly and reliable. This is a critical component of the energy transition, which is a prerequisite for achieving smart cities. Among viable solutions, the micro-grid (MG) connects DERs in local areas into a mini-grid that has a controllable aggregated node from the utility-grid side. In the relevant literature, MG is defined in different ways formally. According to the US Department of Energy, the MG represents "a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid" (Madushan and Ralalage, 2020) (Ton and Smith, 2012). Furthermore, the International Council on Large Electric Systems (CIGRÉ) defines the micro-grid as "a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid. An MG can connect and disconnect from the grid to enable it to operate in both grid-connected or island mode" (Nordman, 2009).

Drawing upon these definitions, the MG consists of the following primary components: controllers, a set of sensors, AC-DC converters, wires/pipes creating electrical/thermal networks, supply-demand nodes, and switches operating as the MG's central information processing that ensures smart energy management (Karki and Chanana, 2016). MGs represent locally controlled systems; thus, they operate in both grid-connected or islanded modes while meeting network constraints such as nodal voltages and feeder power flow in electric-only MGs. The islanded mode allows MGs to operate all/parts of their critical loads during a crisis such as power outages and storms, whereas the upstream grid is jeopardized in such situations (Shahsavari and Akbari, 2018). Hence, MGs have advantages such as more reliable and resilient service (Ortmeyer et al., 2016); congestion relief and T&D investment deferral through reduced peak loads (Jin, 2015); ancillary services as a result of co-optimization of the DERs' dispatch (CONTRERAS et al., 2019); and environmentally friendly operations owing to increased renewable energy integration enabled by electric/thermal storage capabilities (Abu-Elzait and Parkin, 2019).

Following the design of the MG, a meshed-grid layout with multiple loops is typically selected to improve its reliability and security. The meshed-grid layout incorporates a set of controllable switches, which can ensure the continuity of the service (Ortiz et al., 2020) (Aluko et al., 2020). Furthermore, a critical feature of an MG is optimal selection of the point of common coupling, or more precisely, a static switching node allowing both grid-connected and islanded operation modes. In general, an MG requires a plus-one distributed generation (DG) unit. This one can be in the form of renewable energy sources (RESs), which includes biomass-fueled DGs, fuel cells, wind turbines, and solar panels, fossil-fuel-based dispatchable DGs (DDGs), including gas-fired and diesel-fueled DDGs, or hybrid DGs such as a combined heat and power (CHP) system to maintain operating the critical loads once the MG is islanded. In addition to hybrid DSs, RESs, and DDGs, demand response (DR) resources and energy storage systems (ESSs) and demand response (DR) resources are also classified as DERs when designing an MG. Therefore, DERs act as the prime mover of any MGs whose portfolio is optimized in regard to siting and sizing. The choice of the technology is based on the MG operator's purposes and goals, thermal energy needs, fuel accessibility, and operational parameters. Fundamental for the efficient operation of an MG is to ensure a full state-aware energy management system using metering that can take prompt control actions. The role of the energy management systems is to perform the coordinated operation of DERs within the MG's boundary and continually optimize the supply-demand balance. It also needs to incorporate DR resources as a set of flexible options to respond to changes in demand. The MG and NG, referred to as fractal grids as well, are similar, but the NG represents a smaller scale system. Accordingly, they conduct operations for only one facility or customer. They can function under both DC and AC modes. The most widely used NGs are joint solar-storage systems. Importantly, NGs can be connected to the utility grid through a meter, implemented within MGs, and connected with other NGs (Nordman, 2009).

Considering a technical perspective point of view, the MG and NG concepts are communities capable of supporting the multistage planning of developing smart cities in the smart energy transition (Antonysamy et al., 2020). Such communities, using the concept of community energy, can enhance resiliency and service quality in energy systems, enhance citizens' well-being, and facilitate smart transformation (PriyaDharshini et al., 2022).

3.2 Social Factors and Smart Transformation

Community smart energy transformation can be hindered by social and behavioral elements such as a lack of willingness, acceptance, and awareness, preventing the deployment and expansion of technology alternatives. Therefore, smart transformation must be advocated and implemented through a participatory strategy involving social actors in all horizontal and vertical processes. Human and socio-economic factors ought to be included at all decision-making stages of the smart transformation. Importantly, it is critical to highlight that such factors are case-specific; thus, it is not possible to provide general conclusions. Such factors can be categorized into policy, structural and demographic factors, cultural barriers, and psychological drivers.

For example, demographic factors impact individuals' decisions regarding pro-environmental strategies (Niamir et al., 2018), (De Silva and Pownall, 2014). To illustrate, the studies of Mills and Schleich (Mills and Schleich, 2009) and Michelsen and Madlener (Michelsen and Madlener, 2012) demonstrated that German households consisting of individuals with higher levels of education are more inclined to use solar water heating. Furthermore, Mills and Schleich (Mills and Schleich, 2012) investigated households in European countries and confirmed that those with a university degree are more likely to use energy-efficient technologies. Comparably, Sardianou and Genoudi (Sardianou and Genoudi, 2013) showed that educated Greek households are more inclined to adopt renewable energy resources. In addition, Niamir et al. (Niamir et al., 2020) found that educated households in two European regions invest in housing insulation and solar panels more than those less educated and are more likely to choose a green energy provider. In addition, gender is a critical factor in correlation with the adoption of pro-environmental strategies. Several studies have demonstrated that women are more inclined to adopt energy conservation policies. According to Zelezny et al. (Zelezny et al., 2000), most studies have confirmed that women are more likely to engage in environmental protection. However, studies have also reported that men are inclined to install solar panels (Niamir et al., 2020). Furthermore, age is also a critical factor because older individuals are more skeptical regarding the return on investments in energy solutions (Nair et al., 2010). In contrast, some studies have reported that the older population is more likely to use than younger homeowners [(Long, 1993; Barr et al., 2005; Ghofrani et al., 2021)]. Research on the relationship between income and attitudes toward technology adoption has demonstrated that the inclination to adopt renewable energy technologies is in correlation with monthly income (Sardianou and Genoudi, 2013). Similarly, homeowners with high incomes are more inclined to invest in solar hot water technology (Sidiras and Koukios, 2004).

On the other hand, psychological drivers, primarily personal and social norms, influence smart transformation decision-making. Social norms represent "perceived social pressures from significant others and/or beliefs about how significant others expect one to act in a given situation that impacts the individuals' degree of reliance on policies" (Chen et al., 2017). Furthermore, Allcott (Allcott, 2011) confirmed that social norms influence energy efficiency in the US. These norms provide information about residential end-users, which allows comparing their consumption patterns with the community and envisioning tips and recommendations on energy conservation practices. In addition, in a study conducted in

China, Wang et al. (Wang et al., 2011) demonstrated that social norms are related to increased household electricity saving. Also in the Chinese context, Chen et al. (Chen et al., 2016) demonstrated that social norms positively affect the intention of people to adopt vehicles that use non-fossil fuel energy and solar water heating systems. Moreover, Han et al. (Han et al., 2010) revealed that because of perceived social norms, customers choose environmentally friendly hotels. Furthermore, personal norms represent the perception of having a moral obligation to adopt a new behavior (Huijts et al., 2012). According to Werff et al. (van der Werff et al., 2019), in the Netherlands, households with stronger personal norms are more inclined to exhibit an energy-saving attitude. A study conducted in Spain and the Netherlands by Niamir et al. (Niamir et al., 2018) demonstrated that personal norms positively impact the decision to invest in appliances that help save energy, solar panels, and housing insulation, solar panels. Moreover, cultural barriers such as thermal comfort, vandalism, social exclusion, social status, ethnic bias, and masculinity, can negatively impact (Sovacool and Griffiths, 2020). For instance, social status represents a main cultural barrier to shared transportation in GCC countries because car ownership is a crucial status of wealth (Abulibdeh, 2020b), (Abulibdeh and Zaidan, 2018). Similarly, in Australia and the US, masculinity and machismo are the primary factors behind aggressive driving and speeding (Schmid Mast et al., 2008), resulting in high CO_2 emissions.

Another important social determinants that critically impact the transition is the structural factors, which refer to the characteristics of buildings (e.g., size, age, and type). To illustrate, Mills et al. found that older houses are less energy efficient (Mills and Schleich, 2009). Besides, Niamir et al. (Niamir et al., 2018) argued that homeowners are more inclined to invest in green energy than apartment owners, because owners of new buildings are more likely to invest in solar panels. In addition, there is a positive correlation between the size of the house and the investment in solar panels and housing insulation. It is assumed that the owners of larger houses have a higher income and are able to invest in green energy. However, larger houses also have larger rooftop spaces that can host a solar panel system.

Finally, financial policy factors such as the cost of carbon-neutral products and zero-carbon transition expenses also considerably impact the smart transformation (Zhang et al., 2011), (Cheng et al., 2019). Credits for consumers to purchase energy-efficient cooling and heating systems (e.g., Bulgaria) and the reduction of added-value tax for technology-saving, appliances/technologies that save energy contribute to the energy transition. According to Sardianou et al., subsidies and tax deductions positively influence the adoption of renewable energy resources by households (Sardianou and Genoudi, 2013). Furthermore, in the Chinese context, Li et al. (Li et al., 2016) demonstrated that preferential tax policies and government subsidies help consumers choose new energy solutions. A survey by Wang et al. (Wang et al., 2011) revealed that Beijing would purchase clean energy solutions if subsidized by the government. In addition, higher fossil fuel energy taxes would motivate individuals to opt for renewable energy. As Sardianou et al. (Sardianou and Genoudi, 2013) found, people are more likely to invest in green energy when prices of fossil fuel energy are higher. Drawing upon the literature, various types of incentives (financial, economic, and social) should be investigated to determine particular behavioral factors and evaluate how people adapt to new technologies to facilitate the energy transition process. Importantly, behavioral factors are dependent on social, temporal, and spatial factors. Thus, decision-makers must be informed about these factors to take appropriate actions to raise community awareness and acceptance, as well as to foster adequate norms and attitudes in the smart energy transition of communities.

3.3 Smart Transformation Roadmap

We define a smart community as a dynamic complex system with a hierarchical architecture that evolves over time. Besides, the bidirectional interactions and externalities crossing the system's boundaries and the uncertainties created by factors such as human behavior and weather conditions present even more complexities in the planning and operation of smart communities. The smart transformation of an existing community consists of multiple phases in order to create a hierarchical architecture of information and asset layers that facilitate achieving the energy transition's goals by adopting new technologies and establishing synergy to enable the ubiquity of devices and information fusion. The system should be designed based on an ICT infrastructure that is equipped with local automation systems, sensors and measurement tools, data hubs, database management systems, and central processing modules. For a smart energy transformation, technologies such as DERs, ESSs, district heating/cooling devices, and technologies that enable transportation electrification are inevitable. The end-use loads associated with built environments and mobility can be dynamically managed and reshaped based on the real-time and projected availability of resources and demand. As a result of the synergy within the system, a smart community can be regarded as a self-aware, resource-driven, and connected community that also has bidirectional interactions with its surroundings and the connected world (**Figure 1**).

The goal of this system is to achieve sustainability while having targets concerning cost savings, resiliency, quality of service, human life, system performance, responsiveness, and contributions to municipalities and the surrounding communities. In this framework, a smart community can achieve zero-carbon emissions and ensure the possibility of negative carbon emission by focusing on natural and artificial carbon capture approaches. It should be ensured that the design and information/asset layers are in accordance with environmental measures to achieve a zero-carbon state. Toward this smart and zero-carbon transition, the economic, technological, and social behavior impediments require comprehensive scrutiny. Aside from emissions reduction and performance targets, the impact of involving human factors such as willingness, productivity, and comfort in a smart transformation must be involved in the architecture. Through the use of DERs and shared district assets (e.g., heating and

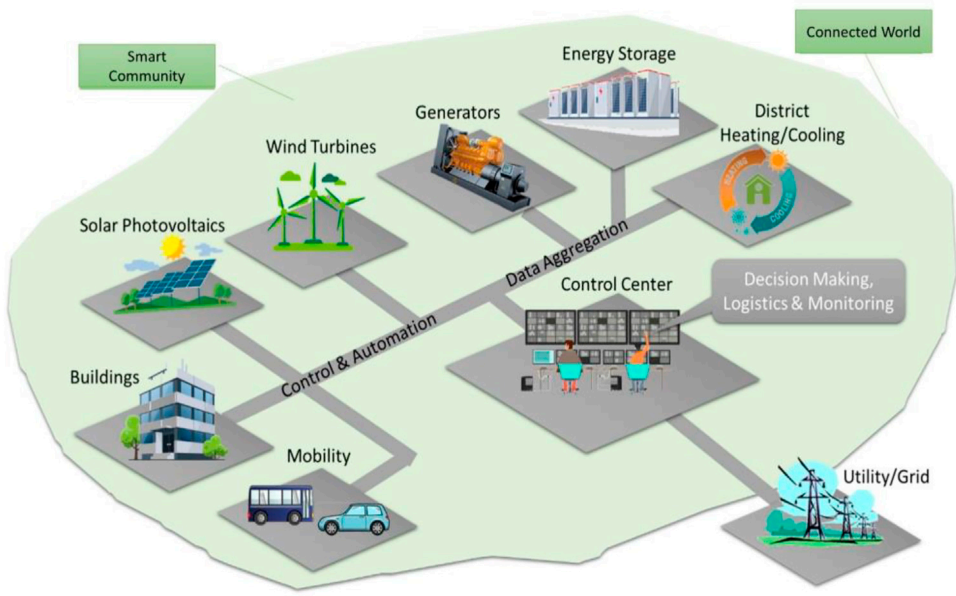

FIGURE 1 | High-level architecture in a smart community.

cooling, thermal storage, community solar, etc.), a smart community can improve its system resiliency to even contribute to its surrounding communities in normal operations and catastrophe events. A smart community can receive various signals from the connected world and combine these inputs with real-time information within its boundary to orchestrate its operation with municipalities based on different circumstances. Communication and IoT infrastructure of smart communities can create a real-time and fast-response system that is aware of single internal variations and external signals to enhance the system's flexibility and responsiveness in planning and operations.

Nevertheless, considering continual technological changes in automation, ESSs, energy resources, computing power, innovative artificial intelligence (AI) solutions, and ICT, the potentials are constrained. AI solutions can be developed further owing to increased data sources with higher resolutions, resulting in comprehensive planning schemes and more reliable and precise predictive modeling, which includes the state of all participating nodes in the system. This is enabled by big data analysis and database management system platforms that are able to analyze enormous amounts of data. In addition, novel IoT architectures facilitate data transmission within the community and enable prompt response decision-making and system monitoring. Considering an increase in technology efficiency and decreased costs, clean power generation and storage systems have been established as economically justifiable. Furthermore, innovative universal gateways and protocols allow for the integration of more technologies as a network, thus increasing the potentials further. However, in order for the communities to comprehend their options and use them in the best way implies a necessity for establishing a scientific framework and a set of decision-making tools. More specifically, it is necessary that these decisions are based on massive amounts of dynamic and static data to develop a feasible solution for the smart transition. The smart transition, accordingly, is based on technological and managerial options and alternatives but constrained by economic, regulatory, and social factors. **Figure 2** shows the decision-making stages required for establishing a transformation plan. The first stage is preliminary assessments, followed by setting targets, policy evaluation, virtual/physical prototyping, and economic analysis. The established targets should be checked by a decision-maker at each stage of the decision-making process. Furthermore, feasibility studies and technical/economic assessments should be considered to revise the transformation plan accordingly.

To test and validate our approach scientifically, we applied the method inspired from (Chang et al., 2018) (Yigitcanlar et al., 2018) (Joshi et al., 2016) (Gondokusuma et al., 2019) including the followings steps to explore the research problem. The concept of smart community and estimated smart transition plans form the observation of our underlying scientific approach, followed by the question of the factors impacting the smart transition and the necessary phases of the smart transition. Next, we hypothesize in line with our observations that smart communities are highly dynamic and complex systems that continually evolve and engage in the interaction between the components within the boundaries of the smart community and with the surrounding beyond the boundaries, where multiple factors have an impact on it.

We conducted virtual prototyping to perform validation and evaluation prior to actual phases and physical implementations. As it was shown, virtual testbed enables for the co-simulation of various components such as data-driven modules, optimization

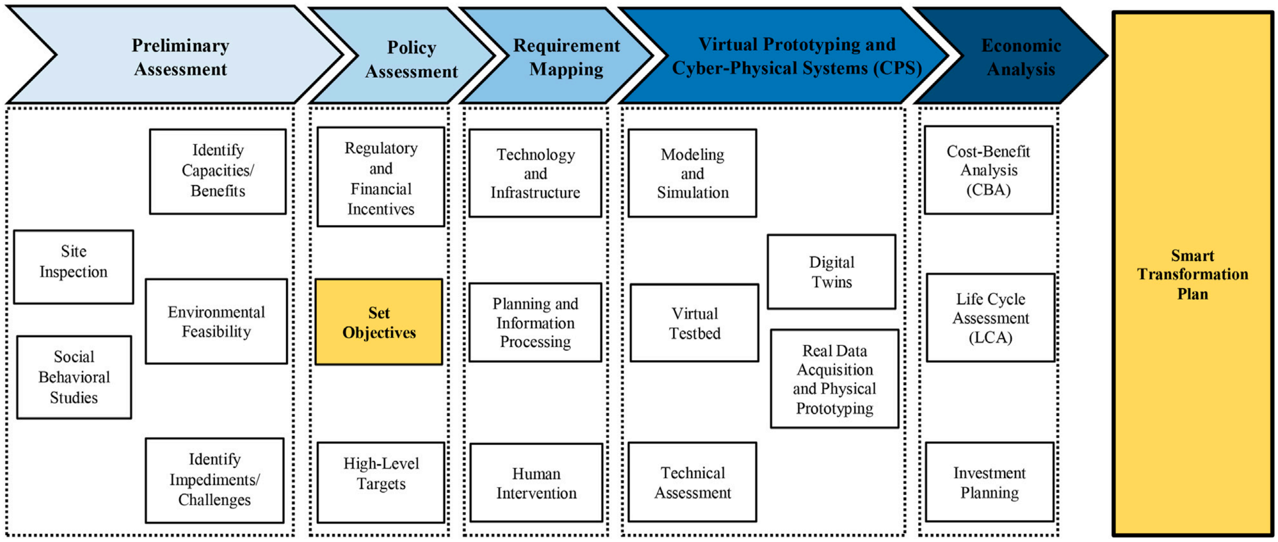

FIGURE 2 | Strategic framework and multiple decision-making stages to establish a smart transformation plan.

modules, simulation programs, and mathematical modules into a computer-aided software environment, which can model information and physical layers and interaction within the smart community boundaries but also beyond them to evaluate various scenarios and contexts impacting a smart transformation. More precisely, we developed a virtual prototype to analyze the dynamics and behavior of a smart community. The virtual prototype allows decision-makers to carry out dynamic modeling on using analytical tools on the performance targets and measures of a smart community and the impact of investment on advanced technologies under various scenarios and circumstances. In particular, we focused on the buildings being a critical element of the smart community. More precisely, buildings represent the most complex systems and primary consumers in a smart community. To illustrate, we conducted both deterministic and probabilistic modeling of input to analyze the state of the community and the state of the surrounding using a local data hub. We defined the inputs (e.g., weather conditions, occupancy patterns, electric equipment use, gas equipment use, and device failure). The following controlled variables were selected: temperature setpoints, mechanical plant setpoints, mechanical plant operation, zone equipment control, air system control, and lighting control. Furthermore, the decision-making engine, which conveys the signals to the smart community, comprises dynamic planning optimization, static planning optimization, adaptive planning optimization, and forecast modeling. In addition, we determined the building outputs to be measured, namely electricity consumption, gas consumption, plant sensor data, zone sensor data, and equipment condition, as shown in **Figure 6**. Furthermore, we developed the decision-making engine of the virtual testbed aimed at obtaining the state of the smart community. This decision-making engine conducts planning optimization, static planning optimization, adaptive planning optimization, and forecast modeling as well. In addition, it aims at ensuring optimal battery dispatch by controlling and analyzing power, total current, total voltage, and discharge; optimal EV charging schedule by analyzing EV SOC, charger, and availability, and district heating/cooling operation schedule by considering cooling energy and heating energy. These local data hubs consist of an analytical layer, exemplified by the decision layer, control signals to simulation, and energy asset simulation layer (**Figure 7**).

In the subsequent step, in order to test the prediction, we designed case scenarios to perform technical feasibility assessments and to determine the primary value propositions of the smart community. We conducted co-simulation of a small community in a virtual testbed (Lawrence Berkeley BCVTB environment) comprising centrally controlled and integrated EVs, a fast-charging station, small-scale wind turbine, solar panels, battery storage, and two buildings. Through this simulation, we estimated power generation using a possible loss of loads, imported power from the grid, the role of energy storage in supporting intermittent renewable power generation, and transportation demand, building, and renewable energy resources to provide insights about surplus power generation and resource contribution to the surroundings, the air quality of the built environment, cost savings, and carbon emission reduction. The technical assessments show how optimization and data-driven frameworks increase performance through fast response, predictive decisions as a dynamic integrated system. Such simulation can lead to results that can serve as a basis for forming new predictions and hypotheses.

3.3.1 Preliminary Assessment

As demonstrated before, communities represent complex systems comprising different geographic and demographic characteristics, which are primary enablers providing capacities and benefits for sustainability targets and establishing the roadmap for the energy transition of a given community.

Because renewable energy primarily depends on the presence or abundance of resources, the priority is a geological site assessment to assess available renewable options. In addition, demographics and social must be included in planning an energy transition. To identify plausible capacities of the site and the expected benefits from the transition, it is necessary to determine first the demographic and geological constraints by inspecting deficiency and abundance of resources and environmental limitations. The challenges to the plan implementation challenges should be taken into account as well.

3.3.1.1 Site Inspections

All communities have distinctive characteristics in terms of resources and current infrastructure and technologies. Typically, communities have on disposal smart lighting, building management system platforms, and district heating/cooling. Thus, an early-stage site inspection is needed to provide information about integrable assets and the necessity to upgrade or retrofit integration in a smart transition. The early-stage inspection includes assessing protocols, safety codes, risks, and asset ownership. In addition, to identify viable technologies and conduct feasibility studies, resource and land availability should be explored. In addition to the given community, it is needed to assess the surrounding and neighboring communities to identify particular limitations, needs, and infrastructure flexibility.

3.3.1.2 Social and Behavioral Studies

The main factors behind the transition to a zero-carbon city are social and human dimensions; therefore, visionary policies and full citizen participation are critical for achieving sustainable, tangible solutions. However, the correlation between human factors and smart transformation has not been clearly established due to a variety of those factors. Accordingly, the social and behavioral characteristics of the given community must be determined to identify the constraints, driving forces, and changing interactions between technology deployment and people throughout the transition. Whereas some behavioral and social attitudes contribute to the implementation of novel technologies during the smart transformation, others can hinder it. To summarize, contextual, economic, psychological, and personal factors together impact public acceptance and must be carefully investigated. In addition, it is necessary to define precisely the indicators for measure social adaptation and acceptance. In particular, it is necessary to include the socio-economic background of community members (e.g., gender, age, education, and employment), social and personal norms, attitudes and behaviors, position toward renewable energy, culture, time, system reliability, financial policy factors, knowledge, intentions to use, perceived enjoyment and sociability, anxiety, and costs. These indicators allow testing individuals' acceptability of a new system of energy technology and willingness to participate in the transition to a zero-carbon energy system. Such investigation will provide significant insights into the public's acceptance and adaptation toward new technologies and the transformation to a zero-carbon energy system. In addition, investigation of historical trends provides important insights into the adaptation of people to new technologies, which leads to their participation in the community transformation process. The transformation acceptance rates can considerably vary among the community members, depending on socio-economic factors, including gender, age, ownership, income, education, and willingness to purchase clean energy technologies. The awareness and acceptability of renewable energy systems and technologies are critical as well. Such insights are necessary to devise steps required for ensuring that new energy sources and technologies are accepted. More precisely, successful implementation depends on a proper understanding of social dimensions of flexibility for private and commercial elements of the community is pertinent to successful implementation.

3.3.1.3 Identifying Capacities and Benefits

The objectives of the system depend on its capacity, the capacities should be determined as well as expanded by a decision-maker in the pre-actional phase. Moreover, this phase should include identifying the communal resources and benefits expecting to result from the smart transformation. In addition, a smart community can operate as a responsive system embedded in future smart and sustainable cities. Importantly, the community has bidirectional interconnections with neighboring communities such as government bases, important facilities, and underprivileged communities. Accordingly, the benefits obtained by the smart community expand beyond its boundaries and therefore, are not limited to it. The benefits result from public welfare, infrastructure, resiliency, revenue streams, cost savings, resources, and the environment.

A strategic energy transition plan uses clean energy resources and energy-efficient solutions to achieve short- and long-term benefits regarding air pollution, ecological factors, climate change, and CO2 emissions. Communities with adequate infrastructure and resources in addition to efficient management can create benefits beyond the community boundaries. The paramount is resource sharing. To illustrate, district heating and cooling systems can be used to provide hot and cold water. Similarly, renewable energy investment opportunities are critical when there is available land within the community. Dynamic management increases capacities and enables the use of devices and information fusion, which, in turn, results in enhanced system performance. Consequently, the improved performance leads to cost-saving and more efficacy. Human comfort and well-being are improved whereas energy is saved via improved operation of the built environment and mobility. ESSs and DERs improve the capacities of the community by increasing its resiliency and preparedness against grid outages. In addition, the resilience of the surrounding is improved as well. Furthermore, during the normal grid operation, the community can be involved in the electricity market through frequency regulation and arbitrage to improve the reliability and operation of the grid and generate revenue streams. The smart community can contribute to a power system by preventing transmission and distribution line upgrades and consequently saving opportunities at a high level. The adoption of clean energy enhances human well-being and life quality and consequently enhances other capacities, which, in turn, result in numerous direct and indirect benefits.

3.3.1.4 Environment Feasibility

Furthermore, even in the case of economically viable and abundant resources, some strategic plans may not be feasible because of environmental constraints such as human health concerns, ecosystem conservation, and the protection of wildlife. Governmental environmental protection regulations also present limitations and prohibit certain practices. To illustrate, offshore wind technologies can endanger sea organisms and marine life. The development of hydropower and other renewable energies can damage the ecosystem, which is opposite to the objectives of the smart energy transition in communities. Therefore, the decision-making process has to take into account tradeoffs and penalizing factors in cost-benefit analysis.

3.3.1.5 Identifying Impediments/Challenges

Following the determination of the transition capacities and preliminary assessments, it is necessary to incorporate the challenges related to economic, social, and environmental dimensions in the transition targets. Any strategy must identify and include the main stakeholders in effective dialogue. The evaluation of deployment and implementation barriers is needed to determine the techno-economic challenges. Similarly, the assessment of challenges related to securing and preserving community goals in the long term is needed, as well as of challenges in effective operational control practices aimed at improving system performance and integrating human factors in decision-making and planning. Some examples are: How to approach equity issues to ensure that savings are properly trickled down among the main stakeholders? What are the social and economic drivers for people residing or working in the community to participate in energy efficiency and zero-carbon communities? What measures need to be taken to create a cost-effective smart community and to quantify the value streams? What are the implications for underprivileged communities close to the smart community? How can a smart community improve its surrounding municipalities socially, environmentally, and economically? What are the options for the last mile and integration of multi-modal transportation? How can electric vehicles (EVs) become a part of a smart community? Challenges related to privacy, system protection, and cyber security must be also considered when setting and mitigated by reliability measures at the asset level and precautionary security measures in ICT infrastructure at the information level. Privacy must be ensured by protecting user information using data protection methods such as encryption and anonymization.

Furthermore, the large-scale penetration of E-buses, E-trucks, and EVs can result in a considerable increase in electricity demand and a highly variable load profile for the community. Thus, it is necessary to envision solutions for this problem of conflicting energy reduction and mobility to minimize conflict. The strategy should look at load impact risks of EVs related to an increase in peak demand, uncertain demand changes to the distribution network, and economic and cost challenges. Researchers estimate a net increase in the overall miles traveled as a consequence of the growing adoption of commercial mobility solutions and autonomous vehicles. A drastic rise in EV and autonomous vehicle loads and its non-deterministic nature is likely to considerably influence the overall load profile of the host distribution network, resulting in transformation and substation failures. A functioning zero-carbon community should respond to these problems.

3.3.2 Policy Assessment

Policy and regulations are among the main drivers in an energy transition. Most of the time, investments and planning for smart energy transitions are not economically viable, or the payback periods are beyond an acceptable range and need government incentives and rebates. Besides, decision-makers put forth specific priorities that might contradict a viable transition plan in an existing community. Therefore, such political factors should be considered at both the early stages of decision-making and before setting the goals of a transition.

3.3.2.1 Regulations, Incentives

At the commercial level, there are financial constructs such as carbon credit or carbon tax, while for individuals, there are various types of economic incentives. Decision-making toward a transition should consider the flexibility to be offered either individually or at the community level through the collaboration of its constituents. The affordability of energy systems among buildings is often low, preventing investments that increase costs for the owners or tenants. Further, many business and technological solutions are developed and result in a lack of cost-effective solutions.

3.3.2.2 Master Plans and High-Level Targets

Governments set different sustainability priorities and targets. Communities are dynamic participating actors within smart cities, and, therefore, should be based on priority or high-level targets to achieve them. Master plans include technological priorities on the basis of factors initiated by legislation or government officials. The governmental master plans and priorities are aimed at unlocking government incentives and creating momentum to achieve sustainability goals and smart city targets (Zaidan and Abulibdeh, 2020).

3.3.3 Setting the Objectives

Considering a lack of a comprehensive definition of a smart system in the context of smart cities and communities, it is necessary to conduct preliminary assessments to set goals within a smart energy transition framework as a multidisciplinary practice. It is recommended that a plan includes measurable financial, social, physical, and virtual boundaries and attributes (e.g., environmental footprint, reliability, economics, efficiency, performance, and capacity). Having initial options that can be further developed is a prerequisite for a community to plan and assess the transition process. Planners and investors must follow a wide range of

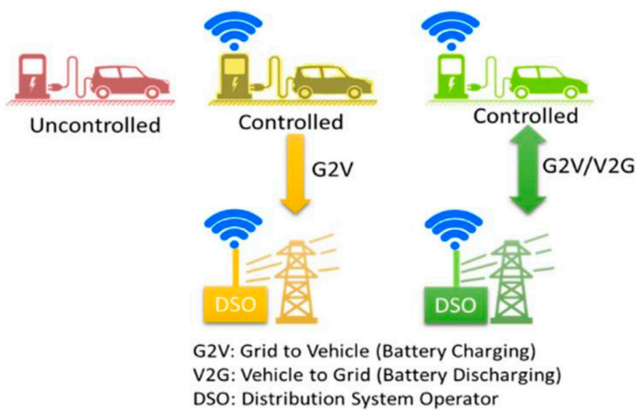

FIGURE 3 | Various options for the integration of EVs in a smart community.

mixed or individual objectives at the pre-decision stage. Considering the importance of emission and monetary factors, they should be sub-categorized. The factors that ensure direction to transition targets are security, welfare contribution to the smart city, human productivity, resiliency, reliability, responsiveness, and service quality. A weighted sum of a set of targets should be a basis of the transition plan of a given community. Nevertheless, it is a challenge to quantify those targets and assign the weight vector.

A critical measure for assessing the goals of a smart community toward transformation into a zero-carbon community is the rate of carbon emissions and other hazardous gases (e.g., NOx). Building/community demand to measure emissions, power import from the grid, emergency backup generators, transportation, and clean on-site resources serve for smart community's continual monitoring of power generation. Using the monitoring system also allows the assessment of the possible loss of load for resiliency metrics, system stability, power quality, cooling/heating demands, and the balance between the supply and buildings' electricity demands. The effectiveness of a smart community can be also assessed via measures such as responsiveness and interoperability of the system, which are based on failures within the network, error rates, data traffic, and the control and device response time. The amount of cooling and heating energy and electricity exported to the surrounding is another measure used to evaluate the system's contribution to the grid. Analyses of human productivity and performance and survey studies serve to monitor human impact dimensions.

3.3.4 Requirement Mapping

Meeting smart transition targets requires appropriate means and infrastructures along with effective management and interventions. Before framing the roadmap and architecture of a smart community, targets and expectations from the transition should be mapped using a set of effective tools. The tools are not limited to physical assets but also include logistic and management plans. There are enablers that can be leveraged to achieve the aforementioned goals. A robust technology plan and its implementation as supported by a life-long commitment are essential in the transition. Different power generation resources, ESSs, energy recovery systems, district heating cooling systems, smart lighting systems, HVAC technologies, and EV fast chargers are among the enablers that are in accordance with the transition targets. These assets can be individualized or shared at the community level, or a combination of both. Besides, one may decide on the use of advanced technology options with regard to automation and ICT such as IoT infrastructure, cloud services, edge technologies, advanced monitoring systems, distributed and adaptive building controls, transactive demand reduction, metering, and sensor devices, and so on. In addition, management and operation policies are necessary to implement the assets and infrastructure in an effective way to improve the overall system's performance. Some of the policies that pave the way toward the community goals include advanced control logic in a built environment's control, optimal scheduling for EV chargers, optimal dispatch planning for energy storage, and prognosis maintenance planning. Finally, the role of human factors in a transition should not be omitted. Most of the time, intervention strategies to shape and establish behavioral factors are necessary for positive motivational, coercive, and incentives approaches.

3.3.4.1 Technology and Infrastructure Requirements

Considering technology, numerous forms of constructs and enablers have been developed in energy and transportation. Following the transition goals, the next step is to compile a high-level matrix of technologies and relate them to the targets. Individual enablers contribute to reaching multiple targets with particular physical and financial constraints. It is possible to categorize the enablers of a smart energy transition into ICT infrastructure, automation, transportation electrification, ESSs, and energy and power generation resources. Technology and infrastructure are aimed at ensuring information fusion for real-time and optimal decision-making and the ubiquity of devices. The responses to the system state should be considered while managing and reshaping the end-use loads related to built environments and mobility. Communication and automation are used to create synergy within the community. To do so, it is necessary to employ decision-making platforms, computation modules, monitoring systems, IoT infrastructure, data aggregation, and sensor device, as well as measurement.

To establish a responsive and resilient energy system that can mitigate emissions and cost, ESSs and DERs should be implemented in smart communities. In the communities with available on-site resources and land availability, DERs can be used. Renewable energy resources such as ocean thermal energy conversion (OTEC), water waves and tidal energy, geothermal energy, offshore and onshore wind generation, and photovoltaic systems, and low and zero-carbon technologies such as CHPs and fuel cells can contribute to zero emissions. ESSs such as flywheels, hydrogen energy storage, and batteries can be integrated with to generate a dispatchable system and prevent an intermittent power supply. Technologies such as natural gas generators and diesel

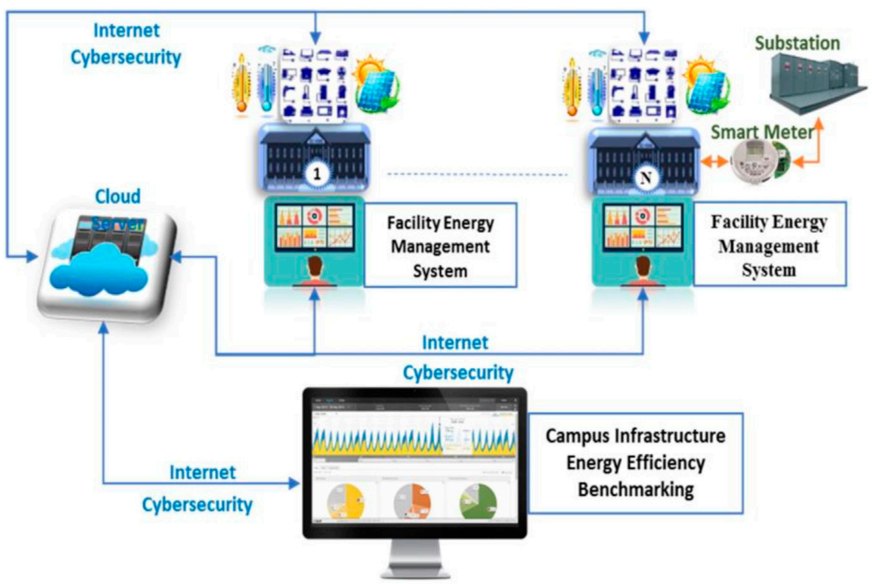

FIGURE 4 | Flow of information and system management in a smart community.

can be used for catastrophe preparedness and in the cases of blackouts as reliable, fast-response emergency backup systems to enhance system resiliency. To integrate these technologies, it is necessary to employ electronic devices such as voltage control across the power network, transformers, and inverters. When integrated with the grid, the system can import and export electricity on the basis of the balance between the supply and the demand on both sides.

District steam, cooling, and heating systems can be established in some communities. Chilled water is generated by chillers, whereas low, medium, and high-temperature water is generated by large-scale boilers. Thermal storage and the heating network combined can control the optimal dispatch of hot water generation. Ice storage units and district chillers combined can enhance their efficacy and displace their demand from peak demand periods to low demand periods. In the case of low cooling and heating demands in a community, the interconnection of steam networks and the hot and chilled water with the surroundings benefit the aggregate system.

Different communities are equipped with various types of light, medium, and heavy-duty vehicles, such as facility service fleets, freight transportation, university transit systems, and personal vehicles. Transportation electrification alternatives to be used in smart communities are battery and plug-in hybrid EVs. There is considerable potential of transportation for electrification and consequently, carbon footprint reduction. A system of distributed batteries can be used to implement EVsto stabilize and balance supply and demand within a power distribution network. EVs have become trustworthy and reliable for users owing to the advancement of fast chargers. Nevertheless, economic and cost challenges and load impact risks related to uncertain demand changes to the distribution network and peak demand increase are associated with fast chargers and EVs. **Figure 3** shows that it is possible to differentiate controlled and uncontrolled EV-charging topologies can be differentiated. Smart communities and controlled topologies can be easily integrated to achieve the building demand through the grid-to-vehicle (G2V) and vehicle-to-grid (V2G) principles and for load balancing. The optimal dispatch control over the state of charge of the batteries contributes to emissions reductions and uses EVs in an economically viable way. V2G can be used efficiently during times of high peak demands and in both parking facilities. Vehicle-to-home (V2H) can also contribute to transacting load flexibility and reducing peak demand.

ICT systems based on a centralized web-based architecture allowing data accessibility across the smart community unlock the information fusion. The architecture is divided into a data sources layer, application layer, and network layer. The demand containing EV charging, occupancy patterns, building meter data and multiple sensor data points is the main data source. Other data segments consist of the state of charge of the ESSs and the time-series data for power supply. Measurement services and sensor points need particular communication protocols and devices with resolutions based on the service application and various granularity levels. Protocols such as BACnet for building management systems serve to ensure information integration and exchange at the local level. On the basis of the gateway protocol architectures of the IoT, as shown in **Figure 4**, they can communicate with the high-level network. Backend servers such as web interfaces for real-time decision-making and control and DBSM and other applications such as failures and anomaly detection the information and data flow. Technologies such as cloud computing, as well as fog and edge computing at an advanced level, are employed to ensure system performance due to the need for fast and responsive control signals and a high rate of data accumulation in a system. To ensure a responsive and infallible computing system, a suitable design for data preprocessing and database structures is needed as well.

The cloud-based decision-making platform acquires an enormous amount of information regarding the state of the sub-systems and processes the input to detect anomalies within a system's components and propose an optimal operation plan for the network. Subsequently, the optimal control signals are implemented using field equipment such as DCS, DDD, and PLC, conveyed to the local facility level processes, and interpreted with the Fieldbus protocols, applications, and supervisory networks.

Smart communities also represent adaptive and dynamic connected systems, creating synergy within the system and beyond its boundaries. Synergy occurs via real-time data exchange and considerable data fusion owing to ICT. Accordingly, an open and expandable ICT infrastructure is required during the smart energy transition to achieve efficiency and connectedness. Thus, ICT is regarded as enabling technology that integrating the human factor into decision-making, serves as a reliable information exchange, measures, assesses and controls to enhance efficiency. Thus, by creating synergy, ICT allows the system's participation outside of its boundaries and in the smart city and connected world. The smart communities consist of the components that are data sources. Accordingly, their state influences the entire framework as a dynamic system. Most of the exchanged information is based on the massive amounts of data flow to be handled by big data manipulation and processing.

Owing to expected responsiveness, real-time system, and scale ICT architecture in the smart community represents an intricate system. Therefore, it is necessary to investigate objectives to set goals for management, data queries, and data acquisition, interconnections, processes, and components. It is needed to classify data sources to evaluate the system's requirements and determine proper granularity levels. Consequently, the connected system can be orchestrated instantly. Thus, a conceptual design should identify the functional requirements, components, consolidation processes, attributes, and entity relationships to build a logical data model before implementing the ICT. Preliminary assessment of performance and technical feasibility of various topologies for data collection and transmission is needed to establish an uninterrupted, continuous system. Centralized control, and flexible connectivity methods for edge device integration, centralized control, lowered installation and configuration periods of costs, reliable and scalable IoT cloud infrastructures, and user-friendly interfaces can lead to connectivity cost reductions. It is required to predefine data collection and protection and incorporate them into a system's architecture.

Metering endpoints and sensors in automation and management systems follow standard industrial communication protocols such as BACnet, analog/digital I/O, Mbus, and Modbus RTU, and identified for the physical layers of the network. In addition, legacy and existing devices unmatched by the architecture can be integrated with interface modules and protocol converters. Wireless network technologies, cloud services, IoT applications, asset tracking applications, gateways, physical and communication layers, hybrid communication strategies, edge devices, and actuators and field sensors should be explored on the basis of different options regarding the coverage and exchange rate to establish a reliable communication system. Anonymization and encryption and other network and application layer security measures such as encryption and anonymization protect user privacy and system's operations.

3.3.4.2 Planning and Information Processing Requirements

Adaptive and dynamic decision-making in the context of advanced technologies and extensive data fusion practices can considerably influence the performance and operation of communities regarding economic, social, and environmental measures, as well as mobility and energy. In addition, these technologies and practices impact the interaction of the smart community with the surroundings because it is a sub-system of smart cities and societies. Decision-making processes are based on methodologies related to data-driven approaches (e.g., reinforcement learning, deep learning, and ensemble learning) and advanced optimization (e.g., adaptive, dynamic, and static) to gain from the data. The transition is highly dependent on such tools in the pre-actional phase and subsequently during the entire system's lifetime.

Short-term and long-term decision-making tools can be used for resiliency preparedness, surrounding interconnection, ancillary services, EV charge station planning, energy storage dispatch, resource planning, optimal power flow, building automation, maintenance planning, system upgrade planning, and investment planning. To illustrate, building operation schedules following optimal plans aim at cost reduction and energy efficiency consider factors such as on-demand planning and control, pre/post-occupancy, environment quality monitoring, temperature and humidity setpoint assignments, equipment control, load shift, resource availability to carry out actions such as smart lighting system control, asset conditions, occupancy, air quality, and weather conditions. The optimal actions stem from advanced optimization models processing input variables to determine a feasible solution by taking into account system constraints and objective functions. Those tools are selected during the pre-actional phase following community needs. When selecting the tools, it is necessary to specify state variables, control variables, technology parameters, and cost elements together with relevant projections and data repositories. At this state, the selection of algorithms and solvers and adequate dynamic/static and deterministic/stochastic is performed. Component behavior and relevant distribution functions are chosen and assessed if simulation tasks are needed.

In addition to the decision-making tools, AI applications and data-driven models serve to support system monitoring and predictive planning, carry out classifications and clustering, determine anomalies, and predict trends. Applications needed in the transition are fault and failure detection of assets, occupancy patterns, EV charge station usage, and prediction of building demands. The data-driven tools can process diverse and massive data sets to conduct predictive modeling, business intelligence, data visualization, and statistical analysis, and implement state-of-the-art AI applications.

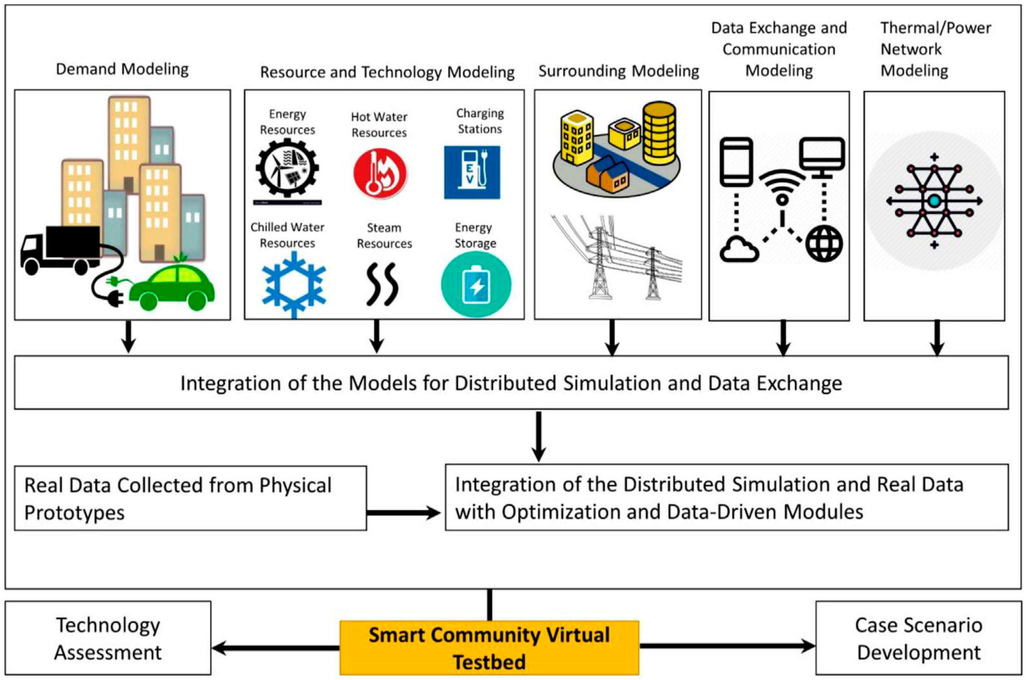

FIGURE 5 | Development of a virtual prototype to analyze the dynamics and behavior of a smart community.

3.3.4.3 Human Intervention Requirements

As discussed before, social and human factors impact the decision-making process and smart transformations. Before the implementation, it is necessary to analyze demographic data and conduct surveys on the target society to determine the amount of acceptance of new technologies and human participation in smart transition practices. If social or psychological factors hinder the smart transition implementation process, it is necessary to conduct intervention measures and the establishment of new norms before the actional phase. It is recommended to establish new behavioral factors such as skills, trust, emotions, attitudes, personal norms, and social norms to increase communal participation and achieve transition targets. In addition, intervention strategies should encompass coercive, motivational, and positive incentives within the community.

3.3.5 Virtual Prototyping and Cyber Physical Systems

Smart communities and smart transformations represent non-deterministic and complex systems; accordingly, virtual prototyping is required to perform validation and evaluation prior to actual phases and physical implementations. It is aimed at establishing a virtual testbed for the co-simulation of various components such as data-driven modules, optimization modules, simulation programs, and mathematical modules into a computer-aided software environment, which can model information and physical layers and interaction within the smart community boundaries but also beyond them to evaluate various scenarios and contexts impacting a smart transformation. The integration and communication between the component blocks during co-simulation development are highly challenging. More precisely, data flow and integration refer to the integration of the components of the smart community. Thus, stochastic and probabilistic modeling of input variables on the basis of validated and real data aimed at ensuring more representative and realistic interactions of the components. As shown in **Figure 5**, the actual representation of a system's dynamics and system's component models allow the development of a virtual prototype for decision-makers to carry out technical evaluations of various technology combinations (see **Figure 5**). The virtual prototype allows decision-makers to carry out dynamic modeling using analytical tools on the performance targets and measures of a smart community and the impact of investment on advanced technologies under various scenarios and circumstances.

3.3.5.1 Mathematical Modeling and Simulation Tools

The behavior and dynamics of components of the system of the smart community are subject to change under various circumstances because they are not deterministic. Transportation systems, cooling/heating plants, storage systems, power and energy resources, and buildings have to be modeled before actional phases during a smart energy transition. It is necessary to integrate those components into simulation testbeds and co-simulations for feasibility assessments and technical analysis of various portfolios. Commercial tools for built environments and community assets used to simulate complex systems are Dymola, Trynsis, and EnergyPlus. Typically, simplified mathematical models are used to perform technical feasibility studies. Also, in decision-making and planning, they can be integrated into optimization

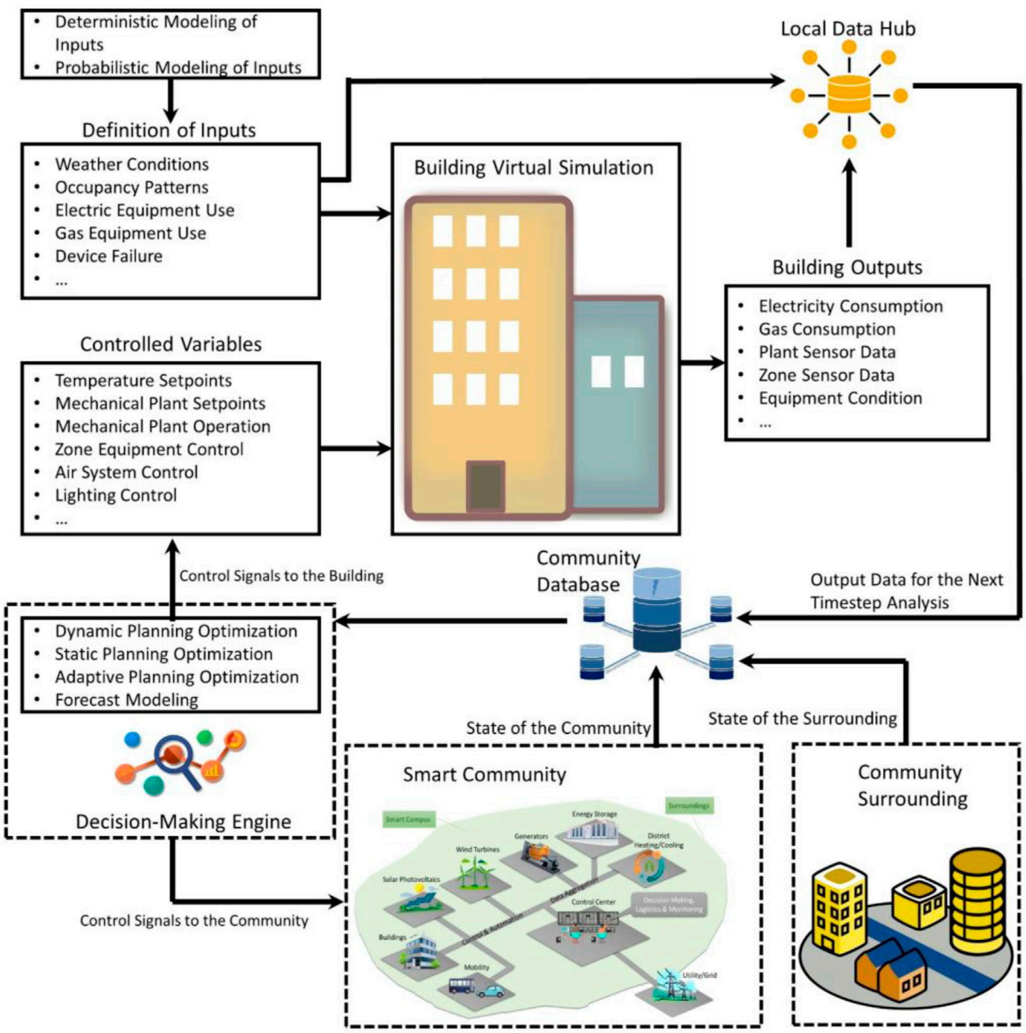

FIGURE 6 | Example of input/output streams of data for a building as a component of a connected ecosystem.

models. In this transition assessment phase, decision-makers decide on adequate computer-aided engineering tools for the modeling process and the complexity level.

The most complex systems and primary consumers in a smart community are buildings (Jafari et al., 2020). Mathematical modeling and obtaining precise results of such systems is challenging; however, TRYNSIS and EnergyPlus can be used to conduct reliable analysis. Under different circumstances, simulations offer different parameters (e.g., indoor air quality) and outputs (e.g., load profiles). For instance, simulations can identify buildings' saving capacities and opportunities. The simulation of a real building is costly and challenging; however, it is possible to calibrate reference models for various functionalities on the basis of weather conditions and actual buildings. Furthermore, DERs are critical components of the smart community aimed at achieving targets regarding interaction with the surrounding communities, cost reductions, resiliency, and emission reductions. Simulation tools and theoretical models investigate the dynamics of such systems within a smart community regarding degradation, asset failure, physical and operational constraints, design parameters, and input and output variables. Those models are processed in planning and optimization models, simplified and linearized forms, and as complex models operating in virtual testbeds and co-simulations. Thermal and power connections and networks are investigating in the modeling process in system simulations and planning optimization to perform a reliable analysis of the dynamics of the system in a smart community. The following factors are including in power flow modeling: loads in decision-making, storage, the interconnection of power generation, active/reactive power, power quality, voltage constraints, and power loss. In addition, piping systems and thermal networks need to be modeled to represent thermal losses and the connection between resources such as physical constraints in the system, heating/cooling demands, heat recovery systems, CHP units, boilers, and electric/absorption

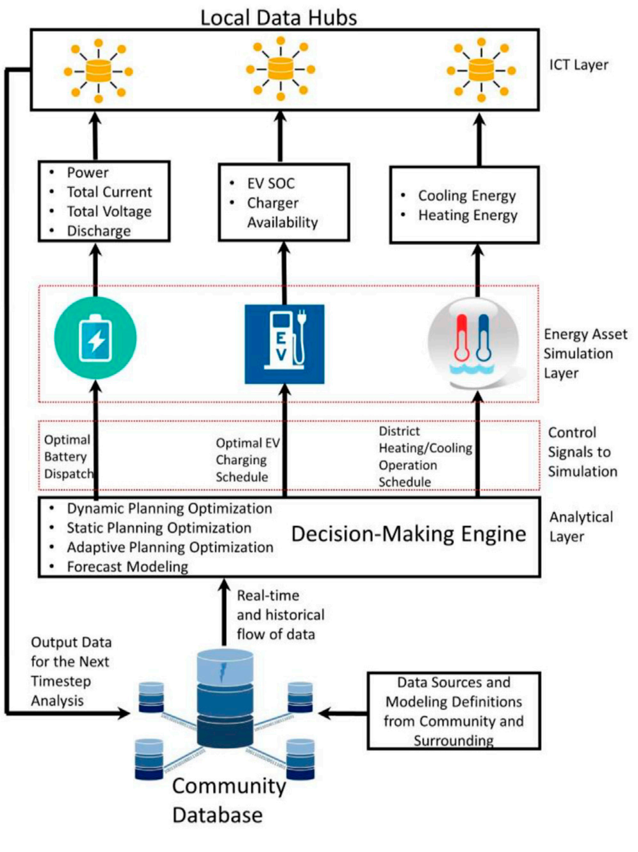

FIGURE 7 | Example of input/output data streams to control shared assets of a smart community.

chillers. Communication and data exchange within a smart community must also be modeled to generate a realistic representation of the following factors: network delay, failure, noise, and data traffic. These assumptions enhance the transition analysis by encompassing factors in dynamic and real-time decision-making to achieve synergy within the system. Transportation systems, particularly charging stations and EVs, can be included in the modeling process to show the behavior of end-users in the system. Modeling the interconnection of a community with the dynamic behavior of the surrounding communities regarding thermal and power demand enhances the transition assessment. The surrounding community behavior is assessed on valid assumptions and historical data to evaluate the demand beyond the system's boundary and the interactions between the available community's resources. Factors such as social dimensions, climate patterns, energy market behavior, contingencies, and power outage events are modeled via historical data.

3.3.5.2 Virtual Testbeds

A virtual testbed is aimed at unlocking the co-simulation of advanced simulations such as TRNSYS and EnergyPlus, decision-making and optimization tools, and possible mathematical models, optimization and decision-making tools, data-driven and predictive models, and advanced simulations such as EnergyPlus and TRNSYS in one software environment to represent a system's components, including surrounding communities, human behavior, data communication, EVs, ESSs, power generation technologies, and buildings. Inter-process communication tools such as Berkeley sockets embedded in building virtual control testbeds (BCVTB) proposed by Lawrence Berkeley Labs allow input/output streams of data among all the components. To illustrate, other variables should be processed in addition to incidental solar radiation and outdoor temperature to simulate a building's physics over time. Controllable variables are related to the operational signals and control generated by decision-making tools embedded in a dynamic simulation to compute the optimal signals, analyze the state of the system, and obtain the state of each simulation block. This structure enables the user to perform various optimization practices regarding adaptive, dynamic, and stating planning and to virtually compare their influences on performance measures and targets of the community. Lastly, the output stream evaluates each component's state, including state of charge of batteries, solar generation, building's indoor temperature, and building demands. Owning to streams of data and information, dynamic simulation stores and tracks all the interactions within a system.

As discussed previously, stochasticity inputs are embedded into the virtual prototype of a smart community to provide a more reliable and realistic assessment. It is possible to use data repositories or on-site real data to assess the model parameters of the stochastic inputs. To illustrate, instead of using deterministic assumptions, stochastic inputs to model occupancy patterns can be constructed using the occupancy data for buildings. Moreover, it is possible to model asset failure using equipment failure data to assess a system's responsiveness and reliability. In addition, the resiliency of the system can be estimated accurately using historical power outages. Examples of a dynamic simulation using virtual prototyping for a set of community-level technologies and building on the basis of the integration of optimization modules and stochastic input models in a system are shown in **Figures 6**, **7**. **Figure 6** shows how model definition inputs such as occupancy and weather patterns are generated on the basis of deterministic and stochastic and passed over a building's simulation. Data streams can be simultaneously transferred to a decision-making engine to compute control signals, such as thermostat setpoints and a sequence of operation of equipment and the database of a virtual testbed by considering the state of a community and its surroundings.

Figure 7 shows a scenario in which the decision-making engine of the virtual testbed obtains the state of the smart community such as occupancy profiles, weather conditions, and its demand/supply patterns, weather conditions, occupancy profiles to establish optimal operation schedules for a district heating/cooling plant, EV charging station, and battery storage. The deployment and integration of the optimization and analytical modules require the engagement of the management of

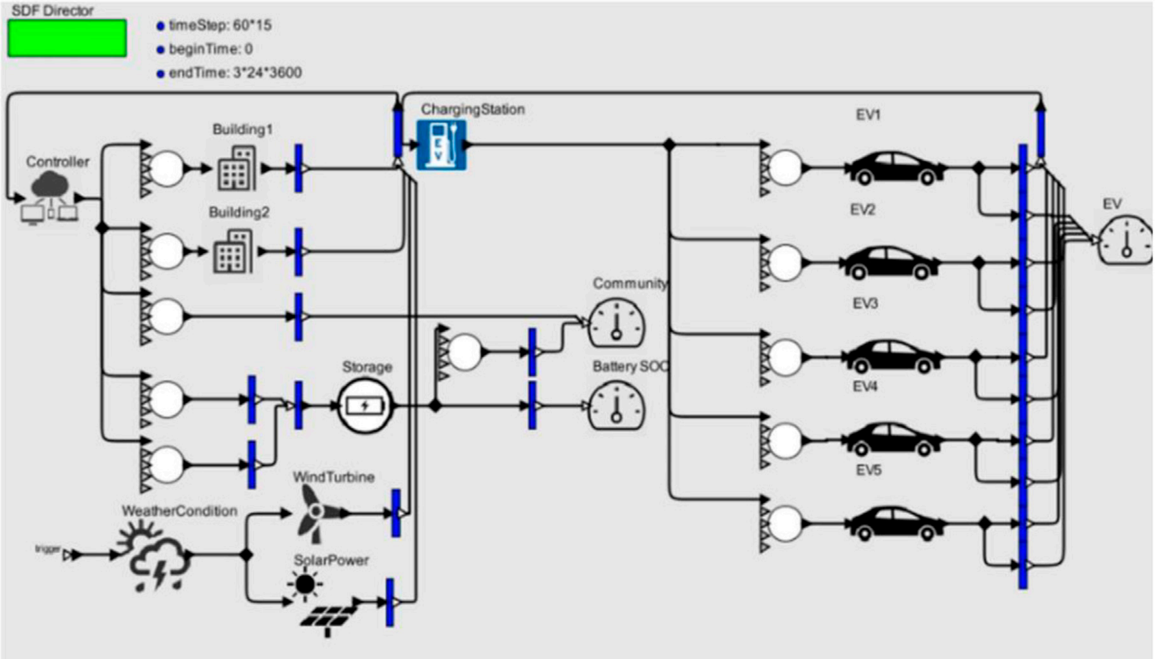

FIGURE 8 | A co-simulation example representing a small-scale smart community.

large data streams of data into a system and must be investigated during the construction phase of a virtual testbed.

3.3.5.3 Technical Assessment

Following the construction and integration of a virtual testbed and testing the system following the smart community's architecture, the next step is to design case scenarios to perform technical feasibility studies and to determine the primary value propositions of the smart community. **Figure 8** shows a co-simulation of a small community in a virtual testbed (Lawrence Berkeley BCVTB environment) comprising centrally controlled and integrated EVs, a fast-charging station, small-scale wind turbine, solar panels, battery storage, and two buildings.

This example shows the simulation of the system for planning externalities such as EV demand and weather conditions and time resolutions and horizons. Such a case scenario estimates power generation using a possible loss of loads, imported power from the grid, the role of energy storage in supporting intermittent renewable power generation, and transportation demand, building, and renewable energy resources to provide insights about surplus power generation and resource contribution to the surroundings, the air quality of the built environment, cost savings, and carbon emission reduction. The model can leverage various control policies in the operation planning of battery storage systems, EV fast chargers, and buildings in terms of the real-time and predicted state of the system. The analysis outcome should be compared with base case scenarios without smart architecture. Various combinations of portfolios and technologies regarding communication systems, control, transportation, buildings, and energy and power resources must be investigated to identify how components of the system contribute to achieving the targets of a smart community. The role of base case scenarios is to show how the smart transition and transformation to a connected system equipped with advanced technologies enhance a system's performance and contributes to sustainability targets. The technical assessments show how optimization and data-driven frameworks increase performance through fast response, predictive decisions as a dynamic integrated system.

3.3.5.4 Digital Twins

To generate digital twin applications, a virtual testbed is implemented at the decision-making stage and throughout the system's entire lifecycle. Digital twins were proposed several decades ago; however, owing to the exceptional advancement of the IoT, they are now regarded as future tools (Jafari et al., 2020). Importantly, digital twins can integrate machine learning and AI to combine contexts, algorithms, and data. Consequently, organizations can monitor items remotely, predict problems, and test new concepts. Previously, digital twins were aimed at enhancing the single asset performance (e.g., engine). Currently, they are used in the systems of assets at the organizational level. Thus, it is possible to implement the virtual testbed as a digital twin engine to include various types of process-based, statistics-based, and physics-based models, or their combinations.

3.3.5.5 Real Data Acquisition and Physical Prototyping

Although virtual testbeds can provide insights toward the impact analysis of smart transitions and technological feasibility, the acquisition of real data samples from the community and physical prototypes can enhance the reliability of the decision-making process. This phase can be regarded as a small-scale field experiment that enables the decision-maker to partially validate the virtual evaluations by real data. An IoT prototype can ensure expectations and system requirements. For instance, the range or data rate can be checked regarding a system's responsiveness. Further, a small-scale PV-battery system or EV charge station can be used for both system assessment and data acquisition. Human interaction with technological prototypes can be tested and selected accordingly. Physical prototypes can even be integrated with a virtual software environment to assess the impact of planning and optimization modules on actual asset performance.

3.3.6 Economic Analysis

The evaluation of the smart community transformation is paramount to determine if it is worth modifying the lifestyle and the infrastructure to incorporate smart features such as optimal resource allocation, grid resiliency and responsiveness, less GHG emissions, energy-saving, and smart transportation. Thus, the assessment should answer if the transformation would enhance the well-being of the residents. The indirect and direct costs of services and technologies must be assessed in order to estimate the economic justification of the project and included in the planning and decision-making process. Moreover, it is necessary to quantify benefits related to system responsiveness, resiliency, environmental factors, energy efficiency, and performance. Government incentives, transfer payments, subsidies, and tax rebates should be analyzed in this phase.

On the other hand, in the phase of the transition's economic analysis, business models and financial concepts should be adopted taking into consideration technological requirements, advancement, pricing, and availability to enable deployment. The smart energy transition must incorporate economic viability and financial sustainability factors. However, many options are not economically viable due to high technology prices, implying that new non-conventional, innovative solutions are needed to ensure financial benefits for individuals and commercial entities benefit from the transition. The justification of the economic viability of the transformation should be based on the quantification of its potentials and benefits of it. The potentials and benefits depend on particular demographics and other characteristics of specific societies.

The analysis should include, base case, time frame, goals, and project alternatives. In the second stage, non-monetary, indirect (intangible), and direct (tangible) impacts are determined. In the third stage, the costs (e.g., operation, maintenance, and capitals costs) and benefits (e.g., tons of carbon saving and kWh energy saving) are determined. In the fourth stage, quantified costs and benefits are combined under common terms. Importantly, other valuation techniques are used to estimate indirect costs, particularly in the cases of market imperfections, including fiscal policies distorting the markets, externalities, and market power. Following the monetization of all factors, their present value is determined in the fifth stage by discounting. Finally, the comparison of costs and benefits is conducted in the last stage by considering different interest rate scenarios.

3.3.6.1 Cost-Benefit Analysis

Owing to its design and objectives, a smart community can significantly benefit its surrounding, and it also must be included in the quantification for the CBA of the project. These benefits can be social, environmental, non-monetary (cost reductions and savings), and monetary. All these factors should be assessed when developing alternatives of smart transformation to estimate their feasibility. More precisely, it is necessary to quantify all the benefits and convert them to monetary values to allow comprehensive economic analysis. Thus, it is necessary to develop performance metrics to assess the benefits and value propositions in regard to targets, including service quality, responsiveness, smartness, resiliency, sustainability, and cost savings. Consideration of detailed economic impacts and investment assessments of technology portfolios is needed to perform CBA.

The critical drivers behind the design and functioning of a smart community are economic factors and costs. The deployment of on-site resources such as thermal and electric storage systems, cooling plants, district heating, and renewable or clean power generation serve to achieve revenue streams and cost reductions. Moreover, this can improve the performance of other communities as well. There is no need to import electricity from the grid in the case of on-site and distributed power generation; moreover, this form of power generation also enables the export of the surplus and participation in the electricity market for ancillary services and operating reserves. Accordingly, revenue streams are created and the operation and reliability of the grid are improved. In addition, on-site power generation is likely to reduce the costs related to the use of electric fleets and create opportunities such as V2G. Furthermore, the dispatch of power generation resources for optimal operation of increased cost-effectiveness can be achieved through energy storage technologies. In smart communities, district heating and cooling technologies can be combined with thermal and ice storage plants to provide additional hot and chilled water resources, leading to cost reductions and revenue generation. Furthermore, indirect cost benefits are created via DERs for a smart community by eliminating expensive new peak power plants and a necessity for distribution/transmission upgrades and new peak power plants, which are generally costly.

Transportation electrification, the energy efficiency of the buildings and the use of renewable and clean energy resources lead to environmental benefits. Furthermore, it is assumed that the interconnection of smart communities at a larger scale is likely to replace fossil fuel-sourced power with clean electrons or to eliminate current power plants. It is necessary to include both the supply and demand sides when evaluating the environmental impacts of smart transformations can be. The demand side benefits are owing to consumer behavior and energy efficiency (e.g., reduction in particles and air pollution) and the supply-side benefits occur because of the increased use of green energies.

Moreover, owing to the service quality and responsiveness of the system, smart communities also improve social and human dimensions. To illustrate, DERs can prevent power outages by evaluated the value of load loss. However, it should be noted that resiliency metrics vary in value depending on the type of the applications (e.g., critical facilities). In addition, with proactive strategies aimed at failure avoidance and data-driven prognosis, it is possible to considerably enhance asset maintaining using asset condition monitoring. Consequently, it enables significant cost savings. Using sensors and automation systems to improve measures such as life quality, productivity, and health, a more comfortable environment is created for building occupants. Reliable EV fast chargers and smart traffic controls lead to improved experience and service quality. The human factor should be included in control loops and decision-making to account for preferences and habits. Smart communities can also contribute to the generation of a new supply chain system to advance further business development and job creation. Smart transformation is also likely to result in additional human involvement. It is also recommended to use beneficiary perspectives such as multi-criteria analysis (MCA), social cost-benefit analysis (SCBA), and private cost-benefit analysis (PCBA) to assess CBA.

PCBA takes into account the costs and benefits from alternatives imposed on or accrued to private sectors (e.g., companies or individuals). More precisely, it takes into consideration the transfer payments such as taxes and subsidies that private entities pay to the administration or receive from it. The financial appraisal is the term used to refer to this variant of CBA. In SCBA, environmental impacts can be assessed or omitted.

SCBA deals with the costs and benefits accrued to society in general. Social costs and benefits are typically not the same as private ones due to current market imperfections, such as government intervention in the market (e.g., price regulations, subsidies, and taxes, imperfect competition in the market (e.g., monopoly power), and externalities and public goods. Thus, MCA represents a decision support method for assessing and comparing different alternatives such as concrete cases of applied instruments or different policy options. To compare the alternatives, it is necessary to use the performance of a selected set of evaluation criteria in the form of a consequence table or performance matrix. In the matrix, each row shows the performance of the alternative against each criterion, whereas each column represents an alternative (case). MCA begins with defining the aims, the decision-makers, and the other stakeholders. In the second step, alternatives are identified, whereas criteria are defined in the third step. In the fourth step, the performance of each alternative is described against the criteria in the performance matrix, and the score matrix is determined. In the fifth step, each criterion receives weight to set the relative importance. The overall values are calculated in the sixth step, whereas the results are analyzed in the final step.

3.3.6.2 Life Cycle Assessment

Smart developments in transportation, resource management, and energy will lead to reducing the damage to the environment. Nevertheless, it is important to note that indirect damage to the environment might increase during the production and implementation stage of smart solutions. Therefore, it is necessary to consider the indirect environmental impact in the smart transformation process. Thus, LCA is an instrument aimed at determining the trade between the ecosphere and the technosphere during the life cycle phase of a system by assessing possible environmental effects and resources allocated during the life cycle (e.g., raw materials, extraction, waste treatment) of the product or service. It is a trustworthy and reliable, reproducible method based on user guidelines published by the European Commission and the ISO standardization (ISO 2006a and ISO 2006b). LCA comprises four stages according to the ISO 14040:2006 guidelines: 1) definition of the goals and scope of the assessment, 2) inventory analysis, 3) impact assessment, and 4) interpretation of the life cycle. The purpose of LCA is to determine the best available life cycles with minimum adverse environmental impacts to choose significant indicants of an organization's environmental behavior and to assist decision-makers with strategic planning and system design.

3.3.6.3 Investment Planning and Economic Feasibility

Following the determination of direct and indirect benefits and cash flows of the transition project, it is possible to implement different capital budgeting approaches to assess the financial viability of the plan. It is recommended to incorporate risk factors and adopt a real-options approach and incorporating risk factors during the investment and planning stages of the project. The project planning at this stage should involve sensitivity analysis, scenario development, cost estimations, and the identification of feasible alternatives. If there is no cost-effective alternative, government incentives and available technologies and government can lead to viable portfolios.

4 DISCUSSION

As outlined previously, this study was aimed at addressing the gaps in knowledge regarding the integration of the multi-dimensional domain knowledge of this transition. The purpose was to create a meaningful roadmap. The objective was to elaborate on human, technological, economic, policy, and environmental factors and to propose a multistage and multidisciplinary transition plan that will incorporate all aforementioned factors into the transformation. More precisely, it was necessary to address non-technical aspects of the transformation. Accordingly, the proposed connected network will allow optimal management to expand sustainability and efficiency. We introduced innovative concepts needed to achieve the transition such as community energy and zero-carbon communities and microgrids and nanogrids and defined their essential components. Subsequently, we addressed the role of the social factors in smart transformation and highlighted the necessity to incorporate them in both vertical and horizontal processes. We precisely identified different factors to be included in the transition plan. More specifically, demographics, psychological drivers (primarily personal and social norms), and cultural barriers all critically impact the transition. In addition, structural factors and financial policy factors are intertwined with more individual factors.

Subsequently, we proposed a smart transformation roadmap. This smart transformation roadmap consists of a strategic framework and multiple decision-making stages to establish a smart transformation plan include preliminary assessment (identification of capacities/benefits, site inspections, environment feasibility, social-behavioral studies, and identification of impediments/challenges), policy assessment (regulatory incentives/rebates, setting of objectives and high-level targets), requirement mapping (technology and infrastructure, planning and information processing, and human intervention), virtual prototyping and CPS (modeling and simulation, digital twins, virtual testbeds, real data acquisition, and physical prototyping, and technical assessment), and economic analysis (CBA, LCA, and investment planning), explained in detail in the manuscript.

The structural approach to the energy transition is highly required considering the complexity of connected communities. More precisely, because energy transition is highly complex, it is not possible to explain it or to model it using a small number of factors or focusing only on technical aspects. Accordingly, it is necessary, as shown in the paper, to devise energy system models using the aforementioned energy system modeling tools. Only using the structural approach, it is possible to ensure the long-term sustainability of societies that were previously highly dependent on fossil fuels.

Furthermore, the structural approach overcomes the limitations of the development of a single model. Single models are typically based on distinctive methodologies and assumptions. Thus, simply linking different models is not recommended. Thus, in this study, we discussed AI applications and data-driven models that serve to support system monitoring and predictive planning, carry out classifications and clustering, determine anomalies, and predict trends. As highlighted in the study, the actual representation of a system's dynamics and system's component models allow the development of a virtual prototype for decision-makers to carry out technical evaluations of various technology combinations. The structural approach regards the energy transition of communities as multi-stakeholder processes.

5 CONCLUSION

The study showed that smart communities can significantly contribute to achieving economic, social, and environmental goals. In addition, we proposed a decision-making framework for the transition of current communities into smart energy systems. Drawing upon the concept from different disciplines, this framework includes economic analysis, physical and virtual prototyping, technology and technological feasibility assessment, objective definitions, policy evaluation, and preliminary assessment of the project. Furthermore, each phase of the planning process must incorporate feedbacks and multiple iterations to make the transition smooth using the full capabilities of the community. Such capacities should be enhanced owing to revolutionary technological changes using automation, ESSs, renewable energy resources, computing power, novel AI solutions, big data analysis, and ICT. Moreover, prompt technological changes require regular revision and updating of logistics, tools, and goals during the lifecycle of the smart community project. For instance, novel IoT architectures play a vital role in facilitating and accelerating the data transmission and share in the community. Consequently, this enables prompt response decision-making and system monitoring. In addition, enormous amounts of data can be managed efficiently using database management system platforms and big data analysis. AI solutions based on increased data sources with higher resolutions lead to be more reliable and precise predictive modeling. Moreover, it can result in comprehensive planning schemes comprising all participating nodes in the system. Technological efficiency is related to the increased productivity of on-site and clean power generation and storage systems. The development of technology will also reduce error rates of controllers, measurement tools, and sensor devices. Furthermore, we assume additional integration of technologies owing to innovative universal gateways and protocols. More precisely, this allows smart communities to obtain signals from their surroundings and combine these inputs with real-time information within the network. The operation of the municipalities based on this information will lead to a sustainable environment enhanced life quality, smart economy, smart society, and smart governance. In the future, we plan to investigate how to allocate efficiently resources and budgeting for improving the capacities of the smart communities. Moreover, it is necessary to validate the proposed framework and tools via a real-world case study.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

EZ, AG, AA, and MJ contributed to the design of the research, to the analysis of the results and to the writing of the manuscript, with EZ leading this research project.

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Deployment of sustainable off-grid marine renewable energy systems in Mexico

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KEYWORDS

energy transition, marine renewable energy (MRE), off grid electrification, hybrid reneable energy system, development of sustainable MRE

Introduction

The needs of modern coastal communities exert high pressure on the ecosystem services that are naturally provided nearby, putting their future socio-economic development at risk. Over the last hundred years, the population and the economy of the coastal states of Mexico have been growing rapidly due to internal migration. It is estimated that by 2030 the total population of Mexico´s coastal states will have reached 60.1 million (Azuz-Adeath et al., 2019). Satisfying the demand for essential services (energy, water, and food security), maintaining ecosystem functionality, and the socioeconomic activities of its communities is a huge challenge. In Mexico, it is estimated that approximately 32% of the population lives in "energy poverty" or has poor quality electricity, making it impossible for them to improve their quality of life (García-Ochoa and Graizbord, 2016). A significant number of these communities are located near the coasts and are vulnerable to climate change, so their adaptation is a priority (Masson-Delmotte et al., 2021).

Renewable energies include many promising options that can mitigate global warming by reducing our dependence on fossil fuels (IRENA, 2021). Diversification and modernization of the energy matrix, improving affordability and efficiency, are of great importance, and marine renewable energies (MREs) can play a crucial role in this. The 1.5% increase in global installed renewable capacity in 2020 was 2.54 TW (representing 35.7% of global installed capacity). Although quite promising, efforts still need to be accelerated to reach the targets to mitigate average carbon emissions by 3.5% per year and reach net zero by 2050 (IRENA, 2021; Europa Publications, 2022) (IRENA, 2021). The reserves of MRE are enormous, with vast potential in the seas and oceans around the world that could enable coastal communities to foster their social and environmental resilience through the development of the blue economy. The creation of multipurpose clusters of MRE systems and coastal industries, such as desalination and aquaculture, could generate many beneficial by-products that improve energy, water, and food security and stimulate the commercialization and competitiveness of the emerging MRE sector (LiVecchi et al., 2019). However, techno-economic challenges, such as the

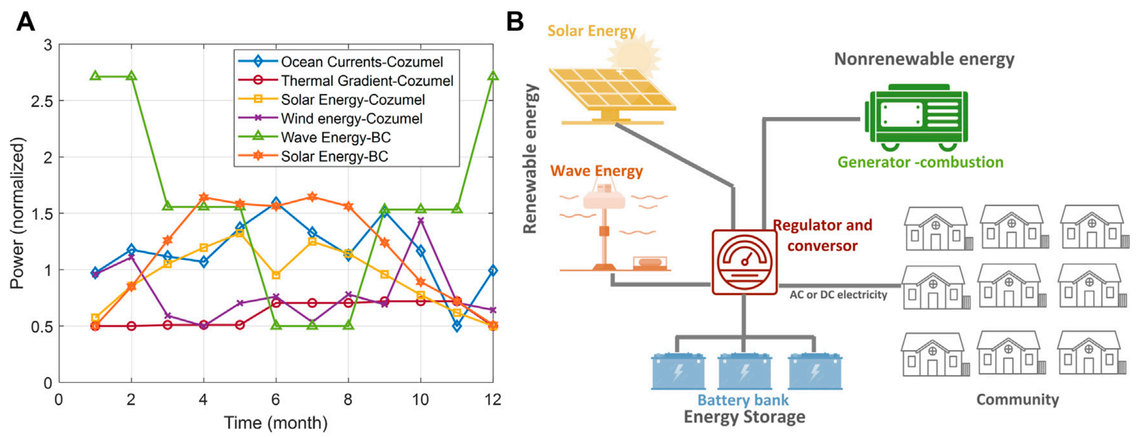

FIGURE 1
(A) Mean monthly variability for different MREs in Cozumel and Baja California. Data taken from CEMIE-Oceano research (Garduño-Ruiz et al., 2021; Gorr-Pozzi et al., 2021; Olmedo-González et al., 2021; Tobal-Cupul et al., 2022). Note: The power units are "normalized" because the graph only represents the power variation considering a minimum power generation of 0.5 units. **(B)** An off-grid, hybrid energy system for isolated communities.

commercial-scale performance, and the high levelized cost of electricity (LCOE) related to higher capital, maintenance, and operating expenses, are obstacles to the deployment of MRE hybrid projects (Babarit et al., 2018). Furthermore, there are other challenges, related to the uncertainties of the potential impacts MRE deployment could have on the coastal environment, society, and the economy (Martínez et al., 2021).

This work evaluates the sustainability criteria of marine energy harnessing through an interdisciplinary approach that identifies the main technical, environmental, social, and economic components to foster the deployment of marine renewable technologies in coastal areas of Mexico.

Off-grid hybrid systems for marine renewable energy harvesting

Mexico has a coastline of around 12,000 km, where a variety of MREs offer significant energy potential for 91–100% of the time, such as Thermal Gradient Energy (TGE), Salinity Gradient Energy (SGE), Ocean Currents Energy (OCE) with 0.5–1 kW/m^2, Tidal Energy (TE), Wave Power (WP) with 10–20 kW/m, and Offshore Wind Energy (OWE) (Hernández-Fontes et al., 2019; Posada-Vanegas et al., 2019). These energy resources compare relatively well with other renewable energies (Garduño-Ruiz et al., 2021).

Depending on their physical nature, weather, and climatic conditions, the various types of MREs have different degrees of inter- and intra-annual variability in their spatio-temporal average energy availability. For example, in latitudes where TGE is feasible there is generally low intra-annual variability because the mean sea temperature is practically constant at depth, 800–1,000 m, and can be considered as "base load". On the other hand, WP is strongly related to the areas where the waves originate, meaning high seasonal dependence and mean annual variability. Figure 1A) shows the monthly variability of three MREs, solar and wind energy in Cozumel and Baja California, Mexico. It can be seen that TGE has low monthly variability compared to ocean currents, wave energy, or solar energy. It is important to note that in regions where the minimum potential for wave energy generation is present, it coincides with the maximum potential of other renewable resources that can be harvested, as solar or ocean currents. Power systems that combine renewable energies could make it possible to reduce monthly variations, allowing a more providing continuous electricity generation throughout the year. For such continuous operation, the harnessing of the MRE can be co-localized with other renewable energy sources, non-renewable energy sources, or energy storage technologies.

The combination of different energy sources in an off-grid system is known as hybridization, and these promising options would thus become economically more viable and, therefore, more attractive to investors. The main function of hybridization is to compensate for daily and monthly fluctuations in electricity generation. However, since up to 60% of the total cost of an off-grid system comes from the energy storage system, it is vital to determine the optimal size and the right degree of hybridization (EERE, 2021; Olmedo-González et al., 2022).

Most often, electricity is supplied *via* centralized generation (large-scale generation), with power plants distributing electricity through electric power gird. However, distributed generation (on-site generation) has been gaining importance as renewable energies are developed (Gorr-Pozzi et al., 2021). Off-grid systems and mini-grids or microgrids can generate electricity efficiently as they are located close to the point of consumption. They are considered an attractive solution for isolated areas lacking electricity services, where the installation of power lines is not profitable.

In many developing countries, it is common to find communities lacking a quality electrical interconnection along the coastline (Alstone et al., 2015). The cost of deploying more traditional electrical infrastructure to provide a service for such a small number of inhabitants and the distance between the communities and the nearest cities mean that off-grid systems, in particular, are a potentially cost-effective option for these areas and could meet part of the electricity demand of isolated communities in Mexico. For example, the fishing community of Puertecitos in Baja California, has only 80 inhabitants. Electricity is supplied by a 60.2 kW hybrid microgrid (55.2 kW solar PV/5 kW Wind energy) and a 522 kWh battery energy storage (Cota-Soto et al., 2017). The Inter-American Development Bank (IDB) co-financed 11 projects for rural electrification in Latin America and the Caribbean for communities with 100–7,000 inhabitants (five now operating and six still being developed) (Graham et al., 2021). Off-grid systems offer the advantage of using emerging technologies for power generation, as their power rating (kW to MW) allows test prototypes in field conditions of an operational environment.

Off-grid systems are quite versatile since their configuration can be adapted to the local community's needs, even if energy demand grows. Figure 1B shows an off-grid renewable energy system with a hybrid renewable energy source, a backup power source (typically a non-renewable system, such as a diesel generator), an energy storage system (e.g., batteries), and a power conditioning system (a regulator DC/DC, DC/AC), (Sawle et al., 2018). For the design and optimization of such systems, several methodologies have been suggested (Siddaiah and Saini, 2016). These focus on minimizing costs by maximizing generation time and reducing energy storage capacity. Furthermore, others also take into account social and environmental aspects to try to overcome potential negative impacts on ecosystems.

A policy framework is needed for national governments to unite countries internationally to commit to a just and inclusive energy transition that strengthens the flow of finance and attracts investors, capacity, and technologies. Five renewable energy innovation centers were created following the Mexican Energy Transition Law of 2013, to contribute to the growth and diversification of the national energy sector. The Mexican Center for Ocean Energy Innovation (CEMIE-Oceano) has been evaluating the possibilities of MRE, conducting studies on potential sites for implementation, taking into account environmental and social impacts. In 2017, the Mexican government developed a "Road Maps" series for ocean energy implementation (IEA-OES, 2022).

Criteria for the deployment of sustainable marine renewable energies

Availability of MRE resources, environmental constraints, regulatory and legal aspects, protection instruments, and maritime spatial planning are factors to be considered when evaluating potential sites for hybrid MRE systems. Most of these factors are site-specific. When considering the different criteria for sustainable MRE deployment, the potential benefits, and adverse effects can be evaluated to promote solutions that mitigate negative impacts. Table 1 shows an overview of the advantages and disadvantages of the technical, environmental, economic, and social components of deploying different MRE systems in Mexico. In turn, these are classified by criteria rated according to a color-coded for each MRE. Green indicates low risk, relative ease of deployment or few additional requirements, while red indicates high risk and less ease of implementation or the need for more conditions.

Discussion

Improving the sustainability of a hybrid MRE generation plant should consider all the components in Table 1 and analyse them using an interdisciplinary and holistic vision. This must reduce the likelihood of failure or potential impacts of MRE projects (Wang and Zhan, 2019).

From the ratings of all the criteria considered, the capacity factor, the climate change potential, and the exclusion zone are the features that most highly endorse MRE implementation in Mexico. However, the MRE variability, the associated potential impacts on threatened ecosystems, and the relatively low generation of by-products highlight the need for continued efforts in developing the feasibility of deploying sustainable energy harvesting devices. Among all current MRE technologies, the most suitable for its sustainable deployment at potential coastal sites in Mexico are TGE and OWE.

TGE offers a low annual variability, and its capacity factor gives a base load of annual energy production and a low LCOE. Furthermore, TGE presents positive environmental aspects, such as negative-CO2 emissions, and the TGE by-products make it more viable (e.g., freshwater production, aquaculture, and seawater conditioning. OWE is the most advanced MRE technology due to its learning rate, which reflect an accelerated increase in the installed capacity of commercial systems tested in the operating environment. It also has a competitive LCOE and more mature commercial deployment than other MREs. In contrast, the deployment of SGE systems presents several challenges as it still lacks technological development, has a high environmental risk related to its low carbon mitigation capacity, and carries a risk to nearby ecosystems associated with brine spills from the discharge pipelines. In addition, SGE is less economically

TABLE 1 Criteria to foster the sustainable deployment of MREs in Mexico's coastal zones.

Components	Criterion	Thermal gradient energy (TGE)	Salinity gradient energy (SGE)	Wave energy (WE)	Ocean currents energy (OCE)	Tidal energy (TE)	Offshore wind energy (OWE)	References
Technical	Low variability							(Huante et al., 2018; Alcérreca-Huerta et al., 2019; Hernández-Fontes et al., 2019; Gorr-Pozzi et al., 2021; Bernal-Camacho et al., 2022)
	Need for Energy Storage							(Zhou et al., 2013; Gorr-Pozzi et al., 2021; Olmedo-González et al., 2022)
	Technology readiness level (TRL)							IEA-OES, (2022)
	Capacity Factor (%)							(Garduño-Ruiz et al., 2021; Gorr-Pozzi et al., 2021; IEA-OES, 2022; Tobal-Cupul et al., 2022)
	Off grid system viability (Power rating)							(Sheng et al., 2017; IRENA, 2019, 2020; Gorr-Pozzi et al., 2021)
	Efficiency (W/m^2)							(Alcérreca-Huerta et al., 2019; Hernández-Fontes et al., 2019)
Environmental	Climate change potential (gCO2 equiv/kWh)							(Rau and Baird, 2018; Paredes et al., 2019; Ma et al., 2022; Smoot, 2022; Tobal-Cupul et al., 2022)
	Affection to threatened ecosystem (% of affection)							Martínez et al. (2021)
Economic	LCOE ($/kWh)							(Garduño-Ruiz et al., 2021; IEA-OES, 2022; Tobal-Cupul et al., 2022)
Social	Food and services (by-products)							Tobal-Cupul et al. (2022)
	Social perception							Tobal-Cupul et al. (2022)
	Exclusion zone (m^2)							(Kim et al., 2012; Gourvenec et al., 2022; Hernández Galvez et al., 2022)

attractive, primarily due to its high capital, operating, and maintenance costs. It is suggested that TGE and OWE prototypes-technologies be tested under field operating conditions to validate their performance, to have site-specific information on environmental and social impacts, and improve their profitability.

Mexico has substantial detailed information on the MREs available around its coasts. Improving capacity factors and energy production by more efficient MRE prototypes adapted to Mexico's climatic conditions will directly impact its technological capabilities. The combination of electricity generation from various MRE sources, or hybridization, and their integration into off-grid systems will compensate for the variability of the electricity generated and allow isolated communities on the coast of Mexico to have access to this vital resource in a sustainable way. The use and commercialization of by-products in such a hybrid plant will boost the blue economy, creating numerous benefits and accelerating the pre-commercial stage. These conditions could increase the installed capacity of MRE systems and strengthen local human capabilities. In turn, this could improve credibility in MRE and increase confidence in investing in it in the medium term, as well as the perception and social acceptance of using these technologies. Joint work between the different levels of government, the private sector, academia, and the local population must be strengthened to develop public policies and regulations that encourage the sustainable installation of hybrid MRE systems in Mexico.

Author contributions

EG-P, JO-G, and RS contributed to conception and design of the study. EG-P and JO-G organized the database and performed the analysis of the criteria to foster the sustainable deployment of MREs in Mexico's coastal zones. EG-P and JO-G wrote the first draft of the manuscript and RS supervised the manuscript. EG-P, JO-G and RS wrote in all sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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How does institutional support affect the coalbed methane industry?

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Accelerating the construction of a low-carbon, safe, and modern energy system is becoming a critical developmental path toward solving the climate change problem. China provides institutional support in various ways for this clean and efficient new energy, but there is still a gap between the developmental scale and the planned target. Considering the theory of system support and the coalbed methane industry, we combed the existing institutional support for the coalbed methane industry based on grounded theory and defined the initial model. We used the system dynamics method to construct and simulate the model and verified the system's effectiveness by using the goodness of fit. The results show that institutional support promotes the development of the coalbed methane industry, and the interaction between the two forms a dynamic system. Based on the sensitivity analysis method, the enlightenment of the management with respect to the improvement of the development of the coalbed methane industry was obtained. Firstly, the management of coalbed methane mining rights should be supervised and large-scale utilization should be strengthened. Secondly, the central government's subsidies should be raised and local governments should be encouraged to provide support. Thirdly, technological innovation should be enhanced and fair competition should be ensured.

KEYWORDS

institutional support, coalbed methane industry, grounded theory, system dynamics, goodness of fit

1 Introduction

Faced with the increasingly severe global climate change situation, China has been implementing the "carbon peaking and carbon neutral" initiative to actively promote the green transformation of energy production. As a clean and efficient new energy source, the development and utilization of coalbed methane have safety and environmental effects. They are important for the optimization of the energy structure, promotion of economic growth, creation of jobs, and promotion of the healthy and sustainable development of the energy industry. However, China's coalbed methane exploration and development are still in their initial stage of development, and the upstream, midstream, and downstream links of the industrial chain have absorbed many stakeholders. The opportunities and challenges facing the development have new characteristics, and the relevant system is still not perfect. Institutions such as laws, formal contracts, and regulations are considered soft market infrastructures (Peng and Luo, 2000). The absence of reliable institutions can create institutional weaknesses that negatively affect the market; however, institutional support can reduce the impact (Doh and Kim, 2014). To promote the development of the coalbed methane industry, national and local governments have formulated and implemented a series of institutional supports, achieving some results, but there are still certain gaps between the planned goals. China is one of the world's major energy producers and consumers. It is valuable to study how institutional support affects the coalbed methane industry in China to promote the sustainable development of global energy.

We found few studies on the coalbed methane system in the literature. In view of the problems existing in the development of deep coalbed methane, Fan, Wang, and Song proposed a balanced differential subsidy mechanism for enterprises, and they held that the unit subsidy for deep resources should be more than that for shallow resources (Lurong et al., 2023). Mosayebi and Grall's studies on coalbed methane policy and its impact on repair efficiency found a way to reduce maintenance costs (Omshi and Grall, 2021). The relevant studies mainly focused on case studies and technological development. Considering the development of coalbed methane in the Yangquan mining area as an example, Linghu, Chen, and Yan established a model for predicting the monthly demand for coalbed methane and investigated the change in demand under the influence of COVID-19 (Linghu et al., 2020). Wen et al. (2019) summarized the technologies and achievements of China National Petroleum Corporation's coalbed methane exploration and development, analyzed the opportunities and challenges in the development process, and proposed five major research directions to accelerate the development of the coalbed methane industry. Sugata and Saurabh constructed a geological model of the coalbed methane recovery process using the Jharia coalfield in India as a case study (Kumar and Datta, 2021). Li et al. combined the core ideas of machine learning algorithms, coal body deformation mechanisms, and critical layer theory to establish a prediction method for identifying the texture of coal. Their study has had an important influence on the exploration and development of coalbed methane (Cunlei et al., 2022). Other studies on institutional support for unconventional gas have mostly focused on shale gas, and some scholars have proposed policy recommendations in terms of exploring geological resources, sound market mechanisms, environmental protection, etc. Yu et al. (2018) proposed macro-level recommendations for coping with environmental protection by comparing shale gas policy systems. Wu et al. simulated competition in the shale gas industry under scenarios of technology, cost, and subsidies (Yunna et al., 2015). Most relevant research focuses on enterprises, macro theory, and qualitative research. However, when it comes to industry, it is only studied as an environmental component, and there is a lack of targeted in-depth analysis in the industrial field.

The theoretical study of institutional support affecting the coalbed methane industry is insufficient. According to the results of in-depth interviews, we construct a conceptual model based on grounded theory. Grounded theory is a qualitative study based on inductive data. Its core is to collect and analyze data using scientific and standardized operational procedures, which is suitable for theoretical construction (Glaser, 2004; Wang et al., 2020). Based on the conceptual model, we applied the system dynamics method to construct an institutional support system model for the coalbed methane industry. There is a non-linear feedback relationship between institutional support and the coalbed methane industry, which constitutes a complex system. The system involves various of influencing elements, some of which are difficult to quantify. System dynamics can better solve this problem by examining the role of decision-making and feedback relationships in the system through computer simulation (Forrester, 1958; Ross and Chang, 2021; Shal and Laberiano, 2021). Finally, we used the goodness of fit method to investigate the fitting degree of the simulation data and the actual value and verified the validity of the system model (Pinto and Sooriyarachchi, 2021; Shalabh, 2021). Through the combination of qualitative and quantitative research, we discussed the internal influence of institutional support on the coalbed methane industry. We conducted simulations with the aim of expanding the scope and methods of institutional support research, optimizing the combination of institutional supports to promote the development of the coalbed methane industry, and providing a reference for developing new energy.

2 Theoretical analysis

2.1 Institutional support

As an important part of institutional theory, institutional support has received much attention from scholars. Xin and Pearce (1996) defined institutional support as an important resource that the government provides to firms and classified institutional support into two dimensions: formal institutional support and informal institutional support . Formal institutional support refers to the various types of formal support provided by a state administration to enterprises to reduce the negative effects of imperfect market mechanisms. These support policies are regulatory institutional support, including government subsidies, tax breaks, support for building alliances, intellectual property protection, etc., which some scholars also refer to as government institutional support (Shu et al., 2015). Informal institutional support refers to the support provided by institutional agents such as the government through a firm's efforts to establish political ties and, thus, the relationship between the firm and the government. Similarly to most scholars, we support this view. Li and Atuahene-Gima (2001a) studied the impacts of political connections between organizations and governments on organizations by comparing formal and informal institutional support. Tellis et al. (2009) suggested that governments should provide innovative firms with certain tax breaks, R&D subsidies, etc. to avoid unreasonable costs and risks in promoting the development of firms. Peng argued that institutional support promotes business development but is often arbitrary and artificially manipulable, triggering political behavior or unhealthy competition among firms (Peng et al., 2009).

Most current institutional-support-related research highlights the role of external institutional support from the government and its impact on firm structure, strategy, and behavior and less frequently examines the impact of institutional support on the industry. Focusing on the government as a non-market force, we looked at the impacts of formal and informal institutional support on the development of the coalbed methane industry.

2.2 Coalbed methane industry

An industry is a collection of enterprises or organizations with similar attributes, and this paper defines the coalbed methane industry as a collection of enterprises engaged in coalbed methane exploration, development, and production. China is rich in coalbed methane resources. According to a government work report, there are 114 gas-bearing zones in the country. The coalbed gas area that is <2,000 m is 415,000 square kilometers. The prospective resources make up 36.81 trillion cubic meters, equivalent to the conventional natural gas resources on land and ranking among the top three in the world. More than 100 favorable exploration target areas have been evaluated at present, and more than 10 rich target areas with resources of $1,000 \times 10^8$–$7,000 \times 10^8\ m^3$ have been selected. Some authors predict that the surface production of coalbed methane in China will increase steadily and annually (Bo and Hui, 2021), providing a solid foundation for industrializing coalbed methane in China.

Demand is the fundamental driving force behind the industrialization of coalbed methane. China has been a net importer of crude oil since 1993 and a net importer of natural gas since 2007, and its imports of natural gas are rising rapidly. With the rapid development of the national economy, the energy supply situation has become increasingly tight, with oil and natural gas being particularly prominent. From the perspective of energy demand and energy security, China must develop and utilize new energy sources to continue its rapid economic growth, and the coalbed methane industry is one of the best choices.

2.3 Institutional support and the coalbed methane industry

2.3.1 Research design

The United States was the first country to develop and utilize coalbed methane, providing much experience in policy support, key technology breakthroughs, and infrastructure construction for coalbed methane development. Australia, Canada, the United Kingdom, and Germany have all introduced legal and fiscal incentives for developing and utilizing coalbed methane resources and have regulated the management of coalbed methane exploitation. To solve energy supply problems and ensure coal mine safety, China attaches great importance to coalbed methane development and utilization and has provided institutional support in various ways.

Grounded theory summarizes concepts from the original data and generates theories through step-by-step coding. The concepts are interrelated to form a unified, intrinsically linked whole (Critical, 2019). This method can overcome the shortcomings of the lack of a normative process of other qualitative methods, so it is widely used (Estrada et al., 2021; Xie et al., 2021). The existing theoretical framework in related research is still not perfect, and the grounded theory has a scientific and standardized operation process. The generation of the theory is rooted in real data, which helps produce a realistic and robust theory (Strauss and Corbin, 1990). Therefore, this study uses grounded theory for its analysis. Through in-depth interviews, the institutional support affecting the development of the coalbed methane industry was investigated. The respondents included relevant practitioners and researchers in the coalbed methane industry. According to Fassinger's study, a sample size of 20–30 is appropriate (Fassinger, 2005). This study draws on the experience of research in grounded theory, and 30 people were selected as the survey objects to ensure the theoretical saturation of the sample. The questions are based on the questionnaires of Li and Atuahene-Gima (2001b) and Peng and Luo (2000). These included the following: "What do you think of the policies and projects provided by the government that are conducive to the development of companies or industries? What do you think of the technical information and technical support provided by the government? What do you think of the current fiscal policy in favor of the company or industry development? Do you think a good relationship between the company and the government is beneficial to the development of the company or industry?". In order to ensure the reliability of the database, a sample return visit was conducted based on a preliminary collation of the collected data, and the required data were supplemented in a targeted manner according to the literature. Twenty-five interview records were randomly selected for coding analysis, and the remaining five were used for testing. Finally, data analysis was conducted by using open coding, spindle coding, and selective coding.

2.3.2 Data analysis

2.3.2.1 Open coding

Open coding is the initial step in theory formation through the examination of data row by row and the definition of events. Based on an analysis of sentences or paragraphs, the collected interview materials are initially processed to carry out conceptualization and categorization. Conceptualization refers to selecting or creating concepts that best reflect the nature of the original material. Categorization refers to abstract concepts that are higher than general concepts in a hierarchical structure. By excavating and collating in-depth interview records and literature, the initial concepts with less than two occurrences were eliminated, and finally, 13 concepts and 13 categories were abstracted, as shown in Table 1.

2.3.2.2 Axial coding

Spindle coding is a process of linking the categories obtained in open coding by using a coding model, that is, "causality → phenomenon → context → condition → strategy → result". In order to ensure comprehensive coding, through cluster analysis, we divided our study into the open coding data and the associated category in order to establish more general categories. Six main categories were summarized according to the relationships between the different categories: formal institutional support, informal institutional support, disposable funds, profits, fair competition, and the coalbed methane industry. The canonical model is shown in Figure 1.

2.3.2.3 Selective decoding

Selective coding involves selecting core categories and establishing connections based on the concepts and categories that already exist in a system analysis. Incomplete categories in the conceptualization are supplemented by verifying the relationships between the core category and the other categories. All of the categories in this study were derived from China's 13th Five-Year Plan and in-depth interview reports. The relationships are shown in Figure 2, with the coalbed methane industry as the core category. On the one hand, the government provides formal institutional support for the development of the coalbed methane industry in five ways: priority, financial subsidies, cost reduction, tax incentives, and property rights protection. They increase the disposable funds of enterprises, which is conducive to the expansion of reproduction and an increase in profits. Property rights protection promotes the innovation of coalbed methane technology, reduces enterprise costs, and expands profit margins. On the other hand, the government provides informal institutional support for the coalbed methane industry. A good corporate political relationship between enterprises and the government will promote more policy tilt, accelerate technological innovation, reduce costs,

TABLE 1 Axial coding of institutional support for the coalbed methane industry.

Scope	Initial concept
Priority	The priority of coalbed methane enterprises in the process of exploration, development, extraction, and utilization
Financial subsidies	Government financial subsidies for the coalbed methane industry, including civil subsidies, development and utilization subsidies, and central financial funds, are used to promote the development and utilization of coalbed methane and the transformation of safety technology
Cost relief	The cost of coalbed methane in the process of exploration and development is reduced or exempted
Tax incentives	Coalbed methane enterprises' tax incentives, including tariffs, value-added tax, corporate income tax, and resource tax
Property rights protection	Improvement of the industrial intellectual property protection system, building R&D innovation centers, increasing the transfer of scientific and technological achievements, and demonstration of industrial applications
Corporate political relations	Support for and tilting of industrial policy, resource allocation, government orders, and other aspects
Coalbed methane production	The amount of coalbed methane extraction includes surface drilling and underground gas drainage
Coalbed methane utilization	The quantitative value of coalbed methane use includes pipeline gas, compressed natural gas (CNG), liquefied natural gas (LNG), low-concentration gas, and wind power generation
Disposable capital	Funds available for profit distribution, technical research, and expanded reproduction of coalbed methane enterprises
Technological innovation	The innovation of technical means in each link of coalbed methane exploration, development, storage, transportation, and final utilization can maximize the economic, social, and environmental benefits of the industry
Fair competition	Coalbed methane enterprises jointly accept the role and evaluation of the law of value and survival of the fittest under the same market conditions and realize the specialized production and enterprise management of coalbed methane
Cost	The average cost of mining per cubic meter of coalbed methane
Coalbed methane sales price	The average price of selling coalbed methane is determined by the negotiation between the supply and demand sides or by maintaining a reasonable ratio of the equivalent calorific value of alternative fuels

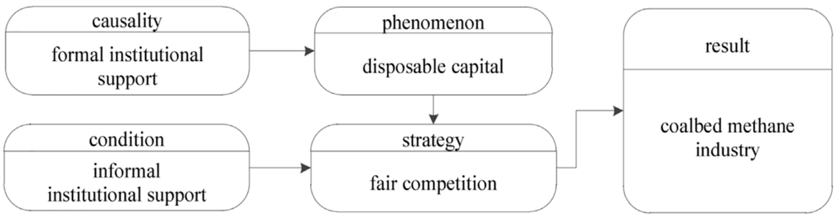

FIGURE 1
Canonical model of institutional support for the coalbed methane industry.

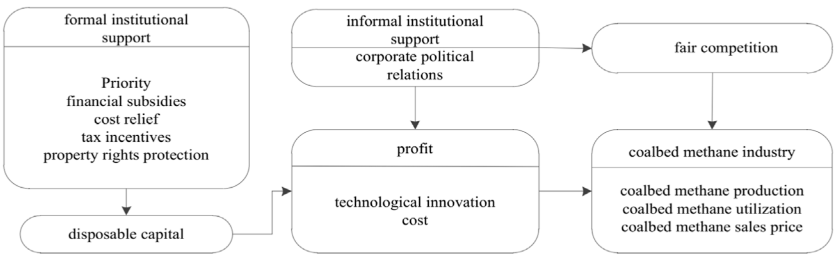

FIGURE 2
Initial model of institutional support for the coalbed methane industry.

and enable enterprises to obtain more profits, affecting fair competition. Increased profit will attract more enterprises to enter the coalbed methane industry, promote the increase in coalbed methane production and utilization, reduce the sales price, and promote the development of the coalbed methane industry. Fair competition will play a negative role in industrial development.

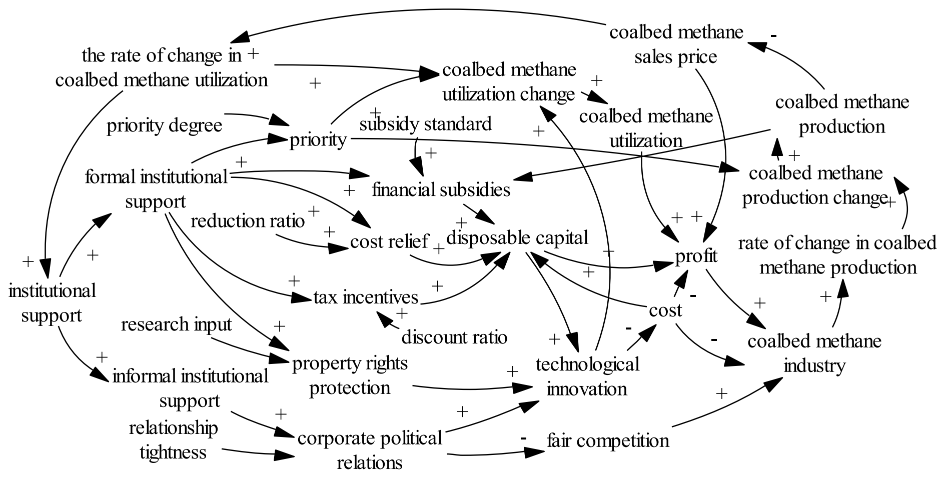

FIGURE 3
Systematic causality analysis.

3 System model construction

3.1 Basic system assumptions

Based on the theory of system feedback control, system dynamics is an applied discipline that uses computer simulation technology to study the dynamic behavior of system development qualitatively and quantitatively (Forrester, 1958). It is an effective method for analyzing complex systems (Morales and Andrade-Arenas, 2021). There is an information feedback relationship between institutional support and the coalbed methane industry that conforms to the modeling conditions of system dynamics. Moreover, using the system dynamics method to study system structure and behavior helps in thoroughly analyzing the dynamic evolutionary relationships between the internal mechanisms of the system. Therefore, the system dynamics method is suitable for analyzing the relationship between institutional support and the development of the coalbed methane industry. The influencing factors involved in the system and their correlations are complex. Therefore, we simplified the system and determined three basic assumptions.

H1. *The system model only considers the impacts of major variables on the coalbed methane industry.*

H2. *The relationships between some system variables and other system variables arenot significant and are set as constants.*

H3. *Each variable of the system is non-negative.*

3.2 Causality analysis

We analyzed the causal relationships in the system based on the above theoretical analysis and the initial model. The system's causality and the main loop relationships are shown in Figure 3.

Institutional support includes formal institutional support and informal institutional support. Formal system support includes five dimensions: priority, financial subsidies, cost relief, tax incentives, and property rights protection. Priority can solve the problem of overlapping mining rights, promote the priority for use of coalbed methane, increase the amount of coalbed methane utilization, and reduce emptying. Financial subsidies, fee reductions, and tax incentives increase the disposable capital of enterprises, which is conducive to the expansion of reproduction and increase in profits. Property rights protection promotes technological innovation for coalbed methane and reduces the costs of enterprises. Enterprises gain more profits from increases in customers and disposable funds and reduce their costs, thus promoting the development of the coalbed methane industry. Informal institutional support refers to the political relationship between an enterprise and the government. Good corporate political relations will promote technological innovation, reduce costs, and promote industrial development, but may affect fair competition. From this perspective, they will play a negative role in industrial development.

The development of coalbed methane will increase production, reduce the sales price, stimulate the rate of change in utilization, and promote greater institutional support.

3.3 System model construction

Based on the diagram of the system's causality, the symbol for the flow is introduced into the diagram of the system dynamics, and a matching variable for the unit demand is added to obtain the diagram of the system flow, as shown in Figure 3.

There are twenty-seven variables in the system, including two state variables (coalbed methane production, coalbed methane utilization), five rate variables (coalbed methane utilization change, coalbed methane production change, financial subsidies, cost relief, tax incentives), fifteen auxiliary variables (institutional support, formal institutional support, informal institutional support, priority, property rights protection, corporate political relations, technological innovation, fair competition, rate of change in coalbed methane utilization, disposable capital, profit, cost, coalbed methane sales price, coalbed methane industry, rate of change in coalbed methane production), and six constants (priority degree, reduction ratio, discount ratio, subsidy standard, relationship tightness, research input). The unit- and time-matching coefficients are hidden in

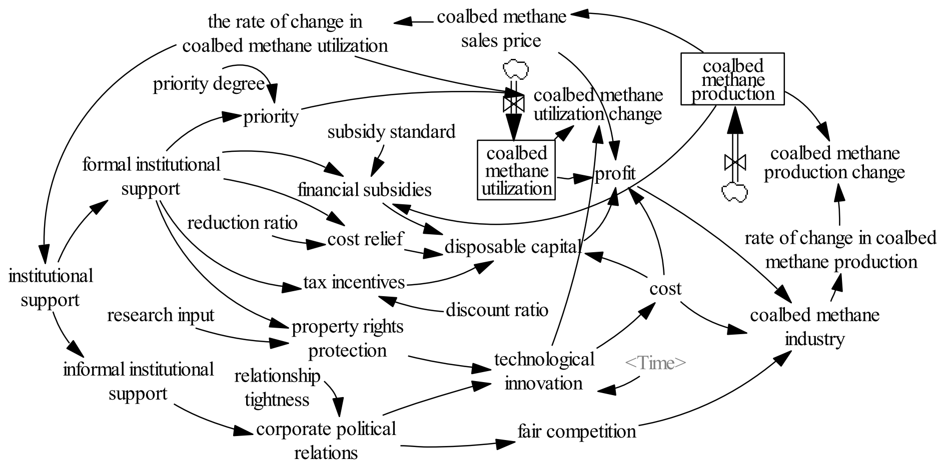

FIGURE 4
Analysis of the system flow diagram.

TABLE 2 The main equations of the system.

Equation design	Unit	Basis
coalbed methane production = INTEG(coalbed methane production change/(35 × unit matching coefficient),92)	billion cubic meters	data research collation
coalbed methane utilization = INTEG(coalbed methane utilization change/(160 × unit matching coefficient),37)	billion cubic meters	data research collation
coalbed methane utilization change = coalbed methane utilization × rate of change in coalbed methane utilization × (1 + priority) × (1 + technological innovation)	billion cubic meters	causality analysis
rate of change in coalbed methane production = coalbed methane production × rate of change in coalbed methane production × priority	billion cubic meters	causality analysis
financial subsidies = (1 + formal institutional support) + subsidy standard × coalbed methane production/(unit matching coefficient ×10)	dmnl	data research collation
cost relief = reduction ratio × formal institutional support ×100	dmnl	initial model
tax incentives = formal institutional support × (1 + discount ratio)	dmnl	initial model
institutional support = rate of change in coalbed methane utilization × 0.9	dmnl	causality analysis
coalbed methane sales price = WITH LOOKUP (2000 × unit matching coefficient/coalbed methane production),([(0,0)-(120,3.51)],(0,2.1),(120,3.51)))	yuan	data research collation
profit = (1 + disposable capital) × (1 + coalbed methane utilization/unit matching coefficient ×100) × (coalbed methane sales price/unit matching coefficient −cost/unit matching coefficient)	dmnl	causality analysis
disposable capital = tax incentives + financial subsidies + cost relief −cost/2	dmnl	causality analysis
cost = 1.5-technological innovation/2	yuan	data research collation
technological innovation = WITH LOOKUP(Time × (1 + property rights protection) × (1 + corporate political relations)/(2 × time matching coefficient),([(0,0)-(120,1)],(0,0.3),(120,1)))	dmnl	causality analysis
coalbed methane industry = (1 + fair competition) + (1 + profit) −(1 + cost/unit matching coefficient)	dmnl	causality analysis

Figure 4 to make the relationships between variables in the system flow diagram appear more intuitive.

3.4 Design of the main equations

Vensim PLE was used to simulate the system model based on the system flow diagram. This paper's simulation period was set from 2010 to 2020, with a duration of 120 months. The model involved three types of equations, and the main equations were designed as shown in Table 2.

3.4.1 Constant equation

The variables of priority, reduction ratio, subsidy standard, preference ratio, relationship tightness, and research input were set as constants with values between 0 and 1.

TABLE 3 Test of the fit of the simulated and real values of the system model.

Variable	Coalbed methane production	Coalbed methane utilization
R^2	.92	.95

3.4.2 Table function equation

The variables of financial subsidies, cost relief, and tax incentives were expressed in the table function, and the initial values were set according to the "13th Five-Year Plan" of the National Energy Administration for coalbed methane development and utilization. Due to the slightly different policies for each province and city, the system simulation data were based on central financial support.

3.4.3 Auxiliary equation

The auxiliary equation was set according to the relationships between the variables, where the initial values of the coalbed methane production, coalbed methane utilization, and cost were obtained from coalbed methane research reports and China's energy bureau.

4 Simulation and analysis of the system model

4.1 Initial value selection and parameter settings

Vensim PLE was used to simulate the system model based on the system flow diagram. The simulation period was 120 months, from 2010 to 2020. According to the data from the National Energy Administration, the initial value of coalbed methane production in the model was set to 9.2 billion cubic meters, and the initial value of coalbed methane utilization was set to 3.7 billion cubic meters. According to the coalbed methane research report and the Twelfth and Thirteenth Five-Year Plans, the coalbed methane sales price was set between 2.1 and 3.51 yuan. The initial cost was 1.5 yuan, the subsidy standard was .2–.3 yuan/m^3, and the tax preference was the preferential tax rate. The values of the time- and unit-matching coefficients were both 1.

4.2 Tests of the system model's validity

The system model was shown to be consistent with the real system structure by testing the causality diagram, system flow diagram, variable sources, and equation design. The main units of the system model variables were a billion cubic meters, yuan, dmnl, etc. The model ran normally, the dimensions were consistent, and the unit conformance test was passed.

In order to further test the validity of the model, the goodness-of-fit formula (Eq. 1) was used to test the simulated and historical data. The closer the R^2 value of the goodness of fit is to 1, the more effective the system model is (Strauss and Corbin, 1990).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - y_i')^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{1}$$

where y_i is the simulated value of the relevant variable in the ith year of the experimental period. y_i' is the true value for year I, and $\bar{y}$ is the average. The test results are shown in Table 3. The degree of fit of the simulated and real values of the main elements in the model was >.9, and the fitting effect was good (Anna and Tamás, 2022). The model was able to reflect the actual situation well.

The simulation model shows that, under the support of the current system, the coalbed methane industry shows an upward trend (as shown in Figure 5). The production and utilization of coalbed methane continue to increase. With the development of the coalbed methane industry, the utilization rate increases, thus further promoting institutional support.

4.3 Sensitivity analysis

The developmental prospects of the coalbed methane industry are broad, and the output and utilization of coalbed methane are increasing annually. However, due to the large proportion of difficult-to-recover resources, limited technological development, weak market competitiveness, and other reasons, there is still a gap between the production and utilization of coalbed methane and the goals of the 12th and 13th Five-Year Plans. It is necessary to strengthen institutional support for the coalbed methane industry.

According to the results of the initial model and system simulation, the institutional support for the coalbed methane industry can be improved in six dimensions: priority, financial subsidies, cost relief, tax incentives, property rights protection, and corporate political relations. Among them, cost relief and tax incentives have received greater support. According to the simulation results, exemption from all user fees and taxes on the existing basis has little impact on the coalbed methane industry. The priority of gas extraction has been established; however, coalbed methane utilization must be further strengthened. Financial subsidies have been reduced since 2019, and property rights protection and corporate political relations must be strengthened. Therefore, in the sensitivity analysis, the reduction ratio and the discount ratio remained unchanged. In Current1, the priority degree, subsidy standard, research input, and relationship tightness must increase to obtain Current2. These changes significantly increase coalbed methane production and utilization (as shown in Figure 6) in comparison with Current1. The subsidy standard will be restored to .3 yuan, and coalbed methane planning objectives can be achieved. At the same time, increasing research input and relationship closeness can promote technological innovation and enhance the development of the coalbed methane industry.

Increasing the priority increases the production and utilization of coalbed methane. By raising the subsidy standard, enterprises receive more financial subsidies. Increasing disposable capital is conducive to expanding coalbed methane reproduction, increases profits, attracts enterprise investment and development, promotes the development of the coalbed methane industry, and improves coalbed methane production and utilization. Increasing research input and enhancing property rights protection can stimulate technological innovation. At the same time, the relationships are closer, and

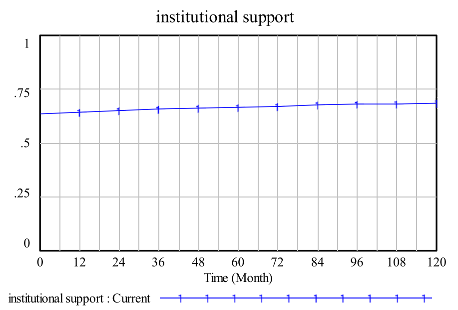

FIGURE 5
Simulation results.

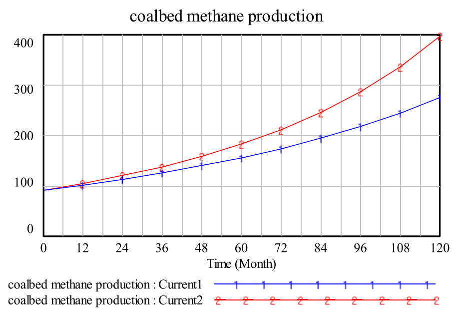

FIGURE 6
Changes in coalbed methane production and utilization.

good corporate political relations promote technological innovation. Improving technological innovation can increase the use of coalbed methane, increase profits, promote the development of the coalbed methane industry, and increase coalbed methane production.

5 Conclusion and management inspiration

5.1 Research conclusion

Unlike in previous studies, we examined policies concerning the coalbed methane industry through in-depth interviews and grounded theory from the perspective of institutional support. In combination with the collection of survey data, we constructed and simulated a dynamic model of the institutional support system for the coalbed methane industry. Suggestions for the sustainable development of the coalbed methane industry were obtained.

(1) The interaction between institutional support and the coalbed methane industry constitutes a dynamic system. Formal institutional support includes the five areas of priority, financial subsidies, cost relief, tax incentives, and property rights protection, and informal institutional support corresponds to corporate political relations.
(2) Institutional support promotes the development of the coalbed methane industry. Combinations of increases in the priority degree, subsidy standards, research input, and relationship tightness are effective means of institutional support for the promotion of the development of the coalbed methane industry.

5.2 Management insights

(1) The management of coalbed methane mining rights should be supervised and the scale of use should be strengthened. The implementation of gas mining priority mechanisms and the prioritization of the allocation of mining rights by coalbed methane enterprises should be ensured. Coalbed methane priority self-use, priority sales, the strengthening of the facilities of the gas pipeline network, the establishment of efficient innovative marketing systems, and an increase in the scale of use for coalbed methane should be considered.
(2) The central financial subsidy standards should be improved and local government subsidies should be encouraged. The recovery of the central financial subsidy standard of .3 yuan/cubic meter will help the production and utilization of coalbed methane meet the planning objectives. Local governments can set up special funds to increase incentives and subsidies, constantly improve the management system, and mobilize the enthusiasm of enterprises.
(3) The level of technological innovation should be improved and fair competition should be ensured. R&D investment in the basic theory of coalbed methane should be increased, and key technologies and equipment should be developed and utilized.

Intelligent information technology should be developed, importance should be attached to intellectual property protection, and the intelligence level of the coalbed methane industry should be improved. A "government–industry–university–research" collaborative innovation platform should be built, the training of coalbed methane professionals and technical personnel should be strengthened, and innovation capabilities should be enhanced. Coalbed methane enterprises should consider their political relations and encourage the government to increase policy support. At the same time, the government will guarantee fair competition through bidding and other means.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization, JW and C-HN; Methodology, JW; Software, JW; Validation, JW; Writing—original draft preparation, JW; Writing—review and editing, C-HN; Supervision, C-HN; Funding acquisition, C-HN. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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A complex grid investment decision method considering source-grid-load-storage integration

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With the widespread use of renewable energy worldwide, the impact of its randomness and volatility on the grid is increasing. To promote the consumption of renewable energy, the traditional grid is being transformed into a complex grid with integrated source–grid–load–storage. Since the complex grid has the characteristics of source–grid–load–storage interaction, the traditional grid investment decision method will no longer be applicable. First, this study proposes the unilateral indexes of source, grid, load, and storage in complex grids and the interactive indexes considering grid–source interaction, load–grid interaction, source–load interaction, source–storage interaction, load–storage interaction, and grid–storage interaction are proposed to establish the investment decision system. Then, a hesitance fuzzy linguistic term set combined with regret theory is used to calculate the specific values of the subjectivity index, taking into full consideration the regret avoidance and loss avoidance psychology of investors. In order to comprehensively consider the index preference of investors and the objectivity of weight assignment, a combined weighting method based on the analytic network process (ANP) and entropy weight method (EWM) is obtained according to the game theory method. Finally, using a grid in a region of southwest China as an example, the results demonstrate that the construction order obtained in this study can prioritize the projects with the largest comprehensive benefits while considering the subjective preferences of decision-makers and the objectivity of the indexes.

KEYWORDS

complex power grid investment decision, source–grid–load–storage integration, index system, analytic network process, the entropy weight method, combined weighting method, regret theory

1 Introduction

In recent years, with the rapid growth of the world economy and progress of the society, energy consumption is increasing. Although governments have strongly supported the use of renewable energy recently, traditional fossil energy still dominates the global energy structure. For example, data from the National

Energy Administration indicate that the proportion of coal in China's energy composition reaches 56% (NEA, 2022), which greatly exceeds the proportion of other energy sources. The large amount of greenhouse gases emitted by the large-scale use of coal puts a huge pressure on the environment. New energy sources such as wind power and photovoltaics have the advantages of low pollution, large reserves, renewable, and low pressure on the environment (Mohtasham, 2015), making them the primary choice for solving today's serious environmental pollution and resource depletion problems. However, with the widespread use of new energy sources, their randomness, volatility, and uncertainty (Li et al., 2019) add modulation difficulties and operational risks to the need for safe and stable operation of power grids, which restricts the development and utilization of renewable energy sources to a certain degree and also cause difficulties in grid connection. Electrochemical energy storage (Zhang, 2013) and flexible load (Chen et al., 2018) can achieve a balance between electricity production and consumption which is why they are widely used in grids containing large amounts of renewable energy. With the rise of renewable energy, flexible load, and electrochemical energy storage in traditional power grids, their degree of grid–source, load–grid, source–load, source–storage, load–storage, and grid–storage interaction is deepening and their integration is strengthening, forming a complex grid with source–grid–load–storage integration. The construction of a safe, stable, economical, and efficient complex grid has become an urgent need for investors (Liu et al., 2016).

Since the traditional grid investment decision method focuses mainly on the unilateral indexes of source–grid–load–storage, the coupling influence between source–grid–load–storage is not considered comprehensively, and its investment decision may have inaccurate results. For example, electrochemical energy storage and grid interaction can regulate peak and frequency (Dasgupta et al., 2015), reduce grid-side grid loss and the amount of heavy load line, improve its network coordination, and thus achieve the purpose of slowing down the construction of new lines. The construction of flexible load near power sources can promote the local consumption of new energy (Yang et al., 2021), which can play a role in reducing the pressure of new energy outgoing and thus slow down the construction of new lines. In the interaction between electrochemical energy storage and flexible load and power supply, both can play a role in reducing abandoned wind and solar power and maintaining the power balance of the grid, so electrochemical energy storage and flexible load will also influence the construction order of each other. Due to the aforementioned reasons, the traditional investment decision method is difficult to meet the complex grid construction needs under the source–grid–load–storage integration conditions, and a new investment decision method is urgently needed.

The main contributions of this study are as follows: 1) an investment decision index system that takes into account the interaction of each side of the complex grid is established, which can comprehensively evaluate the safety, technicality, and economy of each part of the source–grid–load–storage. 2) An EWM–ANP combination weighting method based on game theory is established, considering the interaction and feedback relationship of each part of the complex grid, and the subjective preferences of decision makers and the objectivity of the indexes are fully considered. 3) A subjective index calculation method based on hesitation and regret theory is obtained, taking into account the hesitation and regret psychology of decision makers. The subjective index calculation method based on hesitation linguistic fuzzy term set-regret theory is obtained by accounting for the hesitation and regret psychology of decision makers.

Our study analyzed a total of 16 projects to be built on each side of the source–grid–load–storage in an actual grid in a region of southwest China, and the construction order of the projects to be built on each side of the complex grid is derived using the distance vector merging algorithm (Wang et al., 2019). Our results emphasize that 1) the method in this study comprehensively considers technical, economic, and safety perspectives, and not the better economic projects are built first. 2) The weights in this study consider the different interaction and feedback relationships of each side of source–grid–load–storage, so the weights of each side are different.

2 Literature review

The power system investment decision method mainly focuses on the establishment of the index system and the research with the weighting method. For the establishment of the index system, the Zhang et al. (2021a) constructed the distributed generation source investment decision system from economic benefits and environmental benefits. (Şengül et al., 2015; Koponen and le Net, 2021) constructed the renewable energy investment decision index system from technology, economy, environment, and society. (Ma et al., 2019; Wang et al., 2019; Qian et al., 2022) established a comprehensive decision system for grid investment from technical benefit, economic benefit, and social benefit. Zhang et al. (2021b) established a comprehensive decision system for multi-energy systems from the investment cost of the distribution grid, renewable energy, and electrochemical energy storage equipment. Li et al. (2021) evaluated the effect of flexible load participation in grid interaction from interaction participation, interaction effect, and grid security. Han et al. (2016) established an economic decision method for coupled photovoltaic-storage-microgrid systems based on cost–benefit analysis with the objective of the maximum life-cycle net profit.

In the study of weighting methods, there are methods such as the analysis hierarchical process (Gao et al., 2021), analytic network process (Xiao et al., 2004), Delphi method (Zeng et al., 2016), principal component analysis (Liu et al., 2015), entropy weight method (Kao and van Roy, 2014), anti-entropy weight method (Liu et al., 2019), gray relational analysis (Xiang et al., 2019), coefficient of variation method (Zhang et al., 2018), and the combination methods of the aforementioned methods for weighting (Zhu and Zhang, 2019). In the analysis hierarchical process (AHP), the indexes are independent of each other, which is not applicable for assigning weight investment decisions with interactions in a complex grid. The analytic network process has a very complex computational process. The Delphi method is time-consuming. The principal component analysis method needs to ensure that several principal components extracted have an actual background and meaningful interpretation. The entropy weight method, anti-entropy weight method, and the coefficient of variation method generally have the disadvantage that the subjective preferences of decision makers are not taken into account and the weights change with the modeled samples. Gray relational analysis requires a large amount of data, and the data should follow a typical distribution of some mathematical statistics.

To solve the aforementioned issues, an investment decision system that takes into account the source–grid–load–storage interaction of a complex grid was established in this study. In order to consider the hesitation and regret psychology of experts, hesitance fuzzy linguistic term sets combined with regret theory were used to calculate the qualitative index. In order to consider the dependency and feedback relationship of source–grid–load–storage indexes and overcome the shortage of the subjective assignment method, a combined weighting method based on the game theory of the analytic network process and entropy weight method was proposed so that the assigned weights have the advantage of expert experience and avoid the subjective arbitrariness of assignment. It can be observed from the results of the algorithm (Ma et al., 2019) that the method can provide decision-making support for complex grid investments.

However, to our knowledge, there are few index systems that comprehensively consider the interactions between source–grid–load–storage and can simultaneously evaluate projects on each side of the source–grid–load–storage in a complex grid. Regarding weighting methods, there is rarely any weighting method that considers the interaction and feedback of the components in a complex grid and the subjective preferences of decision makers and the objectivity of the indexes.

3 Interaction of a complex grid

The electrochemical energy storage has different interactions due to the different construction locations. If the electrochemical energy storage is built on the power side, it can interact with the power source and play a role in reducing curtailment of wind power and solar power. However, if the energy storage is built on the grid side, it can interact with the grid and play the role of peak shaving and frequency regulation. Similarly, if the energy storage is built on the load side, it can play the role of earning the difference between peak and valley electricity price. Figure 1 illustrates the source–grid–load–storage interaction.

4 Investment decision index system of a complex grid

Here, a two-dimensional structure model of a complex power grid investment decision-making index system, which considers the single side and multiple interactions of source–grid–load–storage, is established. In Figure 2, the *i*, *j* flat represents the interaction of the source–grid–load–storage. The points on the axis parallels represent the influence within a single side, for example, point M represents the influence of the source itself. Points beyond the axis bisector indicate the influence of multiple interactions. For example, point N indicates the influence of grid–source interaction, and point P indicates the influence of source–load interaction.

From Figures 1, 2, the security impact and economic benefits generated by the energy flow of each part of the complex grid are analyzed. Its investment decision index system contains unilateral indexes of source–grid–load–storage and interactive indexes of grid–source, load–grid, source–load, source–storage, grid–storage, and load–storage. The decision indexes are selected according to the principles of comprehensiveness, comparability, operability, and qualitative with quantitative combination. On the power side, the single-side indexes in Figure 4 are selected to measure the operational characteristics of the complex grid under high penetration of new energy. On the grid side, the single-side indexes in Figure 5 are selected to measure its security. On the load side, the single-side indexes in Figure 6 are selected to measure its participation in the grid regulation process and its impact on the grid. On the electrochemical energy storage side, the single-side indexes in Figure 7 are selected to measure its degree of interaction with the complex grid and its own technical sophistication. In terms of single-side indexes, each side contains four quantitative indexes and one qualitative index. On the interaction side, each side

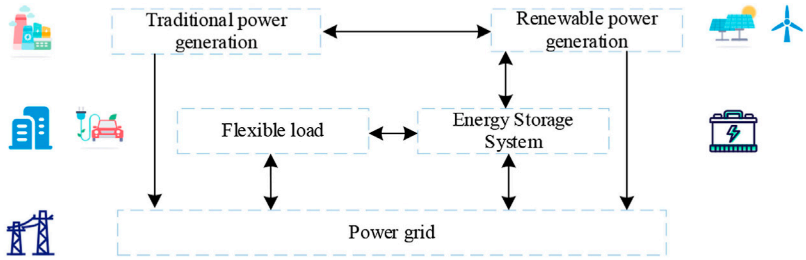

FIGURE 1
Diagram of source–grid–load–storage interaction.

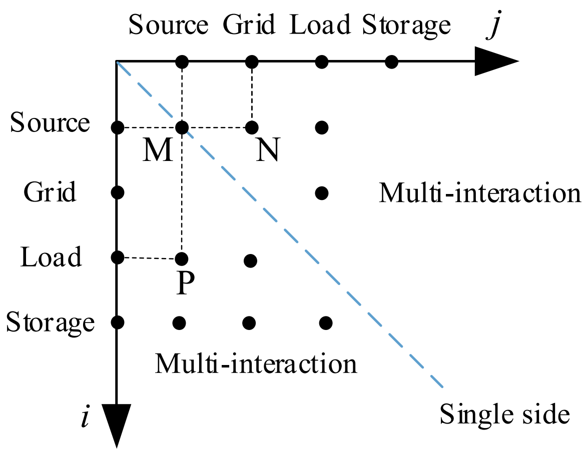

FIGURE 2
Two-dimensional structural model of source–grid–load–storage decision indexes.

contains four economic efficiency indexes (quantitative indexes), of which the first two indexes are the interaction benefits and the next two indexes are the annual investment benefit ratio and payback period. The adoption of an index system with a completely consistent structure on each side of the source–grid–load–storage can ensure the accuracy of subsequent weighting using the ANP and AHP.

4.1 Calculation of the qualitative index

The unilateral subjectivity index (Q) for each side of the source–grid–load–storage is calculated from the four attributes (S1 to S4) in Figure 3 under different risk states (W_1 to W_3).

Step 1: Determine the fuzzy level and its corresponding triangular fuzzy number.

The set of hesitant fuzzy linguistic terms is represented by the triangular fuzzy number $\tilde{x} = (\tilde{x}^l, \tilde{x}^m, \tilde{x}^u)$. The fuzzy rank of the triangular fuzzy number (very poor, poor, rather poor, normal, good, and very good) is used to represent the scoring of the experts, and the set of linguistic terms is $\tilde{S} = \{S_0, S_1, S_2, S_3, S_4, S_5, S_6\}$. $M = \{1, 2, \ldots, m\}$, $N = \{1, 2, \ldots, n\}$, and $T = \{1, 2, \ldots, t\}$.

$X = \{X_1, X_2, \ldots, X_m\}$ represents the set of m alternatives, where X_j represents the jth alternative, $j \in M$. $Y = \{Y_1, Y_2, \ldots, Y_n\}$ represents the set of n attributes, where Y_i represents the ith attribute, $i \in N$. $w = \{w_1, w_2, \ldots, w_n\}$ represents the set of n weights,

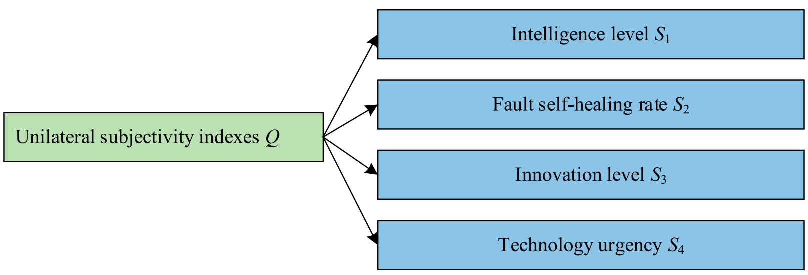

FIGURE 3
Unilateral subjectivity index.

where w_i represents the weight of attribute Y_i satisfying $w_i \geq 0$ and $\sum_{i=1}^{n}\omega_i = 1$. $W = \{W_1, W_2, \ldots, W_k\}$ represents the set of natural states, $k\in T$, in Supplementary Appendix Tables SA1–SA3. The risk-based multi-attribute decision matrix table given by the expert is shown in Supplementary Appendix S1. There are three natural states of W_1, W_2, and W_3 and four attributes of Y_1, Y_2, Y_3, and Y_4.

The optimal value of each attribute for each alternative for different states of nature is determined to be the positive ideal point of the attribute value and is expressed as Eq. 1:

$$\tilde{x}_i^{k+} = \begin{cases} \left(\max\limits_{1\leq j\leq m}\{x_{ji}^{kl}\}, \max\limits_{1\leq j\leq m}\{x_{ji}^{km}\}, \max\limits_{1\leq j\leq m}\{x_{ji}^{ku}\}\right), c \in N_b, \\ \left(\min\limits_{1\leq j\leq m}\{x_{ji}^{kl}\}, \min\limits_{1\leq j\leq m}\{x_{ji}^{km}\}, \min\limits_{1\leq j\leq m}\{x_{ji}^{ku}\}\right), c \in N_c. \end{cases} \tag{1}$$

According to equation Eq. 1, the positive ideal points of state W_1 can be taken as $\tilde{x}_1^{1+}$, $\tilde{x}_2^{1+}$, $\tilde{x}_3^{1+}$, $\tilde{x}_4^{1+}$. The positive ideal points of state W_2 are $\tilde{x}_1^{2+}$, $\tilde{x}_2^{2+}$, $\tilde{x}_3^{2+}$, $\tilde{x}_4^{2+}$. The positive ideal points of state W_3 are $\tilde{x}_1^{3+}$, $\tilde{x}_2^{3+}$, $\tilde{x}_3^{3+}$, $\tilde{x}_4^{3+}$.

Step 2: Normalization of the matrix.

The decision matrix D can be normalized using the following equation to eliminate the influence of different physical magnitudes on the index values, thus obtaining the normalized decision matrix B. equation.

$$\begin{aligned} B &= \left[\tilde{b}_{ji}^{k}\right]_{m\times n\times t}, \tilde{b}_{ji}^{k} = \left(\tilde{b}_{ji}^{kl}, \tilde{b}_{ji}^{km}, \tilde{b}_{ji}^{k\mu}\right) \\ &= \begin{cases} \left(\tilde{x}_{ji}^{kl}/x_i^{k\mu+}, \tilde{x}_{ji}^{km}/x_i^{km+}, \left(\tilde{x}_{ji}^{ku}/x_i^{kl+}\right)\wedge 1\right), j\in M, i\in N_b, k\in T, \\ \left(\tilde{x}_j^{kl+}/x_{ji}^{ku}, \tilde{x}_i^{km+}/x_i^{km}, \left(\tilde{x}_i^{ku+}/x_{ji}^{kl}\right)\wedge 1\right), j\in M, i\in N_c, k\in T. \end{cases} \end{aligned} \tag{2}$$

Step 3: Regret perception computing.

Regret perception is calculated by the following equation.

$$R\left(\Delta\tilde{b}\right) = 1 - \exp\left(-\delta\Delta\tilde{b}\right), \tag{3}$$

where δ (δ > 0) is the regret avoidance coefficient, which represents the difference between the utility values of the two options. The larger the δ is, the greater the degree of regret avoidance of the decision maker. According to Eq. 4, the obtained perceived attribute values for each attribute in the plan are as follows.

$$\tilde{h}_{ji}^{k} = \tilde{b}_{ji}^{k} + R\left(\Delta\tilde{b}\right) = \tilde{b}_{ji}^{k} + 1 - \exp\left(-\delta\Delta\tilde{b}\right) = \tilde{b}_{ji}^{k} + 1 - \exp\left(-\delta\left(\tilde{b}_{ji}^{k} - \tilde{b}_i^{k+}\right)\right),\ \tilde{b}_i^{k+} = \left(\max_{1\leq j\leq m}\left(\tilde{b}_{ji}^{ku}\right), \max_{1\leq j\leq m}\left(\tilde{b}_{ji}^{km}\right), \max_{1\leq j\leq m}\left(\tilde{b}_{ji}^{kl}\right)\right). \tag{4}$$

Then, the regret perception decision matrix is $H = [\tilde{h}_j^{k}]_{m\times k\times t}$.

Step 4: The group utility value and individual regret value can be solved by Eq. 5.

$$\begin{aligned} S_j^k &= \sum_{i=1}^{n}\omega_i\left\|\tilde{h}_i^{k+} - \tilde{h}_{ji}^{k}\right\| \Big/ \left\|\tilde{h}_i^{k+} - \tilde{h}_i^{k-}\right\|, \\ R_j^k &= \max_{1\leq i\leq n}\left[\omega_i\left\|\tilde{h}_i^{k+} - \tilde{h}_{ji}^{k}\right\| \Big/ \left\|\tilde{h}_i^{k+} - \tilde{h}_i^{k-}\right\|\right], \\ \tilde{h}_i^{k+} &= \left(\max_{i\leq j\leq m}\{h_{ji}^{kl}\}, \max_{i\leq j\leq m}\{h_{ji}^{km}\}, \max_{i\leq j\leq m}\{h_{ji}^{ku}\}\right\}, \\ \tilde{h}_i^{k-} &= \left(\min_{i\leq j\leq m}\{h_{ji}^{kl}\}, \min_{i\leq j\leq m}\{h_{ji}^{km}\}, \min_{i\leq j\leq m}\{h_{ji}^{ku}\}\right]. \end{aligned} \tag{5}$$

Step 5: Decision values for subjective indexes are shown as Eq. 6.

$$\begin{aligned} Q_j^k &= \frac{\nu\left(S_j^k - S^{k+}\right)}{S^{k-} - S^{k+}} + \frac{(1-\nu)\left(R_j^k - R^{k+}\right)}{R^{k-} - R^{k+}}, \\ Q_j &= \sum_{k=1}^{t} p^k Q_j^k, j \in M, k \in T, \end{aligned} \tag{6}$$

where $S^{k+} = \min\limits_{l\leq j\leq m} S_j^k$, $S^{k-} = \max\limits_{l\leq j\leq m} S_j^k$, $R^{k+} = \min\limits_{l\leq j\leq m} R_j^k$, and $R^{k-} = \max\limits_{l\leq j\leq m} R_j^k$, and the value of v is 0.5 in this study.

Step 6: Solving the optimal solution.

$$\begin{aligned} &\min Q_j \\ &\text{s.t.}\quad p_k^l \leq p_k \leq p_k^u, k \in T, \\ &\sum_{k=1}^{t} p_k = 1, \\ &Q_j = \sum_{k=1}^{t} p^k Q_j^k, j \in M, k \in T. \end{aligned} \tag{7}$$

It should be noted that Q_j is the calculated minimal index, which needs to be transformed into a maximal index when performing the calculation of the combined value of indexes. The values of Q_j are shown in Supplementary Appendix Table S4. In the subsequent calculation of the combined value of indexes for the project to be built, Q_j is used to represent the combined value of indexes S_1, S_2, S_3, and S_4. The calculation results are shown in Supplementary Appendix S1.

4.2 Calculation of quantitative indexes on the source side

The wind speed is simulated as follows:

$$f_w(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1}\exp\left[-\left(\frac{v}{c}\right)^k\right], \tag{8}$$

$$P_w = \begin{cases} 0 & v \leqslant v_{\text{ci}}, v \geqslant v_{\text{co}} \\ P_{\text{r}} * \dfrac{v^3 - v_{\text{ci}}^3}{v_{\text{r}}^3 - v_{\text{ci}}^3} & v_{\text{ci}} < v < v_{\text{r}} \\ P_{\text{r}} & v_{\text{r}} < v < v_{\text{co}} \end{cases}. \tag{9}$$

In Eq. 8, c and k are the scale and shape parameters, respectively, and c reflects the average wind speed of the wind power plant. c is taken as 22.64 and v as 24.1. The wind power

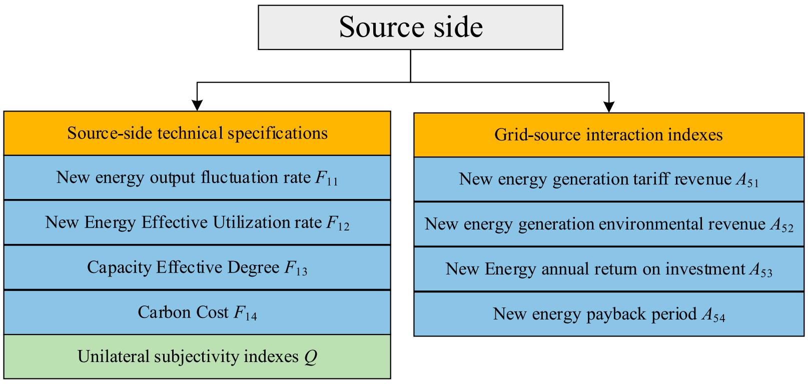

FIGURE 4
Source-side investment decision indexes.

output is calculated as follows. In Eq. 9, v_{ci} is the cut-in wind speed, v_r is the rated wind speed, and v_{co} is the cut-out wind speed. The calculation method of photovoltaic output is the same as that of wind power and will not be repeated here.

The source-side investment decision indexes are shown in Figure 4.

The new energy output fluctuation rate (Liou and Wang Maojiun, 1992) is calculated as Eq. 10.

$$F_{11} = \frac{P^{NE}_{\max} - P^{NE}_{\min}}{P^{NE}_{\max}}. \tag{10}$$

PNE max is the maximum power generated by new energy in a typical day, MW; *PNE* min is the minimum power generated by new energy in that day, MW.

The new energy effective utilization rate (Zhao et al., 2015) is calculated as Eq. 11.

$$F_{12} = \frac{E^{NE*}_{\mathrm{NG}}}{P^{NE}_{NG}\mathrm{T}}. \tag{11}$$

*ENE** NG is the actual annual output of new energy, MW·h; *PNE NG* is the installed capacity of new energy, MW; and T is 8760 hours (total number of hours in a year).

The capacity effective degree is calculated as Eq. 12.

$$F_{13} = \frac{E^{NE*}_{\mathrm{NG}}}{E^{*}_{all}}. \tag{12}$$

E all* is the actual annual generation capacity of all units, MW·h.

Carbon cost is calculated as Eq. 13.

$$F_{14} = k_{\mathrm{CO_2}} E^{NE}_{\mathrm{NG}} \lambda_{\mathrm{CO_2}} {}^{*}0.1. \tag{13}$$

In the aforementioned Eq. 13, k_{CO2} is the carbon emission factor, and the typical value of the carbon emission factor of the southern power grid (Zhang et al., 2018) is 0.5721 kg/(kW·h), λCO_2 is the unit carbon emission trading price of 0.0585 yuan/kg, and the unit of $F_{14,power}$ is 10000 yuan.

New energy generation tariff revenue is calculated as Eq. 14.

$$A_{51} = E^{NE}_{\mathrm{NG}} {}^{*} M_{Newenergy} {}^{*}0.1. \tag{14}$$

$M_{Newenergy}$ is the new energy generation tariff, yuan/(kW·h), and the unit of $A_{51,G\text{-}p}$ is million yuan.

New energy generation environmental revenue is calculated as Eq. 15.

$$A_{52} = E^{NE}_{\mathrm{NG}} {}^{*} k_{\mathrm{CO_2}} {}^{*} M_{Carbon} {}^{*}0.1. \tag{15}$$

M_{Carbon} is the unit price of the environmental revenue of new energy generation, yuan/kg, and the unit of $A_{52,G\text{-}p}$ is 10000 yuan.

New energy annual return on investment is calculated as Eq. 16.

$$\begin{cases} Annual_{Powercost} = \left(\left(1 + x_{wp}\%\right) c_{wp} E_{wp}\right) \dfrac{(1+r)^{T_{\text{Lifespanp}}} r}{(1+r)^{T_{\text{Lifespanp}}} - 1}\ Photovoltaic, \\ Annual_{Powercost} = \left((1 + x_{ww}\%) c_{ww} E_{ww}\right) \dfrac{(1+r)^{T_{\text{Lifespanw}}} r}{(1+r)^{T_{\text{Lifespanw}}} - 1}\ Wind, \\ A_{53} = \dfrac{A_{51} + A_{52}}{Annual_{Powercost}}. \end{cases} \tag{16}$$

c_{wp} and c_{ww} are the unit power price of photovoltaic and wind power, million/MW; E_{wp} and E_{ww} are the rated power of photovoltaic and wind power, MW, respectively. $T_{lifespanp}$ and $T_{lifespanw}$ are the full life cycle of photovoltaic and wind power, years; r is the social average annual return on investment, which is taken as 8% in this study. x_{wp}% and x_{ww}% are the ratio of the operating cost and initial investment of photovoltaic and wind power, respectively. The unit of $Annual_{powercost}$ is 10000 yuan.

The new energy payback period is calculated as Eq. 17.

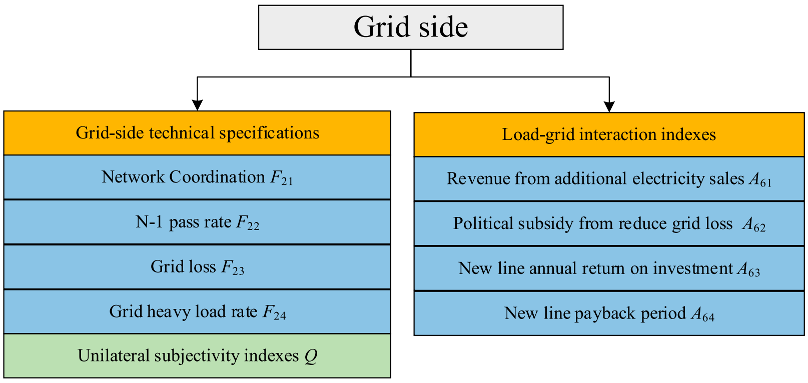

FIGURE 5
Grid-side investment decision indexes.

$$A_{54} = \begin{cases} \dfrac{Annual_{Powercost} {}^{*} T_{\text{Lifespanp}}}{A_{51} + A_{52}} \; Photovoltaic, \\ \dfrac{Annual_{Powercost} {}^{*} T_{\text{Lifespanw}}}{A_{51} + A_{52}} \; Wind. \end{cases} \tag{17}$$

4.3 Calculation of quantitative indexes on the grid side

The grid-side investment decision indexes are shown in Figure 5.

Network coordination is calculated as Eq. 18.

$$F_{21} = \frac{P_{\max}^{NE} - P_{\min}^{NE}}{P_{\max}^{NE}}. \tag{18}$$

N_{L} is the total number of power grid lines, L_k is the load rate of the ith line, and $\bar{L}$ is the average of the load rates of N_{L} lines.

The N-1 pass rate is calculated as Eq. 19, and N_{p} is the number of lines that passes the N-1 security check.

$$F_{22} = \frac{N_{\mathrm{p}}}{N_{\mathrm{L}}}. \tag{19}$$

Grid loss is calculated as Eq. 20.

$$F_{23} = \sum_{(ij)\in\Omega_l} \left[g_{ij} \left(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij} \right) \right] {}^{*} 10^{-6}. \tag{20}$$

Ω_l is the set of all branches in the grid. V_i and V_j are the voltage amplitudes of nodes i and j in the grid, respectively. g_{ij} and Θ_{ij} are the conductance and phase angle differences of nodes i and j in the grid, respectively. The unit of $F_{23,grid}$ is MW.

The grid heavy load rate is calculated as Eq. 21.

$$F_{24} = \frac{N_{\mathrm{HL}}}{N_{\mathrm{L}}}. \tag{21}$$

N_{HF} is the number of heavy load lines. In this study, the annual maximum load rate exceeds 70% and lasts for more than 1 hour as a heavy load line.

Revenue from additional electricity sales is calculated as Eq. 22.

$$A_{61} = E_{IE}^{Loss} {}^{*} M_{\mathrm{Grid}} {}^{*} 0.1. \tag{22}$$

ELoss IE* is the annual incremental electricity sales, MW·h. M_{Grid} is the electricity sale price, yuan/(kW·h). The unit of $A_{61,L\text{-}g}$ is 10,000 yuan.

Political subsidy from reduced grid loss is calculated as Eq. 23.

$$A_{62} = E_{IE}^{Loss} {}^{*} M_{\mathrm{Grid}} {}^{*} 0.1. \tag{23}$$

M_{reward} is the unit price of the reward, yuan/(MW·h). The unit of $A_{62,L\text{-}g}$ is 10000 yuan.

New line annual return on investment is calculated as Eq. 24:

$$\begin{cases} Annual_{gridcost} = \left(\left(1 + x_g\% \right) c_g L_g \right) \dfrac{(1+r)^{T_{\text{Lifespang}}} r}{(1+r)^{T_{\text{Lifespang}}} - 1}, \\ A_{63} = \dfrac{A_{61} + A_{62}}{Annual_{gridcost}}. \end{cases} \tag{24}$$

c_g is the cost per kilometer of the transmission line, 10000 yuan/km. L_g is the length of the transmission line, km. $T_{lifespang}$ is the full life cycle of the transmission line, years. $x_g\%$ is the ratio of the operating cost of the transmission line to the initial investment. The unit of $Annual_{gridrcost}$ is 10000 yuan.

The new line payback period is calculated as Eq. 25.

$$A_{64} = \frac{Annual_{gridrcost} {}^{*} T_{\text{Lifespang}}}{A_{61} + A_{62}}. \tag{25}$$

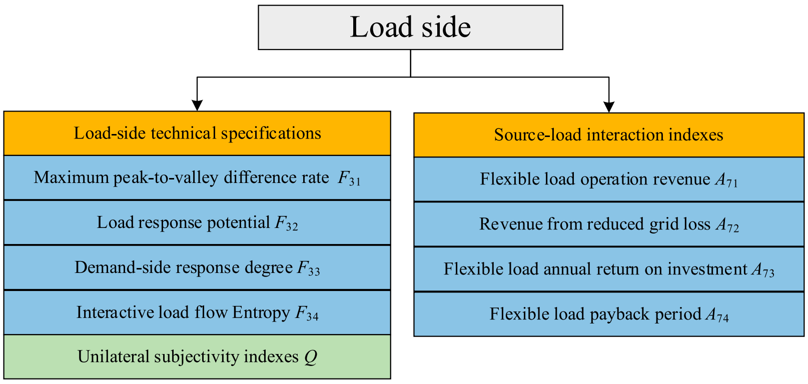

FIGURE 6
Grid-side investment decision indexes.

4.4 Calculation of quantitative indexes on the load side

The load-side investment decision indexes are shown in Figure 6.

The maximum peak-to-valley difference rate is calculated as Eq. 26, and $PLoad\ t$ is the power of the flexible load at moment t in day D, MW. $\max_{t\in D}(P_t^{Load})$ and $\min_{t\in D}(P_t^{Load})$ are the maximum and minimum values of the flexible load on day D, respectively.

$$F_{31} = \frac{\left(\max_{t\in D}(P_t^{Load}) - \min_{t\in D}(P_t^{Load})\right)}{\max_{t\in D}(P_t^{Load})}. \tag{26}$$

Load response potential is calculated as Eq. 27.

$$F_{32} = \\ = \begin{cases} \dfrac{P_{i,\max}(t) - P_{i,0}(t)}{P_{i,0}(t)}, & Increased\ power\ after\ \text{interaction}, \\ \dfrac{P_{i,\min}(t) - P_{i,0}(t)}{P_{i,0}(t)}, & Decreased\ power\ after\ \text{interaction}. \end{cases} \tag{27}$$

$P_{i,\max}(t)$, $P_{i,\min}(t)$, and $P_{i,0}(t)$ are the maximum power, minimum power, and rated power that can be reached after the flexible load participates in the demand-side response at time t, respectively, all in MW.

The demand-side response degree is calculated as Eq. 28, and $P_i(t)$ is the actual interactive power of the flexible load, MW.

$$F_{33} = \frac{P_i(t) - P_{i,0}(t)}{P_{i,0}(t)F_{32,load}(t)}. \tag{28}$$

Interactive load flow entropy is calculated as Eq. 29.

$$F_{34} = -\ln 10 \sum_{j}^{n-1} \frac{l_j}{N_L} \ln N_L. \tag{29}$$

Given a constant sequence $R = \{R_1, R_2, R_3, \ldots, R_n\}$, l_j is the number of lines whose load rate r_j satisfies $r_j \in (R_j, R_{j+1}]$.

In this study, the internet data center load is used as an example of a revenue stream in the form of rack rental, IT electricity tax credit revenue, settlement revenue, and bandwidth revenue. Flexible load operation revenue is calculated as Eq. 30.

$$A_{71} = P_{i,0}(t)^* M_{\mathrm{IDC}}{}^* 100. \tag{30}$$

M_{IDC} is the unit revenue of the internet data center, yuan/W·years. The unit of $A_{72,P\text{-}l}$ is 10000 Yuan.

Revenue from reduced grid loss is calculated as Eq. 31.

$$A_{72} \overset{*}{=} \left(E^{Loss}_{BeforeLoad} \overset{*}{-} E^{Loss}_{AfterLoad}\right)^* M_{\mathrm{Grid}}. \tag{31}$$

$ELoss^*$ BeforeLoad and $ELoss^*\ AfterLoad$ are the total annual loss of the grid before and after the new flexible load, MW. The unit of $A_{71,P\text{-}l}$ is 10000 yuan.

Flexible load annual return on investment is calculated as Eq. 32.

$$\begin{cases} Annual_{Loadcost} = \left((1 + x_l\%)c_l P_l\right) \dfrac{(1+r)^{T_{\mathrm{Lifespanl}}} r}{(1+r)^{T_{\mathrm{Lifespanl}}} - 1}, \\ A_{73} = \dfrac{A_{71} + A_{72}}{Annual_{Loadcost}}. \end{cases} \tag{32}$$

c_l is the price per unit power of the flexible load, million/(MW·h). P_l is the rated power of the flexible load, MW·h. $T_{lifespanl}$ is the full life cycle of the flexible load, years. $x_l\%$ is the ratio of the operating cost of the flexible load to the initial investment, and the unit of $Annual_{loadcost}$ is 10000 yuan.

The flexible load payback period is calculated as Eq. 33.

$$A_{74} = \frac{Annual_{Powercost} {}^{*} T_{\text{Lifespanw}}}{A_{71} + A_{72}} \tag{33}$$

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4.5 Calculation of quantitative indexes on the storage side

The storage-side investment decision indexes are shown in Figure 7. The electrochemical energy storage whole life cycle cost is calculated as Eq. 34.

$$F_{41} = \Big((1 + x_s\%)c_e E_{storage} + (1 + y_s\%)c_p P_{storage}\Big)\frac{(1+r)^{T_{\text{Lifespan}}} r}{(1+r)^{T_{\text{Lifespan}}} - 1}. \tag{34}$$

c_e and c_p are the price per unit capacity and the price per unit power of electrochemical energy storage, respectively, 10000 yuan/(MW·h). $E_{storage}$ and $P_{storage}$ are the rated capacity (MW·h) and rated power (MW) of the electrochemical energy storage power plant, respectively, and $T_{lifespan}$ is the whole life cycle of the electrochemical energy storage power plant. $x_s\%$ and $y_s\%$ are the ratio of the operating cost of electrochemical energy storage capacity and power to initial investment. $F_{41,storage}$ is in million yuan.

The electrochemical energy storage average discharge depth is calculated as Eq. 35.

$$F_{42} = \frac{1}{k}\sum_{i=1}^{k} ED_i. \tag{35}$$

ED_i is the electricity released during the ith discharge of the electrochemical energy storage system, MW. k is the number of discharges of the electrochemical energy storage device during the year.

Electrochemical energy storage annual electricity loss is calculated as Eq. 36.

$$F_{43} = \sum_{t=1}^{T}\left(u_t^{ESS} P_t^{ESS,c} - v_t^{ESS} P_t^{ESS,d}\right). \tag{36}$$

PESS,c t and *PESS,d t* are the charging and discharging power of the electrochemical energy storage at hour t, MW, respectively. *uESS t* and *vESS t* are the charging and discharging characteristic variables of the electrochemical energy storage, respectively, and cannot be 1 at the same time. When *uESS t* = 1 and *vESS t* = 0, the electrochemical energy storage plant is in the charging state. When *uESS t* = 0 and *vESS t* = 1, the electrochemical energy storage plant is discharging. When *uESS t* = 1 and *vESS t* = 0, the storage plant is in the static state. $F_{43,storage}$ is in MW.

The electrochemical energy storage annual operating hours are calculated as Eq. 37.

$$F_{44} = \sum_{t=1}^{T}\left(u_t^{ESS} + v_t^{ESS}\right). \tag{37}$$

Reduced curtailment of wind power and solar power revenue is calculated as Eq. 38.

$$A_{81} = (E_{\text{AW}} + E_{\text{AP}})^{*} M_{P-s}. \tag{38}$$

E_{AW} and E_{AP} are the annual abandoned wind power and abandoned photovoltaic power reduced by the electrochemical energy storage, respectively, MW·h. $M_{P\text{-}s}$ is the reward coefficient, 10000 yuan/(MW·h). The unit of $A_{81,}$ is 10000 yuan.

Delayed installed generation annual revenue is calculated as Eq. 39, and e_r denotes the price per unit of power backup capacity, million/(MW·h). The unit of $A_{82,P\text{-}s}$ is million yuan.

$$A_{82} = e_r \sum_{t=1}^{T} v_t^{ESS} P_t^{ESS,d}. \tag{39}$$

The difference earned between peak and valley electricity prices is calculated as Eq. 40.

$$A_{91} = \Delta Q\left(p_f - p_g\right)^{*} 0.1. \tag{40}$$

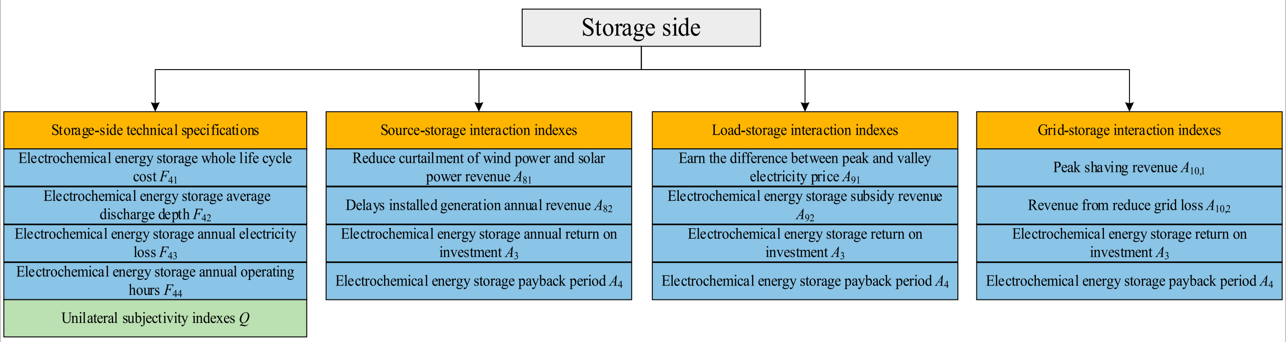

FIGURE 7
Storage-side investment decision indexes.

ΔQ is the total amount of electricity charged through the electrochemical energy storage system throughout the year, MW·h. P_f and P_g are the peak and valley tariffs implemented in the region, respectively, yuan/(kW·h). $A_{91,L\text{-}s}$ are in million yuan.

The electrochemical energy storage subsidy revenue (Han et al., 2014) is calculated as Eq. 41.

$$A_{92} = \Delta p_f m_f {}^*0.1. \tag{41}$$

ΔP_f is the annual peak load reduction after grid access to electrochemical energy storage, MW·h. m_f is the reward received per unit peak load reduction, yuan/(kW·h). The unit of $A_{92,L\text{-}s}$ is 10000 yuan.

The peak-shaving revenue is calculated as Eq. 42.

$$A_{10,1} = e_m P_{RC} {}^*0.1. \tag{42}$$

e_m is the unit peaking revenue of electrochemical energy storage, yuan/(kW·h). P_{RC} is the annual peaking electricity of electrochemical energy storage, MW·h. The unit of $A_{10,1,G\text{-}s}$ is 10000 yuan.

Revenue from reduced grid loss is calculated as Eq. 43.

$$A_{10,2} = \sum_{i=1}^{N^T} \Delta Q_{loss} {}^* M_{\mathrm{Grid}} {}^*0.1. \tag{43}$$

ΔQ_{loss} represents the amount of change in grid loss before and after new electrochemical energy storage, MW. The unit of $A_{10,2,G\text{-}s}$ is 10000 yuan.

Let the electrochemical energy storage and source–grid–load interaction revenue be $A_{1,s}$ and $A_{2,s}$.

The electrochemical energy storage return on investment is calculated as Eq. 44.

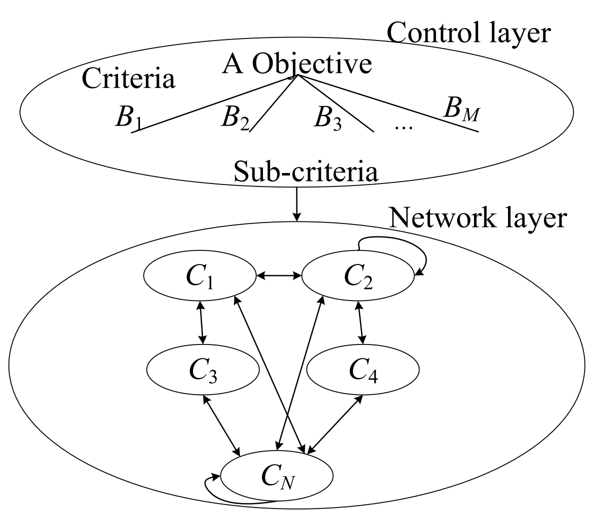

FIGURE 8
ANP structure diagram.

$$A_3 = \frac{A_{1,s} + A_{2,s}}{F_{41}}. \tag{44}$$

The electrochemical energy storage payback period is calculated as Eq. 45.

$$A_4 = \frac{F_{41,storage} {}^* T_{\mathrm{Lifespan}}}{A_{1,s} + A_{2,s}}. \tag{45}$$

5 Determination of index weights

5.1 Entropy weight method

The basic principle of the entropy weight method is to assign different weights to the data according to the magnitude of data variation, which is expressed by information entropy.

$$H(x) = -\sum_{i=1}^{n} \left[p(x_i) \ln(p(x_i)) \right]. \tag{46}$$

x is a situation in which event X happens. Then, the probability of this situation happening is $p(x)$ and n is the number of items.

Applying EWM to the calculations in this study, the index matrix first needs to be standardized matrix Z. The following Eq. 47 is the standardization equation.

$$\tilde{z}_{ij} = \frac{x_{ij} - \min\{x_{1j}, x_{2j}, \ldots x_{nj}\}}{\max\{x_{1j}, x_{2j}, \ldots x_{nj}\} - \min\{x_{1j}, x_{2j}, \ldots x_{nj}\}}. \tag{47}$$

Then, the weight of the ith item under the jth index is calculated and considered the probability in the relative entropy calculation: $\mathrm{p_{ij}} = \mathrm{z_{ij}} / \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{z_{ij}}$, which is then normalized by the information entropy calculation equation.

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^{n} p_{ij} \ln(p_{ij}). \tag{48}$$

Finally, the entropy weight of the indexes is calculated.

$$W_j = (1 - e_j) \Big/ \sum_{j=1}^{m} (1 - e_j). \tag{49}$$

In Eq. 49, m is the number of indexes.

5.2 Analytic network process

The ANP is an extension of the AHP which is mainly aimed at situations where the structure of the decision problem is dependent and feedback-oriented. The structure of the ANP is in the form of a network cycle, where one level of the system can be both dominant and indirectly dominated by other levels,

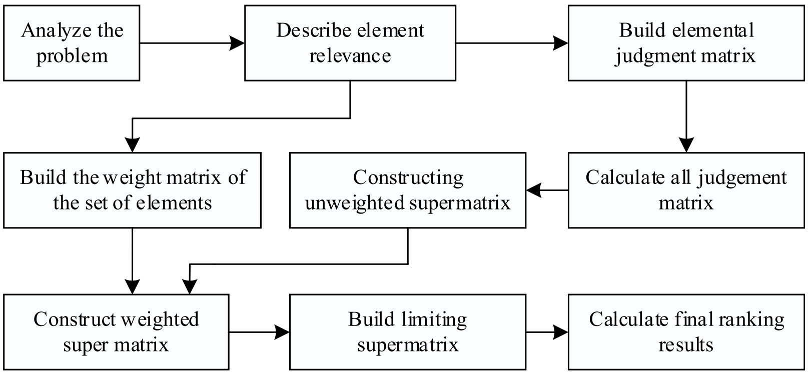

FIGURE 9
ANP calculation workflows.

which can be represented by a network with nodes, as shown in Figure 8 below.

As can be seen from the aforementioned figure, the ANP divides the system elements into the control layer and network layer. The control layer consists of a decision objective A and a decision criterion ($B_1, B_2, \ldots, B_M$). The network layer consists of all the element groups ($C_1, C_2, \ldots, C_N$) that are subject to the decisions of the control layer. The elements in the element group C_i ($i = 1, \ldots, N$) are $e_{i1}, e_{i2}, \ldots, e_{ini}$.

By Figure 9, the calculation flow of ANP is as follows:

Step 1: Describe the element relevance, build and calculate the element judgment matrix, and construct the unweighted supermatrix.

With the control layer B_k as the criterion and the element $e_{jt}(e_{j1}, e_{j2}, \ldots, e_{jnj})$ in $C_j(j = 1, \ldots, N)$ as the sub-criterion. The elements in the element set C_i build the judgment matrix according to their degree of influence on the elements in C_j.

In Eq. 50, the column vector of W_{ij} is the column vector of the degree of influence of the elements in the element set C_i on its own elements, whose value is shown in Supplementary Appendix Tables SB5–SB16.

$$W_{ij} = \begin{bmatrix} w_{i1}^{(j1)} & w_{i1}^{(j2)} & \cdots & w_{i1}^{(jn_j)} \\ w_{i2}^{(j1)} & w_{i2}^{(j2)} & \cdots & w_{i2}^{(jn_j)} \\ \vdots & & & \\ w_{in_i}^{(j1)} & w_{in_i}^{(j2)} & \cdots & w_{in_i}^{(jn_j)} \end{bmatrix}. \tag{50}$$

Then, the unweighted supermatrix W *is* constituted by the degree of influence of all elements in the element set $C_i(i = 1,\ldots,N)$ on all elements in the element set $C_j(j = 1,\ldots, N)$ under the criterion B_k as Eq. 51.

$$W = \begin{array}{c} \\ 1\cdots n_1 \\ 1\cdots n_2 \\ \vdots \\ 1\cdots n_N \end{array} \begin{array}{c} \begin{array}{ccc} 1\cdots n_1 & 1\cdots n_2 & \cdots 1\cdots n_N \end{array} \\ \begin{bmatrix} W_{11} & W_{12}\cdots & W_{1N} \\ W_{21} & W_{22}\cdots & W_{2N} \\ \vdots & & \\ W_{N1} & W_{N2}\cdots & W_{NN} \end{bmatrix} \end{array}. \tag{51}$$

Step 2: Build the weighting matrix of the set of elements.

Taking the control layer B_k as the criterion, a weighting matrix is constructed for the degree of influence of the element set C_i on C_j.

Then, the weighting matrix D is Eq. 52, whose value is shown in Supplementary Appendix Tables SB3–SB4.

$$D = \begin{bmatrix} d_{11}\cdots & d_{1N} \\ d_{21}\cdots & d_{2N} \\ \vdots & \\ d_{N1}\cdots & d_{NN} \end{bmatrix}, \tag{52}$$

Step 3: Using the weighting matrix D to assign weights to the unweighted supermatrix W to obtain the weighted supermatrix as Eq. 53. The value of W is shown in Supplementary Appendix Tables SB17.

$$\bar{W}_{ij} = d_{ij} W_{ij}. \tag{53}$$

Step 4: Build the limiting matrix and obtain the weights of each element.

The elements in the weighted supermatrix $\bar{W}$ are still W_{ij}, which reflects the first-step dominance of element i over element j, recorded as a $\bar{W}^{(1)}$. The value of $\bar{W}$ is shown in Supplementary Appendix Tables SB18. The second-step dominance of element i over element j is $\sum_{m=1}^{N} W_{im}^{(1)} W_{mj}^{(1)}$, recorded as $\bar{W}^{(2)}$. The limiting dominance is the cumulative effect of influence so that the tth-step dominance of element i over element j is as Eq. 54.

$$\bar{W}_{ij}^{(t)} = \sum_{m=1}^{N} \bar{W}_{im}^{(t-1)} \bar{W}_{mj}^{(t-1)}. \tag{54}$$

The limit exists when $\bar{W}^{(t)}$ is at $t \to \infty$, i.e.,

$$\bar{W}^{(\infty)} = \lim_{t \longrightarrow \infty} \bar{W}^{(t)}. \tag{55}$$

Then, the jth column of $\bar{W}^{(\infty)}$ is the weight of each element under B_k. The value of $\bar{W}^{(\infty)}$ is shown in Supplementary Appendix Tables SB19.

5.3 Combined weighting method

The combined weighting method is used to assign weights to complex grid investment indexes so that decision makers can take advantage of their own experience in the decision-making process and avoid the subjective arbitrariness of assigning weights. This study adopts the game theory approach to obtain the combination weights and uses W to represent the weight vector of combination weights, W_a to represent the weight vector derived from the ANP, and W_e to represent the weight vector derived from EWM. According to the Nash equilibrium principle, the optimal value of the combination weight W should be the equilibrium state between the two sides of the game, when the sum of the deviations of W and W_a and W_e is the smallest.

The optimal linear combination coefficients α* and β* are found with the objective function of minimizing the sum of the deviations of W and W_a and W and W_e (Liu et al., 2021). Then, the objective function and constraints for the calculation of W are as Eq. 56.

$$\begin{aligned}&\min\left(\|W-W_a\|_2+\|W-W_e\|_2\right)\\&=\min\left(\|\alpha W_a+\beta W_e-W_a\|_2+\|\alpha W_a+\beta W_e-W_e\|_2\right),\\&s.t.\quad \alpha+\beta=1,\alpha,\beta\geq 0.\end{aligned} \tag{56}$$

According to the principle of differentiation, the conditions for the derivative of Eq. 55 to obtain the minimum value are as expressed as Eq. 57.

$$\begin{cases}\alpha W_a W_a^T+\beta W_a W_e^T=W_a W_a^T,\\ \alpha W_e W_a^T+\beta W_e W_e^T=W_e W_e^T.\end{cases} \tag{57}$$

The values of α and β are then normalized to obtain α^* and β^*.

$$\alpha^*=\frac{|\alpha|}{|\alpha|+|\beta|},\beta^*=\frac{|\beta|}{|\alpha|+|\beta|}. \tag{58}$$

Then, the optimal combination weights are given as Eq. 59.

$$W=\alpha^* * W_a+\beta^* * W_e. \tag{59}$$

Because both EWM and ANP have their limitations, this study uses EWM and ANP to form a combined weighting method which is used to assign weights to the indexes.

5.4 Investment decision method calculation process

First, we determine the project library to be built and then calculate the investment decision indexes of each side of source–grid–load–storage. After index normalization, we form the investment decision index matrix. The EWM is used to assign objective weights to each index first, and then ANP is used to assign subjective weights to each side index. Finally, the combined value of the indexes is calculated using the distance vector combining algorithm, and the indexes are evaluated according to the size of the combined value of the indexes. The calculation flow chart is shown in the following figure.

6 Simulation and analysis

We consider the example of a power grid in a region of southwest China where there are 16 projects to be built on the source–grid–load–storage side. There are 49 buses and 64 branches in the area, of which there are 4220-kV buses, 13 110-kV buses, and 23 35-kV buses. Among them, there are seven generators with a total generation capacity of 477 MW and a total load of 470 MW. The power-side projects are numbered as power 1, power 2, power 3, and power 4, as shown in Table 1. The grid-side projects are numbered as grid 1, grid 2, grid 3, and grid 4, as shown in Table 2. The load-side projects are numbered as load 1, load 2, load 3, and load 4, as shown in Table 3. The storage projects are numbered as storage 1, storage 2, storage 3, and storage 4, as shown in Table 4. The loan interest rate is 0.08, and the wholesale electricity price is 0.4263 yuan/(kW·h).

6.1 Calculation of indexes

According to the index calculation method in Section 3, the unilateral indexes and interactive indexes of each side of the source–grid–load–storage are calculated. The unilateral indexes are normalized, and the interactive indexes are not normalized in order to visualize the economic benefits generated by the interaction of each project. F_1~F_5 are the unilateral indexes of each side, A_1~A_4 are the interactive indexes of each side, and the values of each index are shown in Table 5.

6.2 Determine the weights

Based on the calculated indexes, the weights are calculated by using the ANP, EWM, and combined weighting method, and the results are shown in Table 6. As can be observed from Figure 10, the weighting curve derived from the combined weighting method lies between the EWM and ANP. Since the degree of variation in the values of indexes F1~F4 of the projects to be built on the power side is higher, the EWM assigns them larger weights. The decision makers pay more attention to indexes A1~A4, so the weights assigned to indexes F1~F4 under the ANP are smaller. Similarly, in indexes A1~A4, the EWM assigns smaller weights due to the small degree of variation in the

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TABLE 1 Basic data of projects to be built on the power side.

Projects to be built	Bus	Rated power /MW	Wind/photovoltaic
Power 1	45	90	Wind
Power 2	46	48.3	Wind
Power 3	47	44	Wind
Power 4	48	50	Wind

TABLE 2 Basic data of projects to be built on the grid side.

Projects to be built	Bus
Grid 1	42–1
Grid 2	42–48
Grid 3	3–4
Grid 4	19–8

TABLE 3 Basic data of projects to be built on the load side.

Projects to be built	Bus	Rated power /MW
Load 1	45	25
Load 2	36	20
Load 3	47	18
Load 4	39	11

values of the indexes of the projects to be built, but the decision makers pay more attention to the interaction of indexes A1~A4, so the ANP assigns larger weights to them. We can observe from Figure 10 that index F_1 and index F_5 are too small on the power side, index A_1 is too large on the grid side, and index F_5 is too small on the load side and storage side. These too large or too small index weights are not conducive to a comprehensive evaluation of the overall benefits of each project to be built.

The combined weighting method can rationalize and coordinate EWM and ANP, reduce the subjective arbitrariness of the ANP and the objective absoluteness of the EWM, and make the assignment results more in line with reality. The weights calculated by the combined weighting method of the grid side, load side, and storage side are also shown in Figure 10.

The weights calculated by the AHP are shown in Supplementary Appendix Tables SC1–SC3.

6.3 Results of investment decisions with different weighting methods

First, comparing the decision results of the ANP and AHP in Table 6, we can see that the first, fifth, twelfth, and thirteenth projects to be built in ANP and AHP are the same, and the second project to be built in ANP is Power 1, while Power 1 is the third project to be built in AHP. The above situation occurs because both ANP and AHP are subjective weighting methods that reflect the subjective preferences of decision makers, but because ANP considers the interaction between indexes, and the size of Power 1's indexes exactly matches the size of ANP's weights.

Then comparing the decision results of ANP and EWM, we can see that the first construction project of ANP and EWM is both Grid 1, the second construction project of EWM is Storage 2, While Power 1 is the second project to be built in ANP. Because F3 and A1 indexes contain more information, so they have more weight, while these indexes of Storage 2 are larger. Although the ANP considers the interaction and feedback between the indexes, it cannot reflect the difference in information among indexes. From Table 5, we can clearly see that Power 1 has no significant economic advantage over Storage 2, but Storage 2 has the largest index, F3, of all the indexes, and F3 has a large amount of information.

Further comparing the decision results of the combined weighting method and ANP, we can see that the first construction project of the combined weighting method and ANP is both Grid 1. The second construction project of ANP is

TABLE 4 Basic data of projects to be built on the storage side.

Projects to be built	Bus	Rated power /MW	Rated power /MW	Interaction mode
Storage 1	3	50	20	Grid–storage
Storage 2	18	50	20	Load–storage
Storage 3	43	50	20	Grid–storage
Storage 4	47	50	20	Source–storage

TABLE 5 Per value of indexes.

Construction location	Projects to be constructed	F_1	F_2	F_3	F_4	F_5	A_1	A_2	A_3	A_4
Power	Power 1	0.5105	0.5004	0.7197	0.7385	0.2340	20702	1,426	1.9118	10
	Power 2	0.5917	0.5004	0.4077	0.3963	0.5188	11109	765	1.9113	10
	Power 3	0.6240	0.5001	0.3733	0.3608	0.5829	10116	697	1.9104	10
	Power 4	0.0000	0.4991	0.4200	0.4092	0.5800	11471	790	1.9064	10
Grid	Grid 1	0.4943	0.5000	0.9439	0.0024	0.6700	45	243	0.2544	118
	Grid 2	0.5083	0.5000	0.0175	0.2075	0.4082	1	5	0.0124	2,421
	Grid 3	0.5076	0.5000	0.0000	0.0000	0.4750	0	1	0.0151	1985
	Grid 4	0.4895	0.5000	0.3297	0.9782	0.3985	16	85	0.1508	199
Load	Load 1	0.2989	0.8435	0.8435	0.6655	0.3908	25115	3,080	1.6759	9
	Load 2	0.6748	0.0000	0.0000	0.5848	0.5348	19531	5,177	1.8358	8
	Load 3	0.0000	0.5371	0.5371	0.4638	0.5328	18017	5,325	1.9270	8
	Load 4	0.6748	0.0000	0.0000	0.0000	0.5266	10742	5,271	2.1633	7
Storage	Storage 1	0.0375	0.4961	0.0895	0.5444	0.5133	1905	362	1.2451	16
	Storage 2	0.0375	0.4654	0.9728	0.3816	0.2645	979	1,085	1.1338	18
	Storage 3	0.0375	0.5020	0.0000	0.5587	0.1693	1967	373	1.2854	16
	Storage 4	0.0375	0.5342	0.2135	0.4959	0.7987	1,006	346	0.7422	27

TABLE 6 Integrated investment decision results for different weighting methods.

x	Overall score				Construction sequence			
	AHP	ANP	EWM	ANP-EWM	AHP	ANP	EWM	ANP-EWM
Power 1	0.4160	0.4869	0.4021	0.4393	3	2	3	3
Power 2	0.2758	0.2566	0.2776	0.2693	6	7	6	7
Power 3	0.2420	0.2160	0.2580	0.2389	11	8	8	8
Power 4	0.0663	0.0405	0.0623	0.0525	14	15	15	14
Grid 1	0.4565	0.6008	0.4846	0.5364	1	1	1	1
Grid 2	0.0656	0.0301	0.0661	0.0424	15	16	14	16
Grid 3	0.0539	0.0408	0.0498	0.0436	16	14	16	15
Grid 4	0.4240	0.3282	0.3955	0.3506	2	4	4	4
Load 1	0.2486	0.3165	0.2970	0.3067	9	6	5	5
Load 2	0.2184	0.1704	0.2161	0.1957	12	12	10	12
Load 3	0.2868	0.3167	0.2594	0.2850	5	5	7	6
Load 4	0.2462	0.1964	0.2276	0.2126	10	11	9	9
Storage 1	0.2715	0.2033	0.2126	0.2076	7	9	11	10
Storage 2	0.3519	0.4671	0.4495	0.4585	4	3	2	2
Storage 3	0.2654	0.1970	0.2020	0.1994	8	10	12	11
Storage 4	0.1113	0.1326	0.1359	0.1345	13	13	13	13

Power 1, While the second construction project in combined weighting method is Storage 2. Therefore, the combined weighting method considers the risk preferences of decision makers and takes into account the amount of information contained in the indexes, and the decision results are more reasonable.

Finally, comparing the decision results of the combined weighting method and EWM, we can see that the construction order of their first, second, third, fourth, fifth projects to be built are the same, but the sixth project of the combined weighting method is Load 3, and the sixth project of EWM is Power 2. We can see from Table 5 that the technical

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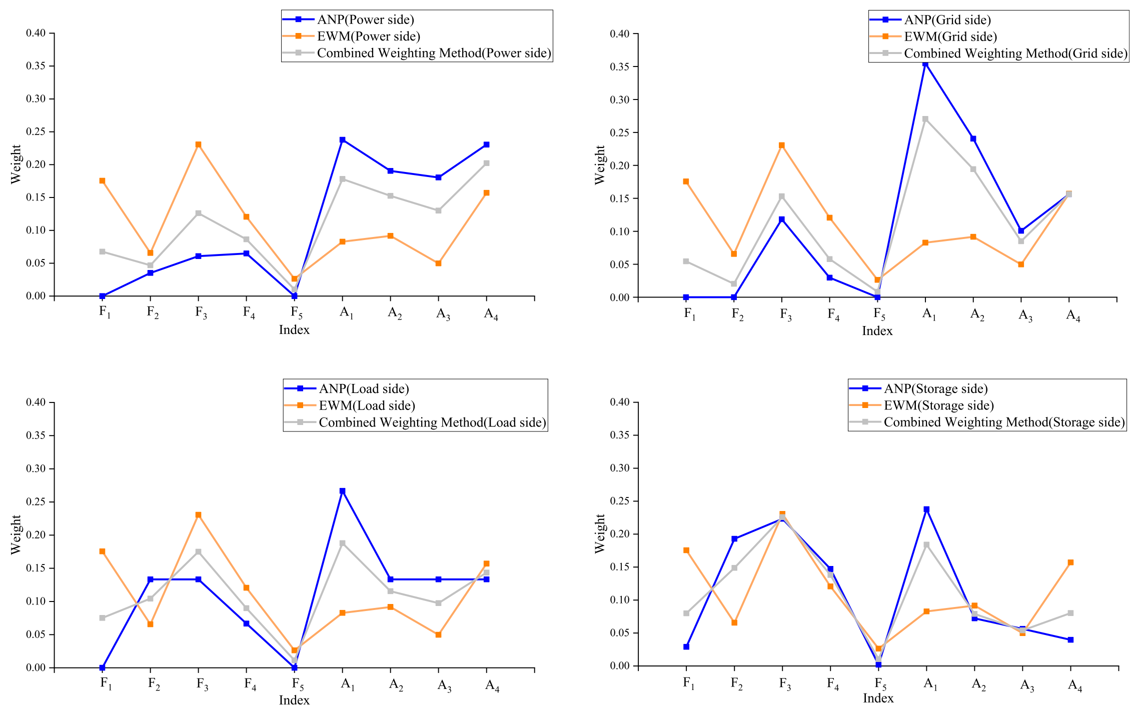

FIGURE 10
The weights calculated by different weighting methods in the complex grid.

indexes of Load 3 are slightly worse than that of Power 2, but its economic indexes are much better. The disadvantage of EWM is that it focuses too much on the information quantity of indexes and lacks the consideration of decision makers' preferences.

The combined weighting method has the same construction sequence as the ANP and EWM for many projects to be constructed, and it solves the shortcomings of the ANP which only considers the investor's index preference and the EWM which only focuses on the amount of index information. It achieves the balance of subjective and objective weighting methods, and its decision results are more scientific and reasonable.

7 Analysis and discussion

7.1 Result analysis

As shown in Figures 4–7, this study proposes a complex grid investment decision index system that includes source–grid–load–storage. The indexes of each side of the index system are both unilateral and interactive, and through the interaction of the interactive indexes, source–grid–load–storage forms an organic whole, which can comprehensively evaluate the impact of new projects on the complex grid as an entire, as shown in Figure 1. For example, indexes A_5 and A_6 can both interact with the grid side, where A_5 is the main economic benefit index and A_6 is the environmental and social benefit.

As observed in Figure 10, the weight of the economic indexes (6–9) is generally larger than the weight of the technical indexes (1–5), except for the electrochemical energy storage side, because the ANP takes into account the psychology of decision makers who emphasize economic efficiency by playing against the weights decided by the EWM, thus increasing the weighting of economic indexes in the combined weighting method. Based on our index system and the weighting of each index, it is important to fully consider the economic and social benefits of the project to be built when making complex grid investment decisions.

As can be seen from Table 5, none of the projects to be built is in the lead for all indexes. Grid 2 and Grid 3 have inferior technical and economic indexes, so they are ranked low among all the projects to be built. The index A_3 in Load 4 is larger than Load 1, but because its A_1 significantly smaller, it can only be ranked behind Load 1. It is clear that when comparing projects on different sides of a complex grid with each other, the value of all the indexes for the project with priority construction must be comparatively large. There is also a special case to be made, as we can see in Figure 10, where index A_1 has a decisive advantage on the grid side and projects with a large index A_1 are built first when there is little difference in the other indexes. For example, there are many indexes that Grid 1 does not dominate, but its F_3 and A_1 are the largest of all indexes, so it is the first to be built.

7.2 Determinant analysis

This study presents a complex grid investment decision method, whose main contribution is in the establishment of an index system and study of the weighting method. The first decisive factor is to establish a framework for a source–grid–load–storage interaction index system. This framework must consider the grid–source interaction, the load–grid interaction, the source–load interaction, the source–storage interaction, the load–storage interaction, the grid–storage interaction, and the single-side technical indexes on the source side, the grid side, the load side, and the electrochemical energy storage side. In order to account for the subjective preferences of decision makers, the index system must include the subjective index. We think that the indexes in the index system can be replaced with other indexes as long as they can meet its framework. The provision is that each side of the source–grid–load–side should have single-side indexes and interaction indexes and that the total number of indexes should not exceed nine in order to meet the requirements of the AHP and other weighting methods for consistency. Of the unilateral indexes, the first four are all technical and the last one is all subjective. Of the interactive indexes, the first is the primary benefit, the second is the secondary benefit, and the third and fourth are the return on investment and payback period, respectively. The second decisive factor is the combined weighting method in this study, where one can choose a subjective and an objective weighting method, and the effect of considering the subjective–objective balance can be achieved. However, in order to take full account of the interactions between the various sides of the complex grid, the subjective weighting method is best used with the ANP. It should be noted that when the indexes in the index system change, the interactions and feedback relationships between the indexes will also change, so the supermatrix of the ANP needs to be recalculated.

7.3 Electrochemical energy storage evaluation and future outlook

Electrochemical energy storage has a supporting role in the complex grid, which is shown in Figure 1, so this requires a analysis of its capacity and effectiveness. We observe Table 6, we can find that the construction order of storage1 is before Grid 2, Grid 3, which is because the integrated benefit of grid–storage interaction is larger than the integrated benefit of load–grid interaction. The construction sequence of storage 2 is before load 1, load 2, load 3, and load 4, which proves that the integrated benefit of load–storage interaction is above that of source–load. The construction order of storage 4 is before that of power 4, which proves that the comprehensive benefits of source–storage interaction are above that of grid–source. We can see from the aforementioned analysis that electrochemical energy storage can indeed partially replace the power source, grid, and flexible load to play a corresponding role in the complex grid. Among them, the source–storage interaction mainly plays the role of reducing wind and light abandonment, while the grid–storage interaction mainly plays the role of peak shaving, and its benefit is not as good as the load–storage interaction which earns the peak-to-valley price difference.

The method proposed in this study does not fully take into account the losses and depreciation on each side of the source–grid–load–storage, which can be taken into account in subsequent studies. In addition, this study only considers the impact of two–two interactions in a complex grid, and the interaction of three sides and four sides can be considered in future studies.

8 Conclusion

In this study, a complex grid investment decision index system under the integrated source–grid–load–storage environment was constructed, which includes unilateral indexes of each side of source–grid–load–storage and interactive indexes between source–grid–load–storage. The unilateral indexes include technical benefits, economic benefits, and social benefits. The interactive indexes include three aspects such as interaction benefit, investment benefit ratio, and investment payback period. The interactive indexes include the interactive benefits of each side of the source–grid–load–storage, the annual return on investment, and the payback period.

The subjectivity index is calculated using hesitation fuzzy linguistic term sets and regret theory to fully consider the hesitation and regret psychology of decision makers.

The game theory approach is used to combine the ANP and EWM to form a combined weighting method, which not only considers the different dependency and feedback relationships of each side of source–grid–load–storage but also achieves a balance between the subjective preferences of decision makers for indexes and the objective situation of indexes.

The distance vector combining the algorithm is used to calculate the integrated value of indexes for each project of the complex grid, and the projects to be built are ranked according to the size of the indexes.

The results show that the proposed complex grid investment decision-making method can provide a scientific basis for complex grid investment decision-making. Among them, the investment decision index system proposed in this study can evaluate the comprehensive benefits of the project to be built, and there is good differentiation among the indexes. The weighting method can well-consider the index preference of decision makers and the objectivity of the index and avoid the extreme situation that the weight of the index is 0 due to the lack of attention of decision makers, which greatly ensures the reasonableness of the weight.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

ZZ established a complex grid investment decision index system, EWM, ANP, and combined weighting method. PX and XZ conducted research on regret theory.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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Nomenclature

EWM Entropy weight method

ANP Analytic network process

$\tilde{x}$ Triangular fuzzy number

$\tilde{S}$ The set of linguistic terms

M The number of alternatives

N The number of attributes of the subjective index

T The number of natural states

X The set of *m* alternatives

Y The set of *n* attributes

w The set of weights of the *n* attributes of the subjectivity index

W The set of states of nature

H The regret perception decision matrix

S_j^k Group utility value

R_j^k Individual regret value

Q_j^k Decision values for subjective indexes

c The scale parameters

k The shape parameters

$\boldsymbol{v_{ci}}$ The cut-in wind speed

$\boldsymbol{v_r}$ The rated wind speed

$\boldsymbol{v_{co}}$ The cut-out wind speed

$\boldsymbol{P_w}$ Wind power output

***PNE* max** The maximum power generated by new energy in a typical day

***PNE* min** The minimum power generated by new energy in that day

***ENE** NG** The actual annual output of new energy

PNE NG The installed capacity of new energy

T 8760 hours

E* all The actual annual generation capacity of all units

$\boldsymbol{k_{CO2}}$ The carbon emission factor

$\boldsymbol{\lambda CO_2}$ The unit carbon emission trading price

$\boldsymbol{M_{Newenergy}}$ The new energy generation tariff

$\boldsymbol{M_{Carbon}}$ The unit price of environmental revenue of new energy generation

$\boldsymbol{c_{wp}}$ The unit power price of photovoltaic

$\boldsymbol{c_{ww}}$ The unit power price of wind power

$\boldsymbol{E_{wp}}$ The rated power of photovoltaic

$\boldsymbol{E_{ww}}$ The rated power of wind power

$\boldsymbol{T_{lifespanp}}$ The full life cycle of photovoltaic

$\boldsymbol{T_{lifespanw}}$ The full life cycle of wind power

r Social average annual return on investment

$\boldsymbol{x_{wp}}$**%** The ratio of operating cost and initial investment of photovoltaic

$\boldsymbol{x_{ww}}$**%** The ratio of operating cost and initial investment of wind power

$\boldsymbol{N_L}$ The total number of power grid lines

$\boldsymbol{L_k}$ The load rate of the *i*th line

$\bar{L}$ The average of the load rates of N_L lines

$\boldsymbol{\Omega_l}$ The set of all branches in the grid

$\boldsymbol{V_i}$ The voltage amplitudes of node *i* in the grid

$\boldsymbol{V_j}$ The voltage amplitudes of node *j* in the grid

$\boldsymbol{\theta_{ij}}$ The phase angle differences of nodes *i* and *j* in the grid.

ELoss* IE The annual incremental electricity sales

$\boldsymbol{M_{Grid}}$ The electricity sale price

$\boldsymbol{g_{ij}}$ The conductance differences of nodes *i* and *j* in the grid.

$\boldsymbol{M_{reward}}$ The unit price of the reward

$\boldsymbol{c_g}$ The cost per kilometer of the transmission line

$\boldsymbol{L_g}$ The length of the transmission line

$\boldsymbol{T_{lifespang}}$ The full life cycle of the transmission line

$\boldsymbol{x_g}$**%** The ratio of the operating cost of the transmission line to the initial investment

PLoad The power of the flexible load at moment *t* in day *D*

$\boldsymbol{P_{i,\max}(t)}$ The maximum power that can be reached after the flexible load participates in the demand-side response at time t

$\boldsymbol{P_{i,0}(t)}$ The rated power that can be reached after the flexible load participates in the demand-side response at time t

$\boldsymbol{P_i(t)}$ The actual interactive power of the flexible load

R A constant sequence

$\boldsymbol{l_j}$ The number of lines whose load rate r_j satisfies $r_j \in (R_j, R_{j+1}]$

ELoss* Before Load The total annual loss of the grid before the new flexible load

ELoss* After Load The total annual loss of the grid after the new flexible load

$\boldsymbol{M_{IDC}}$ The unit revenue of the internet data center

$\boldsymbol{c_l}$ The price per unit power of the flexible load

$\boldsymbol{P_l}$ The rated power of the flexible load

$\boldsymbol{T_{lifespanl}}$ The full life cycle of the flexible load

$\boldsymbol{x_l}$**%** The ratio of the operating cost of the flexible load to the initial investment

$\boldsymbol{c_e}$ The price per unit capacity of electrochemical energy storage

$\boldsymbol{c_p}$ The price per unit power of electrochemical energy storage

$\boldsymbol{E_{storage}}$ The rated capacity of the electrochemical energy storage power plant

$\boldsymbol{P_{storage}}$ The rated power of the electrochemical energy storage power plant

$T_{lifespan}$ The whole life cycle of the electrochemical energy storage power plant

x_s% The ratio of operating cost of electrochemical energy storage capacity to initial investment.

y_s% The ratio of operating cost of electrochemical energy storage power to initial investment.

ED_i The electricity released during the *i*th discharge of the electrochemical energy storage system

k The number of discharges of the electrochemical energy storage device during the year.

PESS,c t The charging power of the electrochemical energy storage at hour *t*

PESS,d t The discharging power of the electrochemical energy storage at hour *t*

uESS t The charging characteristic variables of the electrochemical energy storage

vESS t The discharging characteristic variables of the electrochemical energy storage

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Adoption impact of solar based irrigation facility by water-scarce northwestern areas farmers in Bangladesh: Evidence from panel data analysis

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Introduction: Fossil fuel and electricity-based irrigation practices contribute to greenhouse gases and add substantial costs to water access. Solar-powered irrigation is spreading globally, notably in developing countries, as a solution to the rising energy and climate concerns related to agriculture. This policy perspective devoted to examining the impact of the solar irrigation facilities (SIF) adoption on irrigation cost and return on investment (ROI) based on seven years of panel data seeks to contribute to the efforts to propel solar irrigation toward delivering on the myriad of promises.

Methods: Panel logistic regression was employed to analyze adoption determinants, while adoption impact was evaluated through the propensity score matching with the difference-in-difference (PSM-DID) method. In addition, the time and panel fixed effect DID and doubly robust DID model was also used for robustness check.

Results: The result reveals that SIF adoption significantly increased ROI by 20% to 30% and reduced irrigation costs by 21% to 30%.

Conclusion: The findings call for further research and analysis on evidence-based best practices for solar irrigation solutions at the farm level so that the dissemination of this revolutionary technology, apart from contributing to the advancement of the energy sector, also plays a vital role in driving us towards establishing a more equitable and sustainable world.

KEYWORDS

Energy, Solar Irrigation, Adoption Impact, Panel Data, Difference-in-Difference method, PSM-DID, Fixed effect DID, Doubly robust DID

1 Introduction

The world is confronting a reckoning regarding the energy issue. Despite decades of pleas to minimize dependence on non-renewable energy, nations have intensified the usage of coal, oil, and gas to fuel their economies (WFP, 2022). The consequences of the extensive burning of fossil fuels have intensified the carbon emissions issue and created a globalized world in which food and energy systems are highly concentrated—making them extremely vulnerable to disruption. The world now grapples with consecutive waves (i.e., heat waves, the millennium drought, poverty impacts from COVID-19, and ongoi`ng supply chain challenges due to war) that negatively impact agriculture and have been the instigator of a potentially severe food crisis. These interlocking crises have contributed to global energy and food price spikes and have placed agriculture and irrigation in a precarious position where energy-efficient technology use has become obligatory (UNSDG, 2022; WFP, 2022).

The impact is severe in developing countries, especially Asia, where diesel and electric-based irrigation plays a vital role in domestic food security and poverty alleviation (Sunny et al., 2022a). While Myanmar and Pakistan's daily consumption sits around 2.7 million liters and 3.5 billion liters of diesel, respectively, Nepal's Eastern Indo-Gangetic Plains only have 20% of its irrigation pumps non-diesel reliant (Qureshi, 2014; Foster et al., 2019; Phillips, 2021). Clearly, the region has learned and adapted to the challenges of inconsistent power generation for rural agricultural work, illustrating flexibility and resilience within the sector. However, reliance on such a non-renewable resource may cause some new challenges in the future. In India, for instance, of the total electrical power generated, 18% goes to agriculture; similarly, 5% of the total diesel in the country is allocated for just irrigational purposes (IRENA, 2016). Though not sounding too dire, one must consider what concentrations of which demographic find themselves heavily reliant on diesel as a substitute for the lack of national electrical grid energy supplies. This is a profound question, especially since 1.6 billion people live without electricity in developing countries—most in Sub-Saharan Africa and South Asia (The World Bank, 2018). The struggle to meet energy demands leads to load shedding that disrupts planning and resource management and, more specifically, interrupts the irrigation process (Hoque et al., 2016).

Energy security is one of the major global concerns, as energy deficiencies and resulting economic factors may generate socio-political issues. To ensure food security, enhance energy security, prevent local pollution, and increase climate benefits, the policy manifesto for most developing countries with similar issues has the impetus for adopting reliable, cost-effective, and clean energy irrigation technologies (Schwanitz et al., 2014; Rentschler and Bazilian, 2016; Sarker and Ghosh, 2017).

Like other developing economies, the agriculture sector is regarded as one of the critical drivers of Bangladesh's economy. As a catalyst for sustainable growth of the country, the sector accounts for 12.92% of the gross domestic product (GDP) and 38 percent of the labor force (The World Bank, 2021; The World Bank, 2022). Around 70% of Bangladesh's population's livelihood depends on agricultural activities (Imdad, 2021). The country's natural inheritance of favorable soil, climate, and groundwater availability has alleviated farmers' opportunities to grow tropical and temperate crops on over two-thirds of cultivatable land twice or more annually. Rice (*Oryza sativa*) is the staple food that accounts for approximately 75 percent of the total harvested area and contributes around 95 percent of the total food grain (Shew et al., 2019; Alam et al., 2021). Irrigation is a fundamental operation unit in rice production and is essential for the agriculture life cycle system (Ali, 2018). Even though insufficient rainfall in the dry season and scarcity of surface water has hampered rice productivity in many parts of Bangladesh, especially the northern regions, groundwater utilization has played a vital role in ameliorating agricultural development (Biswas and Hossain, 2013; Hasnat et al., 2014). The development of groundwater policies has resulted in the expansion of Low Lift Pumps (LLP), Shallow Tube Wells (STW), and Deep Tube Wells (DTW) usage in Bangladesh (BGEF, 2016). The first two systems run on diesel, while the latter runs on electricity from the national grid. The maximum capacities of the LLP are 7.5, SWT is 12.5, and DWT is 55 horsepower (hp) (Hossain et al., 2015). These water extraction technologies have greatly aided Bangladesh in attaining near self-sufficiency in rice production. The downside, however, has been the massive energy demand increase (Sunny et al., 2022a; Sunny et al., 2022b). Presently, approximately 1.6 million diesel pumps consume at least one million tons per year to satisfy irrigation needs (Prothom Alo, 2021). When this is estimated in monetary terms, the sum reaches a conservative total of $900 million (Ershadullah, 2021). Between the transportation, added pollution through transportation of the fuel and the use of it at its endpoint, and the potential calamities that could occur environmentally along the production chain - a second thought should be given to diesel as a primary fuel source for extracting 'clean renewables' like water. Recent estimates indicate that even though irrigation consumes 4.58% of the total electricity generated in the nation (ADB, 2018), the electricity demand in the forthcoming irrigation season is projected to rise from 14,097 MW to 15,500 MW (The Business Standard, 2022). The national grid can not ensure regular power without frequent outages, voltage flickering, and constantly increased tariffs and rates (Doby, 2018). The result is major disruptions in irrigation activities and, thus, revenue streams. In some situations, farmers have been forced to adapt by irrigating during low-peak hours (at night) when the power is more stable (Odarno, 2017). Other farmers have chosen to take control of their power provision by investing in diesel pumps, which carry their deficiencies. These pumps are at the mercy of fuel prices, technical defects, service gaps, and mismanaged usage and can sometimes be more problematic than the national grid (Energypedia, 2020; Mirta et al., 2021).

Concerns for alternatives have been raised regarding agricultural sustainability in defying these challenges. Hence, like other emergent nations,' Bangladesh has also embraced the idea of sustainable agriculture practices alongside the overarching concept of sustainable development. Sustainable agriculture advocates adopting measures to conserve the natural environment and resources through technically appropriate, economically viable, and socially accepted approaches (FAO, 1989). It also integrates the ideology of enhancing resilience to shocks and stresses over more prolonged periods and addresses more comprehensive economic, social and environmental outcomes from the local to the global level (Pretty, 2008). Sustainable agriculture is central to attaining many sustainable development goals (United Nations, 2015; FAO, 2019). The key to achieving agricultural sustainability is by ameliorating productivity through adopting technology and practices that remediate the environment from poor agricultural practices abuse and drive the welfare of the food producers (Zilberman et al., 1997; Pretty, 2008). Therefore, besides improving strategic and operational farm management, the government has highlighted up-scaling renewable energy-based irrigation systems. If current climate change estimates were to add sufficient motivation for action, then the proposition holds to establish 50,000 solar irrigation pumps by 2027. The results would be an estimated reduction in greenhouse gas (GHG) emissions by up to 15% by 2030 (Mirta et al., 2021). Apart from that, 10% of conventional energy would be replaced, and fossil fuel reserve depletion would

TABLE 1 Variables used in different models.

Variables	Measurement unit	Description	Mean	S. D
DID basic Variables		re-treatment year is 2015 and 2016, Treatment started in the year 2017, and the follow-up period is 2018–2021	—	—
Year Treatment	Dummy variable	1 = Treated group, 0 = Non-treated/Control group	—	—
Dependent Variables Irrigation costs (IC)	Taka/50 Decimal	Log value of total costs of irrigation	8.53	.58
ROI	Ratio of total return to total variable costs	Return on investment	1.51	.49
Explanatory Variables				
Age	Dummy variable	1 = Farmers age is above 30 years,0 = otherwise	.93	.25
Education (Edu)	Dummy variable	1 = Farmer is literate (can read, write and sign), 0 = Otherwise	.86	.35
Land Ownership (LO)	Dummy variable	1 = Farmer have full land ownership rights, 0 = Otherwise	.95	.23
Land Typology (LT)	Dummy variable	1 = Farmer cultivate in Highland, 0 = otherwise	.20	.40
Farming Experience (FE)	Years	Farmers' farming experience in years	30.02	9.87
Household Size (HHS)	Dummy variable	1 = if HH number is more than 4 person, 0 = Otherwise	.43	.50
Family Labor (FL)	Number	Number of household active labor	1.15	.48
Farm Size (FS)	Decimal	Respondents farm size in decimal	93.74	81.61
Knowledge of SIF (KSIF)	Dummy variable	1 = Farmer possess proper knowledge, 0 = Otherwise	.75	.43
Fee Opinion (FO)	Dummy variable	0 = Farmer thinks the service fee is not high, 1 = Farmers urges for more reduced service fee	.47	.50
Soil Fertility Perception (SFP)	Dummy variable	1 = Farmer perceives the farmland is fertile, 0 = Otherwise	.35	.48
Credit Availability (CA)	Dummy variable	1 = Loan availability during the cropping season, 0 = Otherwise	.58	.49
Soil Water Retention condition (SWR)	Dummy variable	1 = If the soil can hold water long, 0 = Otherwise	.68	.47
Irrigation Machine Ownership (IMO)	Dummy variable	1 = Farmer own diesel or electric pump, 0 = Otherwise	.46	.50
Close Acquaintance's adoption (CAA)	Dummy variable	1 = Close acquaintances have adopted SIF, 0 = Otherwise	.37	.48
Environment Awareness (EA)	Dummy variable	1 = Farmer knows SIFs adoption will reduce carbon footprint, 0 = Otherwise	.43	.50
Secondary Income (SI)	Dummy variable	1 = Farmer seasonal SI is more than 25,000 Taka, 0 = Otherwise	.86	.35

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rapidly regress while ensuring sustainable water management in agriculture sectors (Kanojia, 2019; Sajid, 2019; Rana et al., 2021a). Despite the significant potential, solar irrigation technologies promotion has been sluggish, and the penetration of solar pumps faces the challenge of competing against other conventional systems (SREDA, 2015; Rana et al., 2021a). Given this context, this work attempts to answer the following research questions.

- What key determinants influence our study area farmers to adopt SIF?
- How do SIF adoption impact farmers' irrigation cost and ROI?
- What are the associated challenges to the sustainability of SIFs and the measures to overcome the challenges?

2 Literature review

Several studies have documented the advantage of solar-based irrigation system adoption over conventional systems. For instance: the performance and reliability test of different types of solar-powered water pumping systems in the United States and Spain revealed that these systems are cheaper alternatives for rural, with high performance, ensure customer satisfaction, and are an environmentally-viable energy source for pumping in irrigation networks (Chowdhury et al., 1993; García et al., 2019). A study conducted in northern Benin revealed that compared to non-adopters, commercial-scale solar-powered drip irrigation systems adopters were able to significantly increase production (Alaofè et al., 2016). Likewise, the adoption of solar-based water pumping systems in china has resulted in ameliorating forage productivity, meeting local demand, and minimizing carbon emissions (Campana et al., 2017). Besides, SIF adoption impact analysis in the Philippines revealed that the adoption not only aided in GHG emissions reduction by up to 26.5 tons CO2eq/ha/year but also contributed to the energy sector by savings between 11.4 and 378.5 L/ha of diesel per year with an average of 315% returns on investment (Guno and Agaton, 2022). Furthermore, SIF adoption in Pakistan has significantly contributed to reducing operational costs, increased farmers' income, reduced 17,622 tons of CO2 emissions per year, and saved 41% of water usage (Raza et al., 2022). In addition, apart from irrigation purpose usage and meeting electricity needs, SIFs adoption contributes to facilitating drinking water requirements in water-scarce regions and contributes toward gender empowerment by alleviating the burden of labor-intensive diesel system operation and allowing women to utilize their time for productive purposes (IRENA, 2016; Agrawal and Jain, 2018).

The literature on SIF adoption analysis in the context of Bangladesh revealed that if the economic return is considered based on the internal rate of return (IRR), then the most profitable option would be establishing small-sized SIF (20%), followed by large-sized (10%). On the other hand, the net environmental benefit per kilowatt peak (kWp) is highest (86,000) for the small SIFs, followed by medium SIFs (67,184 kWp) and large SIFs (65,392 kWp) (Islam and Hossain, 2022). Other research findings suggested that SIF adopters could reduce irrigation costs by a maximum of 2.22%, obtain 4.48%–8.16% higher ROI, and reduce nearly 1% of total production cost compared to non-adopters (Sunny et al., 2022a). Another study stated that even though the initial investment cost of SIF was found to be higher than a diesel-powered system, the low maintenance and zero fuel costs make it a cheaper option in the long run (Rana et al., 2021b).

This study compares to others contributing to literature in several ways. Firstly, this study used panel data to assess the impact of SIF adoption on irrigation cost and return on investment (ROI). As the return on investment variable considers the gross revenue of farm production and the production costs, it can better reflect the efficiency of farm performance (Kleemann et al., 2014; Zheng and Ma, 2021). Secondly, we employed propensity score matching (PSM) with the difference in difference (DID or DD) models to estimate adoption impact and address the selection bias issue, which also differs from other related studies (Barreto and Bell, 1994; Coady, 1995; Duflo et al., 2011; Dong et al., 2012; Fanus et al., 2012; Martey et al., 2013; Zhou and Abdullah, 2017; Kumar et al., 2019; Kumar et al., 2020; Sanap et al., 2020). We also used fixed effect DID and doubly robust DID for robustness checking. Finally, examining the role of solar irrigation technology on welfare outcomes is of great significance to policy formulation to tackle future climate vulnerability while enhancing farm productivity, food security, and poverty reduction.

3 Materials and methods

3.1 Study area, and sampling procedure

This study focuses on the drought-prone area of the northern region of Bangladesh that receives merely 372 mm of rain from November to May, compared to 546 mm during the same time in the whole country. The average annual rainfall of this region is 21.83% lower than the country's average annual rainfall. Inadequate rainfall and limited surface water have created high dependence on groundwater for irrigation in these areas (Hossain et al., 2021; Rahman et al., 2022). Nearly 1.6 million diesel pumps (Prothom Alo, 2021) and 3.20 lakh electricity pumps (Ershadullah, 2021) that are operating in the country, a significant proportion is operating in the northern region (Hossain et al., 2021).

For this study, multistage sampling techniques were employed. At first, the Dinajpur district was selected for several reasons. Dinajpur is the largest district among all sixteen districts situated in the northern part, and according to the international 'Köppen climate classification,' the district has a tropical wet-dry climate. The annual average temperature is 25 °C. The average precipitation from November to March is below 20 mm, April and October are below 100 mm, and the remaining 5 months are over 200 mm (Encyclopedia, 2018). Due to the low precipitation rate, the district is considered one of the top drought-prone areas of Bangladesh (Afrin et al., 2019; Islam et al., 2022a; Rahman et al., 2022), where the food insecurity and poverty rate are high (BBS and WFP, 2020). This district is also one of the top districts where more solar irrigation pumps are installed (SREDA, 2022). We used a simple random sampling method to select 3 of 13 sub-districts from the Dinajpur district in the second stage. The randomly chosen three sub-districts were Birganj, Khanshama, and Kaharol. The combined population of these three sub-districts is 643,431 (Population and BBS, 2011).

We then used Krejcie and Morgans' (Krejcie and Morgan, 1970) table to determine the optimal sample size. A sample of 384 farmers was determined based on the population size. However, a 5% additional sample was collected to avoid unexpected future issues such as farmers' discontinuation of SIF or land rented to others. Thus from 50 different solar irrigation sites in three sub-districts, eight farmers were randomly chosen for control and treatment groups.

TABLE 2 Descriptive statistics of the treatment and non-treatment groups.

Variable	Control	Treatment	Difference
Irrigation Cost (IC)	8.580	8.486	.094*** (.022)
Return on Investment (ROI)	1.467	1.546	−.079*** (.018)
Age	.933	.934	−.002 (.009)
Education (Edu)	.843	.875	−.032** (.013)
Land Ownership (LO)	.959	.933	.027*** (.009)
Land Typology (LT)	.152	.250	−.098*** (.150)
Farming Experience (FE)	31.20	28.91	2.289*** (.368)
Household Size (HHS)	.419	.438	−.019 (.019)
Family Labor (FL)	1.152	1.144	.008 (.018)
Farm Size (FS)	94.162	93.346	.816 (3.067)
Knowledge of SIF (KSIF)	.728	.780	−.051*** (.016)
Fee Opinion (FO)	.538	.406	.132*** (.019)
Soil Fertility Perception (SFP)	.334	.359	−.024 (.018)
Credit Availability (CA)	.569	.582	.013 (.019)
Soil Water Retention condition (SWR)	.716	.639	.076*** (.018)
Irrigation Machine Ownership (IMO)	.477	.438	.040** (.019)
Close Acquaintance's Adoption (CAA)	.276	.466	−.190*** (.018)
Environment Awareness (EA)	.385	.479	.094*** (.019)
Secondary Income (SI)	.874	.839	.035*** (.013)

Note: **, *** denotes significant at 5% and 1% level, respectively; and the values in parentheses are standard errors.

These farmers were interviewed each year between February and April, starting from 2015 till 2021.

The baseline of this study was 2015 and 2016, the treatment period stated in the year 2017, and the end line was 2021. Hence finally, we obtained a panel of (50*8 = 405*7) 2,835 farmers. The Boro season (starting in December and ending in June) was chosen since the maximum rice is produced in this season (BBS, 2020), and irrigation demand is very high. The interview schedule was translated into the local language for implementation. Our interview schedule included farmers' demographic and socioeconomic characteristics, environmental, agroecology, technology-related knowledge, fee opinion, service quality, and infrastructure-related questions.

3.2 Analytical technique

3.2.1 Theoretical framework

This study is based on the random utility theory developed by McFadden in 1974 (McFadden and Zarembka, 1974), which is consistent with Lancaster's economic theory of value and neoclassical view that hypothesize individuals would choose alternatives that maximize their utility (Lancaster, 1966; Manski, 1977; Hoyos, 2010; Hess et al., 2018). Based on this theory, we would like to see if solar irrigation adoption compared to other irrigation mediums is beneficial or not.

3.2.2 Empirical approaches of adoption determinants

To estimate the factor that influences our study area farmers' adoption or non-adoption decision of SIF, we consider the following logistic regression model (Neuhaus et al., 1991):

$$logit\,\Pr\left(Y_{ij} = 1 \,\middle|\, X_{ij}\right) = a + X_{ij}\,b* \tag{1}$$

Where Y_{ij} is the binary outcome variable, X_{ij} is the predictor variable, a is constant, and b^* is the population parameter.

3.2.3 Empirical approach of impact assessment

Prior studies on impact assessment suggested that a significant hurdle while conducting related research is constructing appropriate counterfactuals. Because a set of observable and unobservable factors influences the adoption process, failure to do so will cause the corresponding impact estimates to be biased (Mendola, 2007; Wu et al., 2010). Therefore, studies have used various methods to assess the impact of technology adoption that considers selection bias (Mendola, 2007; Becerril and Abdulai, 2010; Wu et al., 2010; Asfaw et al., 2011; Asfaw et al., 2012; Khonje et al., 2015; Alem and Broussard, 2018; Khonje et al., 2018; Nakano et al., 2018; Islam et al., 2019; Manda et al., 2020).

This study, in mitigating the selection and time-invariant source of bias issue and in measuring the adoption impact of SIF on farmers' irrigation cost and their return on investment (ROI), has adopted difference in difference estimation with

TABLE 3 Factors affecting the adoption of solar irrigation facility: Panel logit estimates.

Variable	dy/dx	Robust standard error	VIF
Age	−.00265***	.00232	1.29
Education (Edu)	.10594	.29087	1.06
Land Ownership (LO)	.05328	.44363	1.08
Land Typology (LT)	.19834**	.35135	1.80
Farming Experience (FE)	−.00016	.00045	1.38
Household Size (HHS)	−.00150***	.00236	1.11
Family Labor (FL)	−.01331	.21255	1.16
Farm Size (FS)	−.00026	.00135	1.34
Knowledge of SIF (KSIF)	.00089***	.00118	1.84
Fee Opinion (FO)	.00072***	.00101	1.37
Soil Fertility Perception (SFP)	−.00062***	.00056	1.17
Credit Availability (CA)	−.00368***	.00195	1.35
Soil Water Retention condition (SWR)	−.01867	.27760	1.76
Irrigation Machine Ownership (IMO)	−.02568	.20838	1.12
Close Acquaintance's Adoption (CAA)	.00004	.00109	1.22
Environment Awareness (EA)	.00116***	.00098	1.31
Secondary Income (SI)	.00661***	.00402	1.06

Number of observations = 2,835, Number of groups = 405, Observations per group (average) = 7.
Wald chi2 (Alam et al., 2021) = 134.13, Prob > chi2 = .0000.
Note: *, **, *** denotes significant at 10%, 5% and 1% level, respectively.

propensity score matching (PSM-DID). This approach compares two populace groups (the treated and the non-treated) based on the time sequence of before and after-action states. The effectiveness of the treatment (a course of action) is considered adequate toward the outcome when the intervention group shows off better or worse trends over their controlled counterpart (considering other influencing factors such as ceteris paribus) (Islam et al., 2022b).

The single DID setting proposed by Villa (Villa, 2016) is presented as follows:

$$\begin{aligned}\mathrm{DID} = \{&E(Y_{it=1}|D_{it=1} = 1,\ Z_i = 1) - E((Y_{it=1}|D_{it=1} = 0,\ Z_i = 0)\\ &- \{E(Y_{it=0}|D_{it=0} = 0,\ Z_i = 1) - E((Y_{it=0}|D_{it=0} = 0,\ Z_i = 0)\}\end{aligned} \tag{2}$$

Where the baseline period is $t = 0$ and follow-up is $t = 1$; a treated group to which the treatment is delivered is $Zi = 1$, and a control group to which the treatment is not provided denotes as $Z_i = 1$. $(D_{i,t=0} = 0|Z_i = 1, 0)$ is the treatment indicator that requires in the absence of any intervention in the baseline for either group, and it commands the intervention to be positive for the treated group in the follow-up $(D_{i,t=0} = 1|\ Z_i = 1)$. For a given outcome variable, Y_{it}, the population DID treatment effect is given by the difference in the outcome variable for treated and control units before and after the intervention.

If additional covariates are combined with the single DID setting, the model will be:

$$\begin{aligned}\mathrm{DID} = \{&E(Y_{it=1}|D_{it=1} = 1,\ Z_i = 1,\ X_i)\\ &- E((Y_{it=1}|D_{it=1} = 0,\ Z_i = 0,\ X_i)\\ &- \{E(Y_{it=0}|D_{it=0} = 0,\ Z_i = 1,\ X_i)\\ &- E((Y_{it=0}|D_{it=0} = 0,\ Z_i = 0,\ X_i)\}\end{aligned} \tag{3}$$

The DID is a flexible form of causal inference because it can be combined with other procedures, such as kernel propensity score matching (Heckman et al., 1997) and quintile regression (Meyer et al., 1995). Propensity score matching (PSM) helps estimate treatment effects as this method can balance measured covariates across groups (treatment and control) and better estimate the counterfactual for treated individuals (Rosenbaum and Rubin, 1983; Imbens, 2004; Austin, 2011). Kernel propensity-score weights complement the DID treatment effect model. This matching technique (also known as kernel weighting) is beneficial when other matching strategies are not viable for analyzing survey data with sampling weights or continuous or multilevel categorical treatments (Garrido et al., 2014). Villa (Villa, 2016) suggested that, by following Heckman, Ichimura, and Todds' study (Heckman et al., 1997; Heckman et al., 1998), besides the inclusion of control variables, observed covariates can be used to estimate the propensity score (the likelihood of being treated) and calculate kernel weights. Thus, this alternative approach matches treated and control units based on their propensity score instead accounting for control variables. Each treated unit is matched to the whole sample of control units instead of a limited number of nearest neighbors. To begin, one obtains the propensity score (p_i) for both groups and $p_i = E\ (Z_i = 1,\ X_i)$.

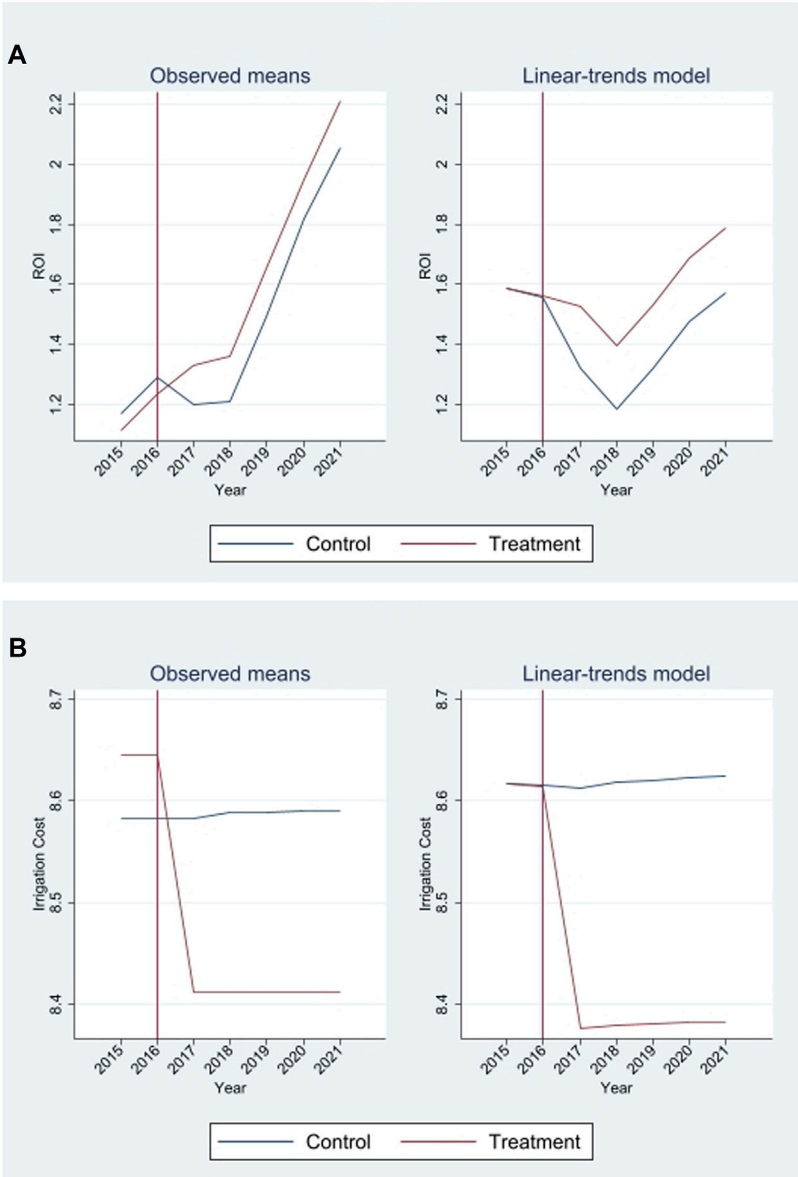

FIGURE 1
Graphical representation of parallel trends for ROI **(A)** and Irrigation Cost **(B)**.

As explained by Heckman, Ichimura, and Todd, kernel matching is an averaging method that reuses and weights all the comparison group observations in the treatment sample (Heckman et al., 1997). Comparison individuals are weighted by their distance in propensity score from treated individuals within a range, or bandwidth, of the propensity score (Garrido et al., 2014; Villa, 2016). Thus, the kernel weights can be defined,

$$w_i = \frac{K\left(\frac{p_i - p_k}{h_n}\right)}{\sum K\left(\frac{p_i - p_k}{h_n}\right)} \tag{4}$$

In Equation 3, K (.) is the kernel function, and h_n is the selected bandwidth.

To obtain a kernel propensity-score matching DID treatment effect, the kernel weights (presented in Eq. 3) are then introduced into Equation 1 is presented below:

$$\begin{aligned} DID = &\{E(Y_{it=1}|D_{it=1} = 1, Z_i = 1) - w_i{*}E\,((Y_{it=1}|D_{it=1} = 0, Z_i = 0)\} \\ &- \{E(Y_{it=0}|D_{it=0} = 0, Z_i = 1) - w_i{*}E\,((Y_{it=0}|D_{it=0} = 0, Z_i = 0)\} \end{aligned} \tag{5}$$

However, in increasing the internal validity of the DID estimand, it is possible to restrict (Phillips, 2021) to the common support (the overlapping region of the propensity for treated and control groups) of the propensity score for both groups. This sample of i units can be restricted to the region defined as,

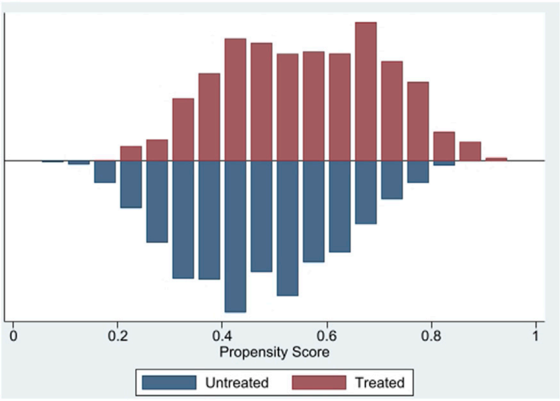

FIGURE 2
The common support of propensity scores.

$$i:\ p_i \epsilon \left[\max\left\{\min\left(p_i\middle|Z_i = 1\right), \min\left(p_i\middle|Z_i = 0\right)\right\}, \min\ \left\{\max\left(p_i\middle|Z_i = 1\right), \min\ \left(p_i|Z_i = 0\right)\right\}\right]\right)$$

Blundell and Dias have stated that in case of inability to follow treated and control units over the baseline and follow-up phases, the DID treatment effects can be estimated with repeated cross-sections (Blundell and Dias, 2009). This is very common when a treatment has been administered to specific regional or demographic groups over several cross-sections. The kernel propensity score matching with repeated cross-section DID treatment effects thus can be expressed as,

$$\begin{aligned}\mathrm{DID} &= \{E\ (Y_{it=1}|D_{it=1} = 1, Z_i \\ &= 1 - w^c_{it=1}{}^*E\ ((Y_{it=1}|D_{it=1} = 0,\ Z_i = 0)\} \\ &\quad - w^t_{it=0}{}^*\{E\,(Y_{it=0}|D_{it=0} = 0,\ Z_i = 1) - w^c_{it=0}{}^*E\ ((Y_{it=0}|D_{it=0} = 0,\ Z_i = 0)\}\end{aligned} \tag{6}$$

Here, $w^c_{it=0}$ and $w^c_{it=1}$ represent the kernel weights for the control group in the baseline and follow-up periods, respectively. $w^t_{it=0}$, on the other hand, symbolizes kernel weights of the treated groups' baseline period.

Besides, the balancing property of the treated and the control can be tested through DID estimates. Given the availability of observable covariates, it can be shown that in the absence of the treatment, the outcome variable is orthogonal to the treatment indicator given the set of covariates. In other words, the balancing property can be tested in the baseline as,

$$Y_{it=0} \perp Z_i|X_i \tag{7}$$

DID estimation also necessitate satisfying the 'parallel or common trend' test. Under the trend assumption, in the absence of treatment, the average outcome changes from any pre-treatment period to any post-treatment period for the treated is equal to the equivalent average outcome change for the controls. In pre-treatment trend differentials, it is customary to adjust the econometric specification to try to accommodate for those differences (Mora and Reggio, 2015).

The parallel trends assumption can be tested graphically or by performing a test on the linear-trends model coefficient that captures the differences in the trends between treated and controls. The specification of the linear-trends model test, adapted from the study conducted by Cai (Cai, 2016), is as follows:

$$Y_{ikt} = n_0 + n_0 Trend_t + n_1 Treat_i + n_2\,(Trend_t)\,(Treat_i) + \delta' X_{ikt} + \varepsilon_{ikt} \tag{8}$$

Where Y_{ikt} is the dependent variable; $Trend$ is the time trend over the pre-treatment period; $Treat$ is a binary variable that equals 1 for households in the treatment group and 0 otherwise; X_{ikt} is a vector of control variables, and the ε_{ikt} is the error term. If the estimated parameter were not statistically significant at conventional levels, it would mean that the treatment and the control households followed parallel trends prior to treatment.

Finally, to grasp the impact of solar irrigation on farmers' irrigation costs, we consider the following econometric expression:

Irrigation cost,

$$\begin{aligned}Y_{it} &= a_0 + a_1 Year_{it} + a_2 Treatment_{it} + a_3{*}Year{*}Treatment \\ &\quad + \sum_{j=0}^{j} a_j Explanatory\ variables_{jit} + \varepsilon_{it}\end{aligned} \tag{9}$$

Besides, the econometric illustration of estimating adoption impact on ROI can be expressed as:

$$\begin{aligned}\mathrm{ROI},\ Y_{it} &= b_0 + b_1 Year_{it} + b_2 Treatment_{it} + b_3 Year{*}Treatment \\ &\quad + \sum_{j=1}^{j} b_j Explanatory\ variables_{jit} + \varepsilon_{it}\end{aligned} \tag{10}$$

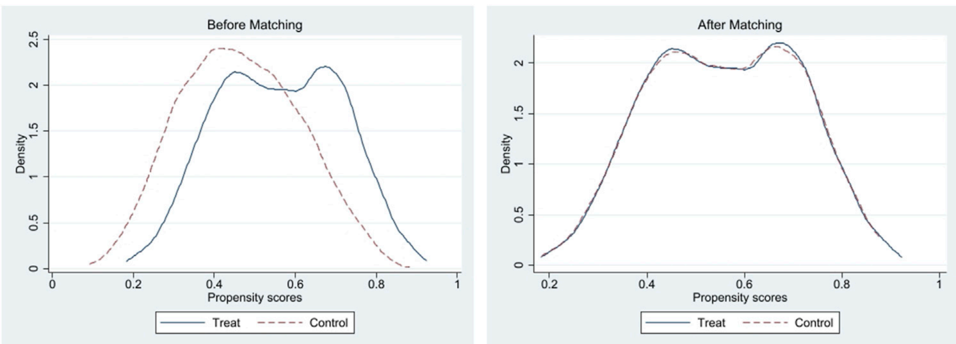

FIGURE 3
The kernel matching of propensity scores.

TABLE 4 Parallel test assumption table.

Parallel-trends test	ROI	Irrigation cost
Pre-treatment time period	F (1, 2,412) = .12	F (1, 2,412) = .98
Hypothesis: H0: Linear trends are parallel	Prob > F = .7263	Prob > F = .3232

In Equations 9, 10, the variable '*Y*' is the outcome variable for 'Irrigation cost' and 'ROI,' respectively. *'Year'* represents time trend. *"Treatment"* represents treated and control groups. The *"Year*Treatment"* variable denotes the DID estimand; *"Explanatory variables"* represent respondents' socio-economic characteristics, and ε symbolizes the random-error term.

3.3 Measurement of key variables

Table 1 in below, presents the DID basic variables Year and Treatment (Card and Krueger, 1994; Villa, 2016). The "Year" variable denotes the pre-treatment, treatment start, and follow-up periods. The end line of the research is the year 2021. The "Treatment" variable is the segmentation by the treatment and control groups.

The outcome variables for this study are irrigation cost and ROI. The irrigation cost for solar and electricity-based irrigation system adopters was calculated based on the fee that individual farmers paid per 50 decimals. For diesel irrigation adopters, the cost was calculated based on diesel machine rent that the farmer pays each season and the total diesel cost per 50 decimal. However, for a farmer who owns a diesel machine, the cost was calculated based on the total amount of diesel used per 50 decimal and the repairing cost that an individual farmer paid each season. All cost is measured in Taka (the Bangladeshi currency) and then converted to logarithmic forms to calculate the cost increase or decrease percentage. On the other hand, the ROI is the ratio of total return to the variable costs, calculated based on the study conducted by the Bangladesh Rice Research Institutes (BRRI) agricultural economic division entitled 'Estimation of costs and return of MV rice cultivation at the farm level' (BRRI, 2021).

The explanatory variables chosen for this study were based on the existing literature on technology adoption (Albrecht and Ladewig, 1985; Caswell et al., 2001; Pandey and Mishra, 2004; Simtowe and Zeller, 2006; Tiwari et al., 2008; Deressa et al., 2011; Idrisa et al., 2012; Genius et al., 2013; Reza and Hossain, 2013; Challa and Tilahun, 2014; Mottaleb et al., 2016; Chuchird et al., 2017; Ntshangase et al., 2018; Sunny et al., 2018; Zeng et al., 2018; Sarker et al., 2021; Sunny et al., 2022a; Sunny et al., 2022b; Sunny et al., 2022c), and their description are given in Table 1.

3.4 Data analysis

The Chi-square and F-test were performed to check if any significant difference exists between the treatment and control groups. Panel logit regression using the "xtlogit" command was performed to determine the influential factors of adoption. In order to satisfy the pre-requisite of DID estimation parallel trend test was conducted. This test asserts that the group participating in the program would have experienced a similar change in the outcome variable between the pre-program and the post-program periods as those not participating. If this assumption holds and we can credibly rule out any other over-time changes that may confound the treatment, then the estimators are highly reliable ((Lechner, 2011). We used the 'diff' command to estimate PSM-DID (Villa, 2016). We chose kernel matching with the Epanechnikov kernel function and used the bandwidth .03 and .06 (DiNardo and Tobais, 2001; Caliendo and Kopeinig, 2008; Islam et al., 2019). The bootstrapped application was applied with 1,000 repetitions of resampling (Wooldridge, 2012). Besides checking overlap and common support, we also conducted balancing tests on the differences in means after matching. For the robustness check, the 'xtdidregress' command was used to estimate the time and panel fixed effect DID and 'drdid' for estimating doubly robust DID (StataCorp, 2021; Sant'Anna and Zhao, 2020). All the analysis was performed through software for statistics and data science (STATA) version 17.0. Finally, these analysis results have been presented using frequency tables and cross-tabulations.

4 Result and discussion

4.1 Basic household characteristics of the survey respondents

Prior studies have suggested that the technology adoption among smallholder farmers is generally influenced by their socio-economic, environmental, and institutional profiles (Albrecht and Ladewig, 1985; Feder et al., 1985; Alauddin and Tisdell, 1988). Descriptive statistics of respondents' important socio-economic characteristics were analyzed to understand the factors affecting adoption decisions. Among the total respondents, 51.4% belong to the treatment group. The $\chi 2$ and F-test result in Table 2 below indicates significant differences between treatment and control groups based on irrigation cost, ROI, educational background, land ownership, farmlands typology, farming experience, knowledge level, fee opinion, soil water retention condition, irrigation machinery ownership, close acquaintances' adoption, environmental awareness, and secondary income status.

The mean irrigation cost of the control group is higher than the treatment group, but their ROI is lower than the treatment group. Among the total respondents, 47.98% of the treatment group respondents' age is higher than 30 years, and the treatment group respondents' literacy rate is nearly 2.7% higher than the control group. 79.75% of farmers cultivate on mid-low land, while 5.43% do not possess land ownership rights. The average farming experience and the farm size for control group farmers is 7.34% higher and .87% larger than the treatment group. Among 42.89% of households with more than four members, 22.50% belong to the treatment and the rest, 20.39%, belong to the control group. Even though 40.04% of treatment and 35.41% of control group farmers hold proper knowledge of SIF technology, 56.65% of total respondents, including 61.49% control and 52.06% treatment respondents, did not know SIFs adoption aids the environment. Regarding fee opinion, 22.47% of control and 30.51% of treatment group farmers, compared to the rest (47.02%), think the acquisition cost is not high. 45.68% of our respondent farmers have also reported owning other irrigation machinery. Among 1,059 respondents whose close acquaintances have adopted SIF holds, 13.44% belong to the control and 23.92% to the treatment group. In addition, 85.61% of farmers' seasonal off-farm income is more than 25,000 Taka.

TABLE 5 The bias of the mean of the explanatory variables before and after kernel matching.

Variable	Unmatched matched	Mean		Bias (%)	(%) Of bias reduction	*t*-test	
		Treated	Control			*t*	*p-value*
Age	U	.93	.93	0.6	−458.8	.16	.872
	M	.93	.92	3.4		.89	.374
Education (Edu)	U	.88	.84	9.3	54.8	2.48	.013
	M	.88	.89	−4.2		−1.22	.021
Land Ownership (LO)	U	.93	.96	−11.8	14.7	−3.14	.002
	M	.93	.96	−10.1		−2.68	.007
Land Typology (LT)	U	.25	.15	24.6	78.9	6.52	.000
	M	.25	.23	5.2		1.30	.193
Farming Experience (FE)	U	28.91	31.12	−23.3	73.4	−6.22	.000
	M	28.91	28.30	6.2		1.77	.077
Household Size (HHS)	U	.44	.42	3.8	−99.3	1.02	.306
	M	.44	.40	7.7		2.08	.038
Family Labor (FL)	U	1.44	1.15	−1.7	−15.9	−.45	.655
	M	1.44	1.15	−1.9		−.53	.593
Farm Size (FS)	U	93.35	94.16	−1.0	−711.1	−.27	.790
	M	39.35	86.73	8.1		2.31	.021
Knowledge of SIF (KSIF)	U	.78	.73	12.0	68.0	3.19	.001
	M	.78	.76	3.8		1.06	.291
Fee Opinion (FO)	U	.41	.54	−26.7	75.4	−7.11	.000
	M	.41	.44	−6.6		−1.78	.075
Soil Fertility Perception (SFP)	U	.36	.33	5.1	22.6	1.35	.176
	M	.36	.38	−3.9		−1.05	.294
Credit Availability (CA)	U	.58	.57	2.7	15.0	.71	.479
	M	.58	.57	2.3		.61	.541
Soil Water Retention condition (SWR)	U	.64	.72	−16.4	87.6	−4.35	.000
	M	.64	.65	−2.0		−.53	.594
Irrigation Machine Ownership (IMO)	U	.44	.48	−8.0	58.9	−2.12	.034
	M	.44	.42	3.3		.89	.375
Close Acquaintance's Adoption (CAA)	U	.47	.28	40.0	93.8	10.62	.000
	M	.47	.45	2.5		.63	.526
Environment Awareness (EA)	U	.48	.39	19.1	98.3	5.09	.000
	M	.48	.48	0.3		.09	.932
Secondary Income (SI)	U	.84	.87	−9.9	96.1	−2.62	.009
	M	.84	.84	−0.4		−.10	.920

4.2 Determinants of adoption

The factors influencing farm households' adoption of solar irrigation facilities were analyzed through panel data logit models, and the results are presented below (Table 3). The marginal effects were estimated, as the coefficient result does not express the probability or magnitude. The calculated Variance Inflation Factor (VIF) ranged from 1.06 to 1.84—well below the conventional

TABLE 6 Sample matching methods and the results of balance tests.

Sample	Pseudo-R2	LR statistics (*p*-value)	Mean bias	Median bias	N(T)	N(C)
Unmatched	.073	288.42 (.000)	12.7	9.9	1,456	1,379
Kernel Matching	.006	24.39 (.109)	4.2	3.8	1,456	1,379

Note: N T) denotes number of treated respondents and N(C) is the number of control respondents.

TABLE 7 Impacts of SIF adoption: PSM-DID model estimation.

Matching types	ROI	Irrigation cost
	ATT	ATT
DID without kernel matching	.21***	−.24***
DID with cluster standard error estimation	.21***	−.24***
DID Kernel matching with common support	.20***	−.23***
Kernel matching with common support and bootstrap 1,000	.21***	−.22***
Kernel matching with common support, bandwidth .03, bootstrap 1,000	.21***	−.23***
Kernel matching with common support, bandwidth .06, bootstrap 1,000	.20***	−.25***
Kernel matching with common support, bandwidth .03, bootstrap 1,000, quantile at .25	.30***	−.21***
Kernel matching with common support, bandwidth .06, bootstrap 1,000, quantile at .25	.20***	−.23***
Kernel matching with common support, bandwidth .03, bootstrap 1,000, quantile at .50	.20**	−.26***
Kernel matching with common support, bandwidth .06, bootstrap 1,000, quantile at .50	.20**	−.30***

Note: **, *** denotes significant at 5% and 1% level, respectively.

TABLE 8 Impacts of SIF adoption: DID robustness estimation.

Models	ROI	Irrigation cost
	ATT	ATT
Time and panel fixed effect DID	.21***	−.24***
Doubly Robust DID		
Doubly Robust IPW	.24***	−.20***
Doubly Robust Improved estimator	.25***	−.20***
Regression augmented estimator	.29***	−.22***
Standardized IPW estimator	.21***	−.22***

Note: Standard Error are presented in the parenthesis; *** denotes significant at 1% level.

threshold of 10, suggesting no issue of multicollinearity (Maddala, 1983).

The estimated marginal effect for the age variable indicates that the receptiveness toward solar irrigation technology increase by .27% if the farmers' age is below 30 years. Similar findings from prior work (Sunny et al., 2018; Sunny et al., 2022a) suggested that younger farmers' more vehement nature invigorates them in trying newer innovations. In contrast, higher experience farmers' cautiousness in technology choices is more highly associated with their knowledge of the technology and the expected return against investment aspects.

Land typology results demonstrate that farmers cultivating in mid-high land are 19.8% more likely to adopt SIF than low-midland cultivators. A prior study states that at higher relative landscape positions, water tends to drain more quickly (Krupnik et al., 2017), and Boro rice cultivation requires an adequate and timely water supply (Sunny et al., 2022c). Therefore, farmers cultivating in mid-high land are more likely to adopt SIF.

The negative marginal effect value signified that the adoption chance of SIF decreases to .15% when a household size is more than four people. Similar findings suggested that the consumption need of a larger household tends to compete with the investment of new technology adoption (Sunny et al., 2022a).

As expected, the marginal effect value suggests that farmers possessing proper SIF knowledge have a .9% higher probability of adopting the technology. Our result matches with prior study findings that suggested knowledge about a specific technology helps farmers to develop insights into the consequences of each option and can counterbalance the negative effect of a lack of years of formal education in the overall decision to adopt a technology (Sunny et al., 2018).

The marginal effects result of the 'Fee opinion' predictor indicates that farmers who urge for more reduced service fees are .07% more likely to adopt SIF. Our descriptive statistics also revealed that approximately 54% of control farmers believed that solar irrigation service fees were excessive. Therefore, the relevant authorities must take appropriate measures regarding acquisition fees so that the scheme can attract more farmers and operational organizations and farmers' possibility of achieving higher economic returns does not diminish.

The negative and significant 'Soil fertility' predictor indicates that a farmer with the greater belief that their farmland soil is fertile is .06% less likely to adopt SIF. This result is coherent with findings stating that soil fertility perceptions for Bangladeshi farmers are not fundamentally based on scientific classifications of soil composition (e.g., soil nutrient composition) but on perceived yield (Sunny et al., 2022b).

TABLE 9 Farmers' opinion of service quality.

Thoughts of the farmers	Year 2018	Year 2019	Year 2020	Year 2021
Operator issue	15	24	22	41
Water issue in cloudy weather	10	16	28	31
Service provider support delay	-	-	6	10

Source: Field Survey Data.

The marginal effect of "secondary income" indicates that the likelihood of adoption is .67% higher for farmers with higher secondary income than their counterparts. This result confirms earlier studies' findings that higher off-farm income influences new technology adoption (Rahman et al., 2021; Sunny et al., 2022b)). However, farmers having no cash constraints during the cropping season have .37% less probability of being SIF adopters. This finding is meaningful because loan availability does not indicate that the farmers have utilized that money for irrigation purposes and not to avail other essential inputs (i.e., fertilizer, pesticide, and herbicides) (Rizwan et al., 2019; Ouattara et al., 2020).

Finally, the marginal effect indicates that farmers knowing that SIF acceptance will aid in carbon footprint reduction are .12% more likely to adopt SIF. This result matches previous research outcomes suggesting that environmental knowledge positively impacts environmental attitudes and environmental attitudes influence behavioral intentions towards the environment. Thus, behavioral intentions toward the environment positively affect pro-environmental behavior (Liu et al., 2020).

4.3 Impacts of SIF adoption

Before finalizing, we tested the appropriateness of the models. Hence, we first checked the parallel trend assumption through the graphical representation. The observed means and the linear-trends model over the pretreatment periods indicate that the trends are parallel (Figures 1A,B). Besides, the insignificant *F* value for the ROI (.73) and Irrigation cost (.32) in Table 4 also suggested the appropriateness of employing the difference-in-differences method. Besides, within the PSM-DID framework, we check the matching quality based on the common support. The common support is the overlap interval of the propensity scores for the treated and control groups. The findings revealed a significant overlap in the propensity scores of treatment and control group respondents, suggesting better matching quality condition is met showed in Figure 2; Figure 3 (before and after matching). The balancing test was also performed to compare the balance of the pre-existing variables between the treatment and the control groups after matching. The test result indicated that the mean bias reduces from 12.7 to 4.2 after matching, which indicates that the propensity score matching method reduces the differences between treatment and control groups and eliminates the biases (Table 5; Table 6).

Tables 7 below represent the PSM-DID estimates for the impact of SIF adoption on ROI and irrigation cost. The findings show that ROI increased by 20%–30% and irrigation costs reduced by 21%–30% for treatment group farmers (adopters) compared to the control group. The findings match studies documenting solar irrigation adoption benefits in water-stressed areas (Hossain and Karim, 2020; Sunny et al., 2022a).

The positive impact of adoption has significant contributions to the energy sector. The recent energy crisis is not unexpected when considering global geopolitical matters. About 320,000 pumps are run by electricity to irrigate crops on a total of 54.48 lakh hectares in the dry season, which consumes approximately 2000 MW of electricity (Kanojia, 2019). Due to Bangladesh's energy crisis, the government has decided not to sanction new electricity connections for irrigation. A recent cost comparison study shows that with falling prices, solar irrigation systems have become competitive with grid electricity, while with increasing diesel prices, diesel-based irrigation is getting more expensive (Haque, 2022). Hence, Bangladesh must strongly take initiatives to keep the agricultural sector free from the negative impact of global diesel and other fossil fuel prices' oscillation and availability issues. The country uses between 15% and 20% of the grid electricity for irrigation purposes. Hence, installing enough solar-based irrigation systems to offset this loss and utilize this energy in other sectors seems more logical.

Studies in India revealed that solar irrigation system adoption not only satisfies farmers' water requirement for irrigation but also provides an incentive to economies for their energy and contributes to the energy sector by supplying unused energy to the grid (Patil, 2017). Another study revealed that the total power needed for irrigation in southern Europe is 16 GW; substituting this with solar power could offset over 16 million tons of CO2 yearly (Gillman, 2017). Likewise, adopting a solar irrigation system in Spain has increased yield by 35% and reduced energy consumption by 478 MW h annually, delivering 52 TEUR/year financial savings (Danfoss, 2020). Therefore, scale-up SIF adoption can contribute significantly to enabling a sustainable supply of food, energy, and water, particularly in water-stressed areas.

4.4 Robustness checks

We conducted several robustness checks to confirm our main results using fixed effect DID and doubly robust DID estimation methods presented in Table 8.

Even though Table 7 result in the above slightly differs from Table 8 results in terms of the magnitude of the ATT, the results are similar in terms of ATT's sign and effect. Both tables' results suggested that SIF significantly increases ROI and reduces irrigation costs, confirming that the PSM-DID estimates are robust.

4.5 Adopters' perception of service quality and operators' view on associated challenges

Table 9 below shows that before 2018 none of the farmers complained about service quality. However, 7.3% of adopters in

2018, 11.7% in 2019, 10.7% in 2020, and 20% in 2021 stated dissatisfaction with the site operators' behavior and performance. These farmers reported that many site operators practice partiality by providing water to their close acquaintances first, and sometimes they do not care about farmers' priority.

Likewise, around 4.9% of farmers in 2018, 7.8% in 2019, 13.7% in 2020, and 15.1% in 2021 were unhappy with the solar irrigation systems' performance as the system fails to supply adequate water in the cloudy period and to mitigate the issue, diesel pumps require reinstating. Similarly, 2.9% in 2020% and 4.9% in 2021 expressed disappointment with the service providers' indifferent attitude toward valuing farmers' views delaying support issues.

Since farmers were not satisfied with site operators, it would be worth knowing what their counterparts think. Among 30 site operators, 63% stated that not allowing adopted farmers to pay less is the main reason for their dissatisfaction. Further, 23.33% expressed that it becomes difficult to satisfy everyone when water requirements are high in the dry season. The rest, 13.33%, indicated that delay in repairing work due to a lack of skilled workforce is associated with dissatisfaction.

While discussing the challenges, five site operators reported that from 2020 they have been encountering steeling issues with cables and solar panels. They reasoned that the diffusion of solar irrigation facilities hampers diesel and electric pump owners' businesses, making them unhappy. Apart from highlighting the need to deal with theft, these findings also urge initiatives for solar technicians' skill development training in remote areas.

5 Conclusion and policy implications

This study examines the impact of solar irrigation facilities adoption on rural household welfare indicators (i.e., irrigation cost and ROI), using panel studies data on 2,835 households from 2015 to 2021. The results of the ATT estimates exhibited a positive impact of SIF adoption on irrigation cost and ROI.

This study's finding has practical policy implications. Firstly, the beneficial effect of SIF adoption highlighted the need for the government, investors, and shareholders greater focus on designing more appropriate schemes through experimentation and multiple iterations. However, to do so, ministries and agencies responsible for reforming and implementing customs duties, tariffs, and tax incentives need to reassess the market condition and find a solution to minimize the bureaucratic complexity for technology producers and distributors. It should be cognizant that the benefactors' loan repayment and the sustainability of the operating company depend on generating satisfactory revenue, which is only possible through appropriate site selection. Therefore, before finalizing the site, the responsible organizations should extensively study farmers' seasonal crop-choosing patterns, future underground pipeline expansion plans, soil slope, potential customers' attitudes regarding acquisition cost and perceptions towards SIF, and the market price of water-intensive crops. Because shifting the solar site from one place to another would not be cost-effective once the installation is done. Anecdotal evidence from service providers and site operators suggested that our study area farmers' crop cultivation patterns depend on earlier years' crop market prices. Likewise, private actors and public agencies need more information and tools to access water resource availability and soil water retention condition to enable more effective and sustainable solar irrigation investment planning. National implementing and regulatory agencies require more robust monitoring capacities. At the same time, the education sector needs to contribute to solar development efforts through training programs and capacity building to expand solar energy and solar irrigation. It is also essential to understand that the schemes to scale up of adoption process must be appealing enough to create strong demand from farmers.

Secondly, respondents' concern regarding SIF performance indicates solar panels' efficiency issues. Even though the project report states that these' panels' estimated shelf life is 10 years, the farmers are experiencing considerable efficiency decreases in the first 5 years of use. Thus, it seems that there is a need to extensively investigate, develop, and improve the technologies involved while emphasizing the technology's quality and after-sales service support. Likewise, substituting polycrystalline solar panels with copper bismuth oxide absorber-based thin-film solar cells or mono-crystalline panels will avoid reinstating diesel irrigation systems on peak time and can enhance the SIFs efficiency. These adjustments, nevertheless, need extra funding. Therefore, authorities should consider raising the tenure and grace period from 10 years to at least 20 years and facilitating lower interest rates than the banks offer for general projects.

Thirdly, SIF adoption, apart from contributing to farmers' wellbeing, can play a vital role in resolving future energy crises if the government speeds up the grid-tied Solar System expansion process. Because due to coal and furnace oil supply-chain disruptions, the future electricity production cost is anticipated to rise compared to the present.

Besides, initiatives introducing insurance schemes or safety nets to hedge against potential theft or production risk are expected to boost farmers' and investors' confidence and downside risk. In addition, focusing on region-specific installation of the small, medium, and high-capacity SIFs and strict prohibition of mixed types installation in the same region to avoid internal conflicts between services providers should include in policy priority.

Our findings also pointed to the significance of creative management strategies emphasizing field demonstration programs and campaigns to raise environmental consciousness and benefit recipients rather than just adoption. To better understand farmers' risk management practices, we also call for more research on how people of different ages perceive SIF and their knowledge of environmental severity.

Finally, implementing farm or community-level evidence-based best practices on solar irrigation solutions while considering the watershed scales and founded on principles of natural resource sustainability and equity will advance us towards achieving a sustainable food production sector.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

FS and MI planned, designed, analyzed and interpreted the data. FS, TK, and JL wrote the first draft. JL, MR, and HZ critically reviewed the manuscript that went through multiple revisions by FS, TK, MI, and MR. All authors read and approved the final manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2022.1101404/full#supplementary-material

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Research on construction schedule risk management of power supply and distribution projects based on MCS-AHP model

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In order to manage the construction schedule risk of power supply and distribution engineering, a construction schedule risk evaluation model, namely the Monte Carlo simulation method - Analytic Hierarchy Process (MCS-AHP) model, is proposed. In this model, the Monte Carlo simulation method is adopted to improve the analytic Hierarchy Process (AHP), and the normal distribution interval is used to replace the specific value when constructing the fuzzy complementary judgment matrix, to reduce the risk of fuzzy thinking and incomplete information or scattered data in the process of investigation and judgment and improve the scientific evaluation. This paper takes a power supply and distribution project in Guangdong Province as an example uses the MCS-AHP model to measure the key factors limiting the project progress, and uses the AHP method for comparative analysis, to verify the feasibility of the MCS-AHP model. The analysis shows that the key influencing factors are material and equipment procurement, production and arrival, installation of 10 kv high voltage switchboard, electrical acceptance and single machine commissioning, installation of low-voltage switchboard and DC switchboard, and foundation construction of power station equipment, etc., which are consistent with the actual situation. Therefore, it is feasible to construct the MCS-AHP model, which can provide a new way of thinking for schedule risk management analysis.

KEYWORDS

power supply and distribution engineering, schedule risk management, MCS-AHP model, Monte Carlo simulation, normal distribution of fuzzy numbers

1 Introduction

1.1 Literature review

In recent years, with the rapid improvement of modernization and urbanization, the demand for electricity supply in the production and life of people in modern society has shown a trend of increasing year by year (Albogamy et al., 2022). The state is paying more and more attention to the investment and construction of electric power projects, and the scale and the voltage level of electric power projects have reached a historical peak (Venkatesh et al., 2022; Zhang and Kang, 2022). As the energy market transformation gradually unfolds, electric energy's supply and demand situation is also changing dramatically, which puts forward higher requirements for the construction of electric power projects (Sun et al., 2022). The power balance between power companies and consumers is crucial (Ali et al., 2022). Therefore, with the increase in power demand, the accelerated progress of power engineering construction will put great pressure on the different stages involved in power engineering construction projects. It also easy to causes the problem of delayed progress in power engineering construction (Sharma et al., 2022). Therefore, it is necessary to study the schedule risk management of power engineering projects.

Before the research on the schedule risk management of power engineering projects, we found that the research on the schedule risk of other construction project management has achieved many research results. In terms of identifying the risk factors of the project schedule, Cheng and Darsa, (2021) established the construction schedule risk assessment model (CSRAM) and identified 22 risk factors. Chen et al. (2020) identified construction schedule risks from the perspective of the dialectical systems at the industry level; Muneeswaran et al. (2020) Statistical analysis using relative importance index and fuzzy ranking was used to identify risks; Chen L et al. (2021) used the decomposition structure method (RBS) to classify the schedule risks of high arch dam concrete projects. In terms of the theory and method of project schedule risk management, Chen M et al. (2021) constructed a critical risk network, including key risks and links. Li X et al. (2020) used the BN-PERT risk assessment model to evaluate the project schedule risk. Cheng et al. (2019) developed a fuzzy Bayesian Network-Monte Carlo simulation (FBN-MCS) to determine the correlation between risk and project duration. In terms of risk management information management, Sami Ur Rehman et al. (2020) established a factor-characteristic matrix to discuss the role of BIM in providing effective solutions for progress management. Lin et al. (2021) uses critical chain technology and combine FMEA management tool with BIM technology to manage the risks in construction projects. Song et al. (2022) used the information to extend project control methods for resource-constrained projects. This paper studies the schedule risk management of construction projects based on previous research on the schedule risk management of power engineering projects.

In the process of research on schedule risk management of power engineering projects, it is found that the research in recent years mainly focuses on construction quality, safety and multi-dimensional risk management. For example, in the aspect of quality risk management of power engineering, Sami Ur Rehman et al. (2020) use the FUCOM method to determine the risk assessment standard. Sun (2020) uses case analysis to identify quality risk factors that significantly impact the quality of power engineering. In terms of power engineering safety risk management, Li (2021) analyzes and evaluates safety risk factors based on the fundamental theories of safety risk management. Bao et al. (2021) put forward a comprehensive risk assessment technique for digital instrumentation and control (DI&C for short) system (IRADIC technique) and put forward opinions and suggestions for risk management. In the aspect of risk analysis of power engineering construction, Shaktawat and Vadhera, (2021) take sensitivity analysis as the primary method to evaluate essential risk factors; Li Y. C et al. (2020) adopted the risk matrix method to assess the risks in the construction process of giant hydropower projects; Zheng et al. (2021) used an improved precise diffusion algorithm to solve the two-stage distributed optimization problem. In terms of multi-dimensional risk management; Liu and Xu, (2022) conducted power engineering risk management from the perspectives of economy, management, society and environmental coordination; Lotfi et al. (2022) studied the robust time-cost-quality-energy-environment trade-off with resource-constrained in project management. After consulting relevant data, it is found that the research results of various risk factors of power engineering are relatively wealthy, only schedule risk management is less studied, and schedule risk is one of the main threats to power engineering project management. Schedule risk control of power engineering construction is also vital to ensure the project objectives' realisation (Huang et al., 2018; Wu et al., 2022). Therefore, it is necessary to carry out relevant research.

Throughout the literature at home and abroad, it is found that the research methods of schedule risk management of power engineering are still in an earlier period, such as the interpretive structural model (ISM) method (Rao et al., 2014), AHP-RII combined method model (Hossen et al., 2015), PERT/CPM simulation model (Lee et al., 2018), etc. The research on the schedule risk of power projects often needs to solve the difficulties of establishing evaluation index systems and evaluation models. AHP is a multi-criteria decision-making tool (Dhingra et al., 2022; Raghav et al., 2022), and MCS can accurately predict through simulation (Khosravi et al., 2022; Ullah et al., 2022). Combining AHP (Li and Xu, 2021) with the MCS method (Koulinas et al., 2021) can well solve the problems of poor evaluation index system setting, complex set evaluation index standard weighting, and unquantifiable qualitative index evaluation. The main contribution of this paper is that the MCS-AHP model built can solve the above problems, and can effectively reduce the subjectivity so that the weight calculated and the relationship between them is more scientific. The MCS-AHP model is a mathematical method which is applicable to the research of power engineering schedule management and can be applied to the research of other projects and can be used for project location problems and project decision-making problems. The construction schedule risk evaluation index system of power supply and distribution engineering can also provide a reference for the research of schedule risk management of power engineering projects worldwide.

Based on the discussion, the rest of the organizational structure of this paper is as follows: In the second section, mainly introduces how to build the MCS-AHP model and its calculation steps. The third section is mainly about the model application. Based on the construction schedule risk assessment index system of power supply and distribution engineering, the MCS-AHP model is used to calculate the key influencing factors, and the traditional AHP model is used for comparative analysis to verify the feasibility of the MCS-AHP model. The fourth section summarizes the research results of this paper and the prospect for the future.

1.2 Problem statement

With the growing scale of power supply and distribution engineering construction projects, the construction period continues to extend, how to scientifically and effectively manage and control the progress of this long-term construction phase of power supply and distribution engineering project management has always been an enduring topic. The main reason is that power supply and distribution engineering is often restricted by various factors during construction, and this restriction factor often causes the actual progress of the project to deviate significantly from the expected progress. Once such tendency factors accumulate to a certain extent and exceed its risk pre-control ability, the project progress will be difficult to achieve its desired purpose. Thus it is easy to cause the project schedule the accident. Therefore, it is necessary to strengthen the dynamic tracking and monitoring of the

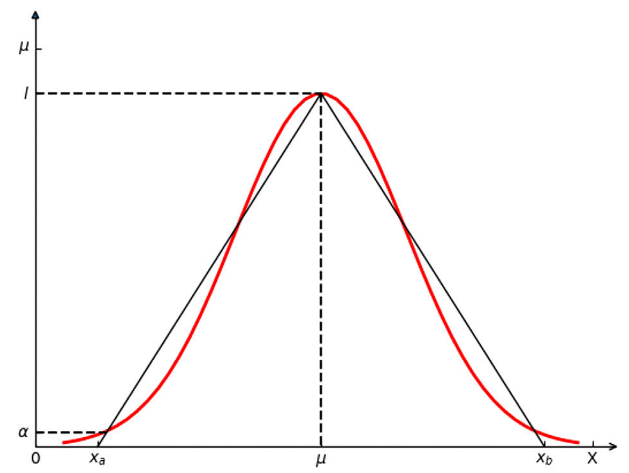

FIGURE 1
Normally distributed fuzzy numbers and triangular fuzzy numbers.

construction progress of the power supply and distribution projects to complete the project and obtain higher economic benefits.

In this section, we propose an MCS-AHP model to evaluate the construction schedule risk of power supply and distribution engineering, which has received little attention in previous studies. It is of great significance to determine, classify and measure the risk factors that bring adverse effects to the progress of the project, and to manage and monitor them effectively on this basis.

2 Model construction

2.1 Normally distributed fuzzy numbers

The standard distribution curve is high in the middle and low at the ends. μ is the centre of the normal distribution preference, and σ is the width, indicating the uncertainty present.

Define the average distribution affiliation function as:

$$f(x:\ \mu,\sigma) = \exp\left[\frac{-(x-\mu)^2}{\sigma^2}\right] \tag{1}$$

The method proposed in this paper will be compared with the triangular fuzzy number, as shown in Figure 1.

$$\alpha = \exp\left[\frac{-(x-\mu)^2}{\sigma^2}\right] \tag{2}$$

$$x_a = \mu - \sigma\sqrt{-\mathrm{Ln}(\alpha)} \tag{3}$$

$$x_b = \mu + \sigma\sqrt{-\mathrm{Ln}(\alpha)} \tag{4}$$

(The curve represents the normal distribution membership function, and the line represents the trigonometric function).

Figure 1 explains the description of the alpha value. Eqs. 5, 6 explain the definition of a customarily distributed fuzzy number as a transformed form of a triangular fuzzy number. It is assumed that Ti is the triangular fuzzy number and Gi is the element of the preference matrix after performing the triangular approximation.

$$S_i = \frac{\sum_j G_{ij}}{\sum_i\sum_j G_{ij}} = \frac{\sum_j\left(l_i^j, m_i^j, u_i^j\right)}{\sum_i\sum_j\left(l_i^j, m_i^j, u_i^j\right)} \tag{5}$$

where, $l_i^j \cong m_i^j - \sigma_i^j\sqrt{-\mathrm{Ln}(\alpha)}$, $u_i^j \cong m_i^j + \sigma_i^j\sqrt{-\mathrm{Ln}(\alpha)}$

To obtain a representative approximation of the triangle, the value of α is set to 0.01. This means that a normal distribution funtion approximates 99% of the values:

$$S_i = \frac{\left(\sum_j l_i^j, \sum_j m_i^j, \sum_j u_i^j\right)}{\left(\sum_i\sum_j l_i^j, \sum_i\sum_j m_i^j, \sum_i\sum_j u_i^j\right)} = \left(\frac{\sum_j l_i^j}{\sum_i\sum_j u_i^j}, \frac{\sum_j m_i^j}{\sum_i\sum_j m_i^j}, \frac{\sum_j u_i^j}{\sum_i\sum_j l_i^j}\right) \tag{6}$$

where,

$$\sum_j l_i^j = \sum_j m_i^j - \sum_j \sigma_i^j\left(\sqrt{-\mathrm{Ln}(\alpha)}\right) \tag{7}$$

$$\sum_j u_i^j = \sum_j m_i^j + \sum_j \sigma_i^j\left(\sqrt{-\mathrm{Ln}(\alpha)}\right) \tag{8}$$

$$\sum_i\sum_j l_i^j = \sum_i\sum_j m_i^j - \sum_i\sum_j \sigma_i^j\left(\sqrt{-\mathrm{Ln}(\alpha)}\right) \tag{9}$$

$$\sum_i\sum_j u_i^j = \sum_i\sum_j m_i^j + \sum_i\sum_j \sigma_i^j\left(\sqrt{-\mathrm{Ln}(\alpha)}\right) \tag{10}$$

$$\text{and, } m_{S_i} = \frac{\sum_j m_i^j}{\sum_i\sum_j m_i^j}, X_{S_i}^L = \frac{\sum_j l_i^j}{\sum_i\sum_j u_i^j}, X_{S_i}^R = \frac{\sum_j u_i^j}{\sum_i\sum_j l_i^j}$$

Will be transformed into an asymmetric normal distribution of fuzzy numbers as follows:

$$\sigma_{S_i}^L = \frac{m_{S_i} - X_{S_i}^L}{\sqrt{-\mathrm{Ln}(\alpha)}} \tag{11}$$

$$\sigma_{S_i}^R = \frac{X_{S_i}^R - m_{S_i}}{\sqrt{-\mathrm{Ln}(\alpha)}} \tag{12}$$

$\sigma_{S_i}^L$ A denotes the width of the left branch of the fuzzy number of the normal distribution and $\sigma_{S_i}^R$ denotes the width of the right branch of the fuzzy number of the normal distribution. The affiliation function of the asymmetric standard distribution number is:

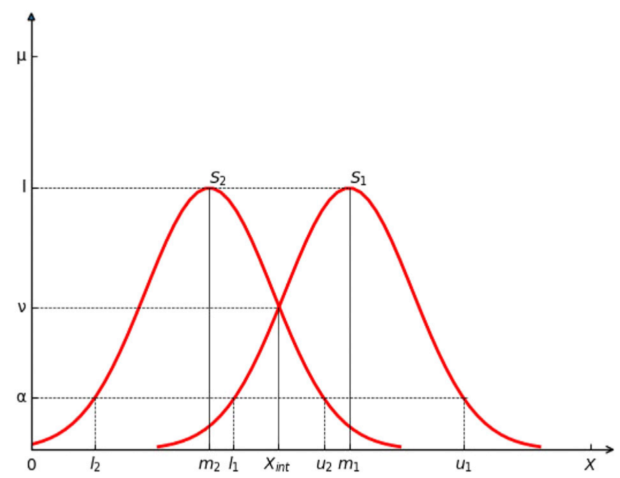

FIGURE 2
The intersection of two normally distributed membership functions.

$$\mu_{S_i(X)} = \begin{cases} \exp\left[-\left(\frac{x - m_{S_i}}{\sigma^L_{S_i}}\right)^2\right], x \le m_{S_i} \\ \exp\left[-\left(\frac{x - m_{S_i}}{\sigma^R_{S_i}}\right)^2\right], x > m_{S_i} \end{cases} \tag{13}$$

Let μ_{S_1} (x) and μ_{S_2} (x) be two normally distributed fuzzy numbers, as in Figure 2 below:

$$\mu_{S_1(X)} = \begin{cases} \exp\left[-\left(\frac{x - m_{S_1}}{\sigma^L_{S_1}}\right)^2\right], x \le m_{S_1} \\ \exp\left[-\left(\frac{x - m_{S_1}}{\sigma^R_{S_1}}\right)^2\right], x > m_{S_1} \end{cases} \tag{14}$$

$$\mu_{S_2(X)} = \begin{cases} \exp\left[-\left(\frac{x - m_{S_2}}{\sigma^L_{S_2}}\right)^2\right], x \le m_{S_2} \\ \exp\left[-\left(\frac{x - m_{S_2}}{\sigma^R_{S_2}}\right)^2\right], x > m_{S_2} \end{cases} \tag{15}$$

$$v = \begin{cases} \exp\left[-\left(\frac{m_{S_2} - m_{S_1}}{\sigma^L_{S_1} + \sigma^R_{S_2}}\right)^2\right], m_{S_1} > m_{S_2} \\ \exp\left[-\left(\frac{m_{S_2} - m_{S_1}}{\sigma^R_{S_1} + \sigma^L_{S_2}}\right)^2\right], m_{S_1} < m_{S_2} \end{cases} \tag{16}$$

The degree of probability of $S_2 = \mu_{S_2}(x) \ge S_1 = \mu_{S_1}(x)$ is defined as:

$$\begin{aligned} V(S_2 \ge S_1) &= \mathrm{hgt}(S_1 \cap S_2) = \mu_{S_2}(X_{int}) \\ &= \begin{cases} 1, & m_{S_2} \ge m_{S_1} \\ \exp\left[-\left(\frac{m_{S_2} - m_{S_1}}{\sigma^R_{S_1} + \sigma^L_{S_2}}\right)^2\right], & m_{S_1} < m_{S_2} \end{cases} \end{aligned} \tag{17}$$

Where X_{int} denotes the vertical coordinate of the inner intersection between μ_{S_1} (x) and μ_{S_2} (x). Both values of $V(S_2 \ge S_1)$ and $V(S_1 \ge S_2)$ need to be compared S_1 and S_2.

2.2 AHP model

The Analytic hierarchy process is one of the multi-criteria decision-making methods that simplify the decision-making process and enables the evaluation of qualitative and quantitative criteria (Alelaiwi, 2019). The calculation steps of the hierarchical analysis method are as follows:

2.2.1 Construct the evaluation index system

In-depth analysis of practical problems, top-down hierarchical analysis of relevant factors, the construction of index layer, factor layer and other index systems.

2.2.2 Construct a fuzzy judgment matrix

The two factors of the same layer are compared and analyzed, and the fuzzy judgment matrix is constructed according to the scale of the fuzzy judgment matrix. The relative importance of each factor is judged within the range of the set judgment scale, and the fuzzy judgment matrix is obtained.

2.2.3 Calculate the index weight

Calculate the weight value of all factors in the fuzzy judgment matrix, Method 1: Root value method

The first step, the matrix R_{ij} is obtained by multiplying each row of elements, namely:

$$R_{ij} = \prod_{j=1}^{n} a_{ij} \tag{18}$$

The second step, the matrix R_i is obtained by taking the square root of the combined result, namely:

$$R_i = \sqrt[n]{R_{ij}} \tag{19}$$

The third step, the weight vector is obtained by normalization processing, namely:

$$W_i = \frac{R_i}{\sum_{i=1}^{n} R_i} \tag{20}$$

Method two: Sum method.

The first step is to normalize the column vectors to obtain the matrix R_{ij}, namely:

$$R_{ij} = \begin{bmatrix} \frac{a11}{\sum_{i=1}^{n} ai1} & \frac{a12}{\sum_{i=1}^{n} ai2} & \cdots & \frac{a1n}{\sum_{i=1}^{n} ain} \\ \frac{a21}{\sum_{i=1}^{n} ai1} & \frac{a22}{\sum_{i=1}^{n} ai2} & \cdots & \frac{a2n}{\sum_{i=1}^{n} ain} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{an1}{\sum_{i=1}^{n} ai1} & \frac{an2}{\sum_{i=1}^{n} ai2} & \cdots & \frac{ann}{\sum_{i=1}^{n} ain} \end{bmatrix} \tag{21}$$

The second step, add the lines of the normalized matrix R_{ij} to get matrix R^*_{ij}, namely:

$$R^*_{ij} = \begin{bmatrix} \frac{a11}{\sum_{i=1}^{n} ai1} + \frac{a12}{\sum_{i=1}^{n} ai2} + \cdots + \frac{a1n}{\sum_{i=1}^{n} ain} \\ \frac{a21}{\sum_{i=1}^{n} ai1} + \frac{a22}{\sum_{i=1}^{n} ai2} + \cdots + \frac{a2n}{\sum_{i=1}^{n} ain} \\ \cdots \quad \cdots \quad \cdots \quad \cdots \\ \frac{an1}{\sum_{i=1}^{n} ai1} + \frac{an2}{\sum_{i=1}^{n} ai2} + \cdots + \frac{ann}{\sum_{i=1}^{n} ain} \end{bmatrix} \tag{22}$$

The third step, the row sum of the added matrix R^*_{ij} is normalized to obtain the weight vector w_{ij}.

2.2.4 Consistency test

In the risk assessment of the power supply and distribution project construction schedule, in addition to the index weight calculated according to expert scores, consistency index CI and consistency ratio CR should also be investigated. The matrix's maximum characteristic roots λ_{max}, CI and CR can be calculated by Eqs. 23, 24. When CI = 0, it indicates that the results have complete consistency; when CI approaches 0, it indicates good consistency; the more significant the consistency index CI is, the greater the degree of inconsistency deviation.

$$\lambda_{max} = \sum_{i=1}^{n} \frac{(AW)_i}{nW_i} \tag{23}$$

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{24}$$

Since the fuzzy judgment matrix presents inconsistency in most cases, in order to measure the consistency index CI value, we need to introduce the random consistency index RI value, which depends on the matrix order:

$$CR = \frac{CI}{RI} \tag{25}$$

When CR < 0.1 indicates that the fuzzy judgment matrix has a good consistency, it passes the consistency test; otherwise, it fails.

2.3 MCS-AHP model

Monte Carlo simulation (Qazi et al., 2021) is used to improve on the fuzzy hierarchical analysis method to quantify the degree of influence of schedule risk factors for power supply and distribution projects. In Monte Carlo simulation, the normal distribution is used as the most appropriate distribution model to approximate the probability distribution functions of the criteria and factors. The method is mainly based on fuzzy hierarchical analysis, using fuzzy hierarchical analysis as the general framework and using regular distribution intervals instead of specific values when constructing fuzzy complementary judgement matrices to reduce the risk of probabilistic uncertainty, as well as to reduce the risk of people's fuzzy thinking and incomplete information or scattered data in the process of investigation and judgement, to avoid the results. The specific steps are as follows.

2.3.1 Establish an evaluation indicator system

Establish a hierarchical decision structure for construction schedule risk management for power supply and distribution projects, using objective layer A, criterion layer B, and factor layer C to complete the structure. This paper describes that objective layer A is the most essential factor in determining criterion layer B and factor layer C. The attributes of the decision target layer A, criterion layer B and factor layer C should be developed based on the actual project.

2.3.2 Expert scoring

The expert interview method and other statistical methods can produce the results of expert scoring and obtain the vital information of each criterion level and factor level, respectively, then use Saaty's scale method for preliminary assessment and then decide the normal distribution range according to the expert scoring results.

2.3.3 Preliminary determination of the regular distribution interval

The results of each expert's score are listed to make a reasonable judgement on the construction schedule of the power supply and distribution project. In general, the total standard deviation σ is uncertain, and we can use the sampling standard deviation s as the point estimate of the total standard deviation to predict the overall parameters, using the sampling standard deviation s as the total standard deviation σ. The sampling means as the total mean μ. A normal distribution is evaluated by sorting the data in a spreadsheet to determine the normal distribution curve's lowest, most likely and highest values. Eq. 28 gives the probability distribution function for a standard distribution curve, and Eqs. 29, 30 determine the independent typical distribution properties. The interval estimates under large samples when σ and μ are unknown are,

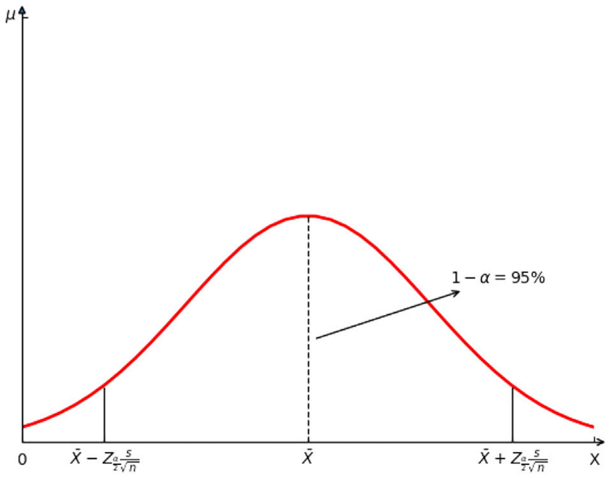

FIGURE 3
Normal distribution curve interval when confidence degree 1-α = 95%.

$$\mu \pm Z_{\alpha/2} \cdot \frac{\sigma}{\sqrt{n}} \tag{26}$$

When s is used instead of σ, the interval estimate at the time of substitution is,

$$\bar{x} \pm Z_{\alpha/2} \cdot \frac{s}{\sqrt{n}} \tag{27}$$

$$f(x|\mu, \sigma) = \frac{1}{s\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2s^2}} \tag{28}$$

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} = \frac{x_1 + x_2 + \cdots + x_n}{n} \tag{29}$$

$$s = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n-1}} \tag{30}$$

$$\hat{a} = \bar{x} - Z_{\alpha/2} \cdot \frac{s}{\sqrt{n}} \tag{31}$$

$$\hat{b} = \bar{x} \tag{32}$$

$$\hat{c} = \bar{x} + Z_{\alpha/2} \cdot \frac{s}{\sqrt{n}} \tag{33}$$

Where: $\bar{x}$ is the mean of the normal distribution, s is the standard deviation of the normal distribution, $\hat{a}$ is the lowest value, $\hat{b}$ is the most likely value, $\hat{c}$ is the highest value, n is the number of data, α is the confidence rate, confidence level, reflecting the credibility of the prediction conclusion. If the confidence level is given in advance, we can look up its corresponding statistical variables through the standard normal distribution $Z_{\alpha/2}$. The typical confidence levels are 90%, 95%, 95.45% and 99.73%. In this paper, we choose 1-α = 95%, and the confidence level is 1.96. Figure 3 below illustrates the a normal distribution curve with a 95% confidence period.

2.3.4 Monte Carlo simulation of a normal distribution interval

A standard distance fuzzy number is generated by generating a random variable for $\bar{x}$, $\bar{x} - Z_{\alpha/2} \cdot \frac{s}{\sqrt{n}}$, $\bar{x} + Z_{\alpha/2} \cdot \frac{s}{\sqrt{n}}$, and applying Monte Carlo to simulate a normal distribution 100 normal random variables are used in this paper and Eqs. 34, 37 describe how the random numbers are generated.

$$F\left(X|\mu,\sigma\right)=\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{x}e^{-\frac{(x-\mu)^2}{2\sigma^2}}\approx\frac{1}{2}\left(1+\mathrm{erf}\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right) \tag{34}$$

Random Monte Carlo numbers can be generated by plotting input variables (X) ranging from 0 to 100, generating random variables from i = 1 to 100 times, and storing the results as columns of random variables. Eqs. 38–40 are then used to determine the Monte Carlo normal distribution mean and standard deviation to account for the values of a, b and c.

$$a=\mu-Z_{\alpha/2}\cdot\frac{\sigma}{\sqrt{n}} \tag{35}$$

$$b=\mu \tag{36}$$

$$c=\mu+Z_{\alpha/2}\cdot\frac{\sigma}{\sqrt{n}} \tag{37}$$

$$\mu=\frac{\sum_{i=1}^{n}x_i}{n}=\frac{x_1+x_2+\ldots+x_n}{n} \tag{38}$$

$$\sigma=\sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1}} \tag{39}$$

Where $F(X|\mu,\sigma)$ is the cumulative distribution function of the normal distribution,μ and σ are the mean and standard deviation of the Monte Carlo normal distribution, and a, b and c are the lower, most likely and higher values for which the mutual inverse fuzzy set values are applicable.

$$(a,b,c)^{-1}=\left(\frac{1}{\mu+Z_{\alpha/2}\cdot\frac{\sigma}{\sqrt{n}}},\frac{1}{\mu},\frac{1}{\mu-Z_{\alpha/2}\cdot\frac{\sigma}{\sqrt{n}}}\right) \tag{40}$$

2.3.5 Normality test

This paper used P-P plots and the Kolmogorov-Smirnov test to test the normality of all judgement data.

For the P-P plot, the actual data cumulative rate of the data distribution, when assumed to be normally distributed, must first be calculated; this is then represented as a split scatter plot, with the X-axis representing the actual cumulative percentage and the Y-axis representing the cumulative percentage of the assumed normal distribution. Because of the normal distribution assumed for the figures, the cumulative percentage of the hypothetical normal distribution is the same as the cumulative percentage of the accurate figures.

The KS test was used to test the normality of the statistics, using the upper exact bound (the maximum value of the difference) between the cumulative distribution function $f_x(x)$ of the sample and the cumulative distribution function $F_n(x)$ of the normal distribution to determine whether the Kolmogorov distribution was met. The KS test significantly indicates normality when the maximum difference in D_n is less than the value in the Kolmogorov-Smirnov table. The mathematical equations for the KS test are Eqs. 41–43.

$$D_n=\sup|f_x(x)-F_n(x)| \tag{41}$$

$$f_x(x)=\int_{-\infty}^{x}f_x(k)dk=\int_{-\infty}^{x}\frac{1}{\sigma\sqrt{2\pi}}e\left(-\frac{(k-\mu)^2}{2\sigma^2}\right)dk \tag{42}$$

$$F_n(x)=\frac{1}{n}\sum_{i=1}^{n}1_{xi\le t} \tag{43}$$

Where D_n is the highest difference between statistics $f_x(x)$ and $F_n(x)$, sup is the exact upper boundary of the distance (supremum), $f_x(x)$ is the cumulative distribution function of the sample, and $F_n(x)$ is the cumulative distribution function of the normal distribution. To simplify the calculation, this paper uses IBM SPSS software to plot P-P plots and perform KS tests to determine whether the data conform to normality. When the data > 0.05, it means that the data form a normal distribution, while when the data ≤ 0.05, it means that the data do not form a normal distribution.

2.3.6 Construct a normal distribution fuzzy two-by-two comparison matrix

Using a two-by-two comparison matrix of normally distributed fuzzy numbers instead of the fuzzy complementary judgment matrix of the traditional hierarchical analysis method, construct a comparison matrix E=(e_{ij})nxn based on the lowest value a, the most probable value b and the highest value c obtained in step 4, and set the random normally distributed values of E_{11} and E_{12} as (a_{11},b_{11},c_{11}) and (a_{12},b_{12},c_{12}) respectively.

$$E=\begin{bmatrix}(1,1,1) & (a_{12},b_{12},c_{12}) & \cdots & (a_{1n},b_{1n},c_{1n})\\ (1/c_{12},1/b_{12},1/a_{12}) & (1,1,1) & \cdots & (a_{2n},b_{2n},c_{2n})\\ \cdots & \cdots & \ddots & \cdots\\ (1/c_{1n},1/b_{1n},1/a_{1n}) & (1/c_{2n},1/b_{2n},1/a_{2n}) & \cdots & (1,1,1)\end{bmatrix} \tag{44}$$

2.3.7 Test of consistency

Like the traditional fuzzy analytic hierarchy process, consistency analysis is required for each fuzzy judgment matrix to ensure that the fuzzy pairwise comparison matrix is adequate for evaluation. Once it is inconsistent, the relevant fuzzy pairwise comparison matrix needs to be adjusted. Since the interval scale is used to replace the point scale, uing the traditional consistency analysis. Some scholars (Ramík and Korviny, 2010) proposed a new consistency index (NI) to measure the consistency of pairwise comparison matrix with fuzzy ternary interval.

$$NI_n^{\sigma}(A)=\gamma_n^{\sigma}\cdot\max_{i,j}\left\{\max\left\{\left|\frac{U_i^L}{U_j^U}-a_{ij}\right|,\left|\frac{U_i^M}{U_j^M}-b_{ij}\right|,\left|\frac{U_i^U}{U_j^L}-c_{ij}\right|\right\}\right\} \tag{45}$$

$$\gamma_n^{\sigma}=\frac{1}{\max\left\{\sigma-\sigma^{(2-2n)/n},\sigma^2\left(\left(\frac{2}{n}\right)^{2/(n-2)}-\left(\frac{2}{n}\right)^{n/(n-2)}\right)\right\}},\ \sigma<\left(\frac{n}{2}\right)^{n/(n-2)} \tag{46}$$

$$\gamma_n^{\sigma}=\frac{1}{\max\{\sigma-\sigma^{(2-2n)/n},\sigma^{(2n-2)/n}-\sigma\}},\ \sigma\ge\left(\frac{n}{2}\right)^{n/(n-2)} \tag{47}$$

Where,

$$U_k^L=C_{\min}\cdot\frac{\left(\prod_{j=1}^{n}a_{kj}^L\right)^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n}a_{ij}^M\right)^{1/n}} \tag{48}$$

$$C_{\min}=\min_{i=1,\ldots,n}\left\{\frac{\left(\prod_{j=1}^{n}a_{ij}^M\right)^{1/n}}{\left(\prod_{j=1}^{n}a_{ij}^L\right)^{1/n}}\right\} \tag{49}$$

$$U_k^M=\frac{\left(\prod_{j=1}^{n}a_{kj}^M\right)^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n}a_{ij}^M\right)^{1/n}} \tag{50}$$

$$U_k^U=C_{\max}\cdot\frac{\left(\prod_{j=1}^{n}a_{kj}^u\right)^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n}a_{ij}^M\right)^{1/n}} \tag{51}$$

$$C_{\max}=\max_{i=1,\ldots,n}\left\{\frac{\left(\prod_{j=1}^{n}a_{ij}^M\right)^{1/n}}{\left(\prod_{j=1}^{n}a_{ij}^u\right)^{1/n}}\right\} \tag{52}$$

TABLE 1 Construction schedule risk evaluation system for power supply and distribution.

Target level	Guideline level	Factor layer
Construction schedule risk for power supply and distribution	Construction preparation A	Construction personnel, materials and equipment approach A1
		Construction plan preparation review stage A2
		Project Department set up A3
		Site temporary facility set up A4
	Civil construction B	Power piping construction B1
		Electric pipe jacking construction B2
		Cable well construction B3
		High and low pressure indoor construction B4
		Power station equipment foundation construction B5
	Installation construction C	Procurement, production and arrival of materials and equipment C1
		Installation of 10 KV high voltage Distribution cabinet C2
		Dry type transformer installation C3
		Install low-voltage PDC and DC panel C4
		High voltage protection, metering system installation C5
		Cable tray installation and cable laying C6
	Commissioning and acceptance by the electricity supply department D	Electrical acceptance and monomer commissioning D1
		System setup and whole group start debugging D2
		Preliminary inspection, elimination, final inspection and handover by Power supply department D3
		Power transmission D4

Where, σ is the pairwise comparison scale (for example, when the expert scores the result of 1/9 and 9, the pairwise comparison scale is 9), γ_n^σ is the regular constant, and $NI_n^\sigma(A)$ is the consistency index of the fuzzy pairwise comparison matrix. When the value of $NI_n^\sigma(A)$ is between 0 and 0.1, the fuzzy pairwise comparison matrix passes the consistency test. When the value of $NI_n^\sigma(A)$ is closer to 0, the consistency test of the fuzzy pairwise comparison matrix is more consistent.

2.3.8 Calculation of weights and ranking

Normalize the two-by-two comparison matrix to obtain the matrix $R = (r_{ij})$ nxn, Method 1: Root value method

$$r_{ij} = \left(\frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}, \frac{b_{ij}}{\sum_{i=1}^{n} b_{ij}}, \frac{c_{ij}}{\sum_{i=1}^{n} c_{ij}}\right), i = 1, 2, 3, ..., n \tag{53}$$

The fuzzy weight values were obtained using Buckley's geometric averaging method FAHP to calculate the fuzzy weights of each fuzzy matrix. The fuzzy weight values were calculated by geometric averaging for each row using Eq. 54.

$$w_{ij} = \left(\prod_{j=1}^{n} r_{ij}\right)^{\frac{1}{n}} \tag{54}$$

Method two: Sum method

It is consistent with the calculation steps of the analytic hierarchy process

The fuzzy final value is calculated by computing the total hierarchical ranking.

$$w_i = \sum_{j=1}^{n} w_{ij} {}^{*} w_j \tag{55}$$

3 Case study

3.1 Project overview

The power supply and distribution project selected in this paper is XX Power Supporting Phase II Project, and the construction site is XX Road, XX District, XX City, Guangdong Province. The construction scope of this project is 2# plant construction, 3# plant construction and power station construction.

3.2 Establishment of risk indicator system

The essential step in the risk analysis of power supply and distribution project construction is to set up the risk assessment index system of progress. Progress risk assessment index system should be scientific and accurate, include all factors that may affect the construction progress of power supply and distribution projects,

TABLE 2 Monte Carlo random generation number of criterion layer.

Indicator	B than A	C than A	D than A	C than B	D than B	D than C
$\bar{x}$	3.875	7.625	3.563	3.813	0.604	0.184
s	0.927	0.992	0.864	1.014	0.460	0.025
Monte Carlo number randomly generated numbers						
1	3.047	7.241	3.478	4.577	1.219	0.213
2	2.897	7.585	2.673	3.729	0.375	0.170
3	2.836	9.096	2.328	2.111	1.050	0.186
...	...	...	...	...	...	...
98	2.833	7.660	4.511	3.158	0.617	0.209
99	5.459	8.837	2.667	1.891	-0.384	0.169
100	4.942	6.393	5.199	4.180	0.964	0.202
μ	3.812	7.597	3.596	3.760	0.620	0.183
σ	0.910	1.022	0.876	1.021	0.459	0.024

and pay attention to redundancy and contradiction among all factors while eliminating human interference factors. Combined with the actual power supply and distribution project situation, this paper summarizes the construction progress evaluation index system of the power supply and distribution project. As shown in Table 1 below.

3.3 MCS-AHP determines the weight of indicators

3.3.1 Expert questionnaire situation

Sixteen experts were invited to evaluate the evaluation index system, including the project leader, deputy project manager, technical person, safety person and full-time safety officer to evaluate all the index factors. In order to construct A fuzzy pairwise comparison matrix, the two factors are compared. For example, the civil construction criterion B is compared with the construction preparation criterion A, and the importance between the two is compared according to the 1-9 scale method proposed by Professor Saaty (Kieu et al., 2021). Details of the expert scores for the guideline and factor tiers are detailed in Supplementary Appendices S1–S5.

3.3.2 Determining Monte Carlo random generation numbers

The mean and standard deviation can be calculated based on the experts' ratings of the two comparison factors. In order to reduce the bias caused by subjective factors, this paper selects a large sample of data to evaluate the construction risk of power supply and distribution projects. However, if the questionnaire method is used to calculate the extensive sample data, there may be a significant error. On this basis, 100 random variables were generated by applying the Monte Carlo random generation number principle. For this purpose, the standard deviation s of the sample was used as the point estimate of the total standard deviation for the prediction of the overall parameters, using the sample standard deviation s as the total standard deviation σ and the sample mean $\bar{x}$ as the total mean μ. The Monte Carlo random generation numbers of the criterion layer are sorted out as shown in Table 2, and the Monte Carlo random generation numbers of other factor layers are shown in Supplementary Appendices S6–S9.

3.3.3 Normality test

After generating Monte Carlo random numbers, it is also necessary to test the normality of the data. There are many methods to test for normality, and this paper takes P-P plots and K-S test tables for verification, the basic principles of which are referred to in Eqs. 41–43. To simplify the calculation and improve the calculation efficiency, this paper mainly uses the software spss for testing. According to the criterion layer, K-S test, Table 3 shows that when all values of asymptotic significance are more excellent than 0.05, so the criterion layer data conforms to a normal distribution. According to Figures 4–7 and Supplementary Appendix S10, the hypothesised cumulative ratios of the normal distribution are consistent with the cumulative ratios of the actual data, so the criterion layer data are consistent with a normal distribution. The data in each factor layer also conform to normal distribution. Due to space limitations, the K-S test and P-P plot for each factor layer will not be developed in detail here.

3.3.4 Construct fuzzy pairwise comparison matrix and consistency test

The population mean μ and the population standard deviation σ of the sample can be determined according to the random numbers generated by the pair comparison of factors. Eqs. 35–37 are used to determine the lower limit a, the most probable value b, and the upper limit c of the fuzzy pair-to-pair comparison matrix. The fuzzy pair-to-pair comparison matrix can be constructed by using Eq. 44, and the constructed pair-to-pair comparison matrix is shown in Tables 4–Tables 8 (In order to distinguish the results calculated by using AHP model, MCS-AHP is added to the table, representing the results calculated by using MCS-AHP model):

According to Eqs. 45–52, a consistency test can be performed on the pair-to-pair comparison matrix of the criterion layer. Combined with Table 4, it can be calculated as follows:

TABLE 3 K-S test of criterion layer.

Kolmogorov-Sminov test								
Number of cases			B than A	C than A	D than A	C than B	D than B	D than C
			100	100	100	100	100	100
Normal parameters[a,b]	Average		3.812	7.597	3.596	3.760	0.620	0.183
	Standard Deviation		0.910	1.022	0.876	1.021	0.459	0.024
Most extreme difference	Absolute values		.027	.033	.025	.018	.027	.032
	positive values		.027	.033	.019	.016	.026	.032
	negative values		−.022	−.024	−.025	−.018	−.027	−.024
Test statistics			.027	.033	.025	.018	.027	.032
Asymptotic saliency (two-tailed)[c]			.200[d]	.200[d]	.200[d]	.200[d]	.200[d]	.200[d]
Monte Carlo significance (two-tailed)[e]	significance		.483	.211	.674	.972	.489	.258
	99% confidence interval	lower limit	.470	.200	.662	.968	.476	.247
		upper limit	.496	.221	.686	.976	.502	.269

[a]The test distribution is normal.
[b]Calculated from data.
[c]Riley's significance correction.
[d]This is the lower limit of true saliency.
[e]Rielly's method based on 10,000 Monte Carlo samples with 2 million starting seeds.

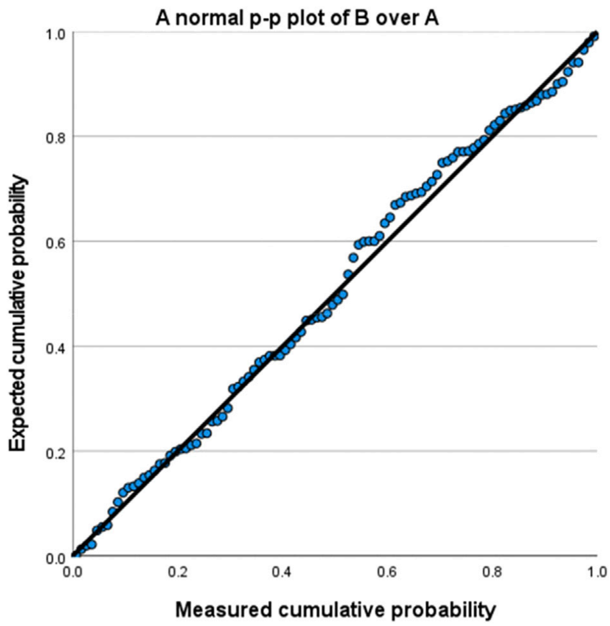

FIGURE 4
A normal p-p plot of B over A.

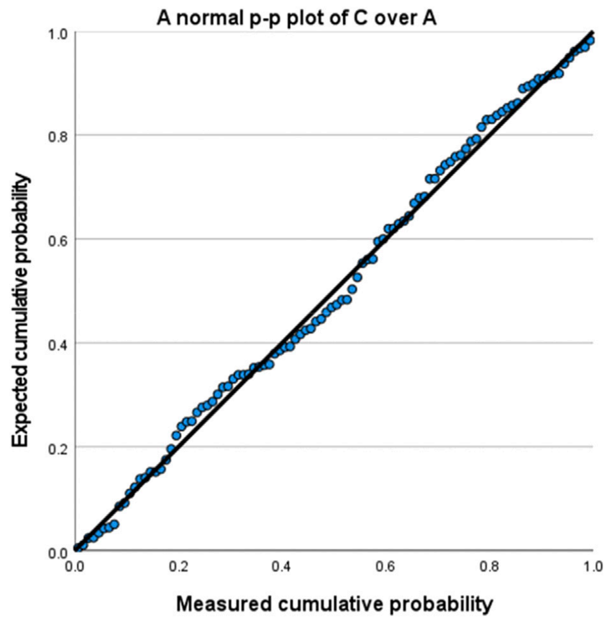

FIGURE 5
A normal p-p plot of C over A.

$$\sigma = \left[\frac{1}{9} .9\right] = 9, n = 4$$

$$9 > \left(\frac{4}{2}\right)^{4/(4-2)} = 4$$

$$\gamma_4^9 = \frac{1}{\max\left(9 - 9^{(-6/4)}, 9^{(6/4)} - 9\right)} = \frac{1}{\max(8.963, 18)} = 0.056$$

$$C_{\min} = 1.008$$

$$C_{\max} = 0.992$$

$$\tilde{u}_1 = \left(u_1^L, u_1^M, u_1^U\right) = (0.054, 0.054, 0.054)$$

$$\tilde{u}_2 = \left(u_2^L, u_2^M, u_2^U\right) = (0.194, 0.196, 0.198)$$

$$\tilde{u}_3 = \left(u_3^L, u_3^M, u_3^U\right) = (0.612, 0.612, 0.612)$$

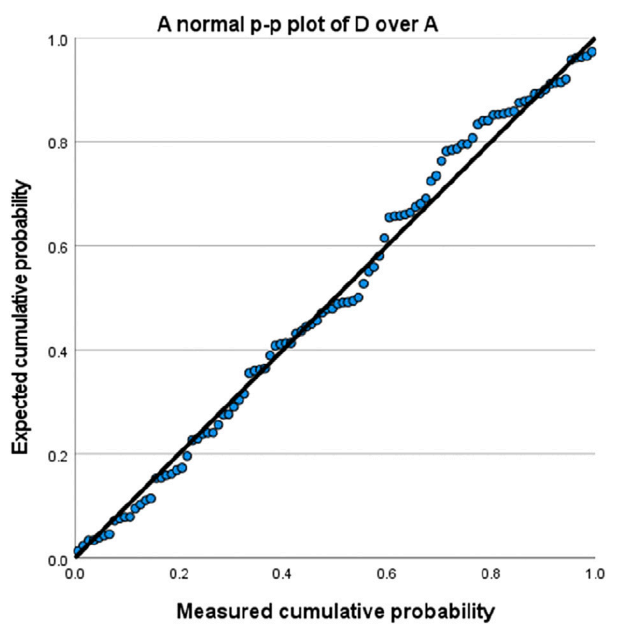

FIGURE 6
A normal p-p plot of D over A.

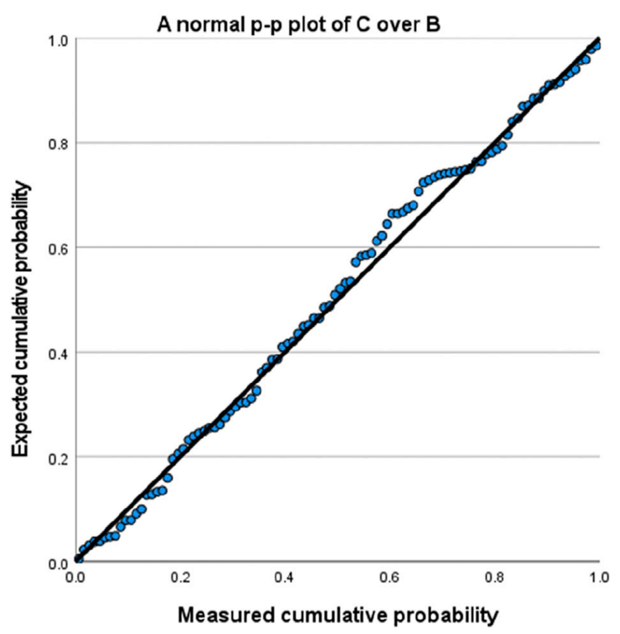

FIGURE 7
A normal p-p plot of C over B.

$$\tilde{u}_4 = \left(u_4^L, u_4^M, u_4^U\right) = (0.137, 0.138, 0.139)$$

$$\max\left\{\left|\frac{U_i^L}{U_j^U} - a_{ij}\right|, \left|\frac{U_i^M}{U_j^M} - b_{ij}\right|, \left|\frac{U_i^U}{U_j^L} - c_{ij}\right|\right\} = \max\{1.032, 1.029, 1.028\}$$

$$= 1.032$$

$$NI_4^9(A) = \gamma_4^9 \cdot \max_{i,j}\left\{\max\left\{\left|\frac{U_i^L}{U_j^U} - a_{ij}\right|, \left|\frac{U_i^M}{U_j^M} - b_{ij}\right|, \left|\frac{U_i^U}{U_j^L} - c_{ij}\right|\right\}\right\}$$

$$= 0.056 \cdot 1.032 = 0.058$$

Because $NI_4^9(A) = 0.058 < 0.1$, it passes the consistency test. The consistency test of other factor layers is the same. Due to space limitations, the calculation will not be carried out in detail.

3.3.5 Determine the relative weight and ranking of each index

Based on the fuzzy pair-to-pair comparison matrix and Eqs. 53–55, the normalized matrix and standard weight of the criterion layer and factor layer can be calculated to determine the objects that should be paid the most attention to, as shown in Tables 9, 14 below (In order to distinguish the results calculated by using AHP model, MCS-AHP is added to the table, representing the results calculated by using MCS-AHP model):

As seen from Table 9, installation construction has the most significant weight. Civil construction, commissioning and acceptance of the power supply department has the third weight, and construction preparation has the least weight. Therefore, installation construction and civil construction should be the critical criteria layer. According to the standard weight and ranking Table 10 of the construction preparation factor layer, it can be seen that the construction of temporary facilities on site has the most significant weight, followed by the construction personnel, materials and equipment entering the site, the construction plan preparation and review stage has the third weight. The construction department has the least weight. Therefore, the critical factors in the criterion layer of construction preparation are the establishment of temporary facilities on site and the entry of construction personnel, materials and equipment. It can be seen from the standard weight and ranking Table 11 of the civil construction factor layer that the weight of power station equipment foundation construction is the first, the weight of high and low-pressure indoor foundation construction is the second, the weight of cable well construction is the third, the weight of power pipe jack construction is the fourth, and the weight of power pipe row construction is the fifth. Therefore, power station equipment foundation construction and high and low-pressure indoor foundation construction are the key factors in the criteria of civil construction. As can be seen from the standard weight and ranking Table 12 of the installation and construction factor layer, the purchase of materials and equipment, production and arrival of goods have the most significant weight. The installation of a 10 kv high voltage distribution cabinet has the second weight, the installation of low voltage distribution cabinet and DC panel has the third weight, and the installation of high voltage protection and the metering system has the fourth weight. The weight of cable tray installation and cable laying ranks fifth, and the weight of dry transformer installation is the least. Therefore, in the criterion layer of installation and construction, we should focus on the procurement, production and arrival of materials and equipment, installing a 10 kv high-voltage distribution cabinet, low-voltage distribution cabinet and DC screen installation. According to the standard weight and ranking Table 13 of the acceptance factor layer of the commissioning and power supply department, the weight of electrical test and single commissioning are the highest, followed by the weight of acceptance and handover of the power supply department, the weight of system commissioning. The whole group starting commissioning is the third, and the weight of power transmission is the least. Therefore, in the criterion layer of

TABLE 4 Pairwise comparison matrix of criterion layer (MCS-AHP).

Indicator	A	B	C	D
A	(1,1,1)	(0.259,0.262, 0.266)	(0.131,0.132, 0.133)	(0.274,0.278, 0.282)
B	(3.756,3.812, 3.868)	(1,1,1)	(0.262,0.266, 0.270)	(1.543,1.613, 1.689)
C	(7.534,7.597, 7.660)	(3.697,3.760, 3.823)	(1,1,1)	(5.435,5.464, 5.495)
D	(3.542,3.596, 3.650)	(0.592,0.620, 0.648)	(0.182,0.183, 0.184)	(1,1,1)
$NI_4^9(A) = 0.058 < 0.1$				

TABLE 5 Pairwise comparison matrix of construction preparation factor layer (MCS-AHP).

Indicator	A_1	A_2	A_3	A_4
A_1	(1,1,1)	(1.482,1.541, 1.600)	(2.559,2.613, 2.667)	(0.734,0.790, 0.846)
A_2	(0.625,0.649, 0.675)	(1,1,1)	(2.231,2.295, 2.359)	(0.787,0.839, 0.891)
A_3	(0.375,0.383, 0.391)	(0.424,0.436, 0.448)	(1,1,1)	(0.314,0.318, 0.322)
A_{14}	(1.182,1.266, 1.362)	(1.122,1.192, 1.271)	(3.106,3.145, 3.185)	(1,1,1)
$NI_4^9(A) = 0.017 < 0.1$				

TABLE 6 Pairwise comparison matrix of civil construction factor layer (MCS-AHP).

Indicator	B_1	B_2	B_3	B_4	B_5
B_1	(1,1,1)	(0.245,0.248,0.252)	(0.256,0.260,0.265)	(0.180,0.182,0.184)	(0.176,0.178,0.180)
B_2	(3.963,4.023, 4.083)	(1,1,1)	(0.609,0.630,0.653)	(0.284,0.288,0.292)	(0.258,0.263,0.268)
B_3	(3.790,3.849, 3.908)	(1.531,1.587, 1.643)	(1,1,1)	(0.303,0.307,0.311)	(0.276,0.280,0.284)
B_4	(5.417,5.481, 5.545)	(3.427,3.474, 3.521)	(3.215,3.260, 3.305)	(1,1,1)	(0.597,0.620,0.643)
B_5	(5.531,5.603, 5.675)	(3.732,3.806, 3.880)	(3.522,3.573, 3.624)	(1.556,1.615, 1.674)	(1,1,1)
$NI_4^9(A) = 0.081 < 0.1$					

TABLE 7 Pairwise comparison matrix of installation and construction factor layer (MCS-AHP).

Indicator	C1	C2	C3	C4	C5	C6
C_1	(1,1,1)	(3.878,3.941, 4.004)	(5.629,5.691,5.753)	(3.718,3.771,3.824)	(3.936,3.992,4.048)	(4.330,4.394,4.458)
C_2	(0.250,0.254,0.258)	(1,1,1)	(3.524,3.577,3.630)	(1.600,1.658,1.716)	(1.223,1.266, 1.309)	(1.880,1.940,1.999)
C_3	(0.174,0.176,0.178)	(0.275,0.280,0.284)	(1,1,1)	(0.269,0.273,0.277)	(0.263,0.267,0.271)	(0.306,0.310,0.314)
C_4	(0.262,0.265,0.268)	(0.583,0.603,0.625)	(3.610,3.663,3.717)	(1,1,1)	(1.748,1.808,1.868)	(1.940,2.000,2.060)
C_5	(0.247,0.251,0.254)	(0.764,0.790,0.818)	(3.690,3.745,3.802)	(0.535,0.553,0.572)	(1,1,1)	(1.390,1.435, 1.480)
C_6	(0.224,0.228,0.231)	(0.500,0.515,0.532)	(3.185,3.226,3.268)	(0.485,0.500,0.515)	(0.676,0.697,0.719)	(1,1,1)
$NI_4^9(A) = 0.042 < 0.1$						

commissioning and acceptance of the power supply department, emphasis should be placed on the two factors of electrical test, unit commissioning and acceptance and handover of the power supply department.

Based on Tables 9–Tables 14 can be obtained. Based on the comprehensive analysis of the standard weights and the overall ranking of all factors, it can be concluded that the purchase of materials and equipment, production and arrival of goods take the first place, the installation of 10 kv high-voltage power distribution cabinet takes the second place, electrical acceptance and single commissioning takes the third place, and the installation of low-voltage power distribution cabinet and DC panel takes the fourth

TABLE 8 Pairwise comparison matrix of factor layer of commissioning and acceptance of power supply department (MCS-AHP).

Indicator	D_1	D_2	D_3	D_4
D_1	(1,1,1)	(6.554,6.618, 6.682)	(5.978,6.036, 6.094)	(7.442,7.509, 7.576)
D_2	(0.150,0.151, 0.152)	(1,1,1)	(0.297,0.300, 0.303)	(1.699,1.756, 1.812)
D_3	(0.164,0.166, 0.167)	(3.300,3.333, 3.367)	(1,1,1)	(3.539,3.593, 3.647)
D_4	(0.132,0.133, 0.134)	(0.552,0.569, 0.588)	(0.274,0.278, 0.283)	(1,1,1)
$NI_4^9(A) = 0.071 < 0.1$				

TABLE 9 Standard weight and ranking of criteria layer (MCS-AHP).

Indicator	A	B	C	D	wj	Rank
A	(0.063,0.062,0.062)	(0.045,0.046,0.047)	(0.083,0.083,0.084)	(0.033,0.034,0.033)	(0.055,0.056,0.057)	4
B	(0.237,0.238,0.239)	(0.180,0.177,0.174)	(0.166,0.168,0.170)	(0.186,0.193,0.199)	(0.192,0.194,0.196)	2
C	(0.475,0.475,0.473)	(0.667,0.667,0.667)	(0.634,0.633,0.633)	(0.658,0.654,0.649)	(0.605,0.607,0.609)	1
D	(0.223,0.225,0.226)	(0.106,0.110,0.113)	(0.115,0.116,0.116)	(0.121,0.120,0.118)	(0.141,0.142,0.143)	3

TABLE 10 Standard weight and ranking of construction preparation factor layer (MCS-AHP).

Indicator	A_1	A_2	A_3	A_4	wj	Rank
A_1	(0.314,0.303,0.292)	(0.368,0.370,0.371)	(0.287,0.289,0.290)	(0.258,0.268.0.278)	(0.306,0.307,0.308)	2
A_2	(0.196,0.197,0.197)	(0.248,0.240,0.232)	(0.251,0.254,0.256)	(0.277,0.284,0.291)	(0.243,0.244,0.245)	3
A_3	(0.118,0.116,0.114)	(0.105,0.105,0.104)	(0.112,0.110,0.109)	(0.111,0.108,0.105)	(0.108,0.110,0.112)	4
A_4	(0.371,0.384,0.397)	(0.278,0.285,0.294)	(0.349,0.347,0.346)	(0.353,0.339,0.327)	(0.337,0.339,0.341)	1

TABLE 11 Standard weight and ranking of civil construction factor layer (MCS-AHP).

Indicator	B_1	B_2	B_3	B_4	B_5	wj	Rank
B_1	(0.051,0.050,0.049)	(0.024,0.025,0.026)	(0.029,0.030,0.031)	(0.054,0.054,0.053)	(0.076,0.076,0.076)	(0.046,0.047.0.048)	5
B_2	(0.201,0.202,0.202)	(0.101,0.099,0.097)	(0.071,0.072,0.074)	(0.085,0.085,0.085)	(0.112,0.112,0.113)	(0.113,0.114,0.115)	4
B_3	(0.192,0.193,0.193)	(0.154,0.157,0.159)	(0.116,0.115,0.113)	(0.091,0.091,0.090)	(0.119,0.120,0.120)	(0.134,0.135,0.136)	3
B_4	(0.274,0.275,0.275)	(0.345,0.343,0.342)	(0.374,0.374,0.374)	(0.300,0.295,0.289)	(0.259,0.265,0.271)	(0.309,0.310,0.311)	2
B_5	(0.281,0.281,0.282)	(0.376,0.376,0.377)	(0.409,0.410,0.410)	(0.468,0.476,0.484)	(0.433,0.427,0.421)	(0.393,0.394.0.395)	1

TABLE 12 Standard weight and ranking of installation and construction factor layers (MCS-AHP).

Indicator	C_1	C_2	C_3	C_4	C_5	C_6	wj	Rank
C_1	(0.463,0.459,0.456)	(0.554,0.552,0.551)	(0.272,0.272,0.272)	(0.488,0.486,0.484)	(0.445,0.442,0.439)	(0.399,0.397,0.394)	(0.433,0.435,0.436)	1
C_2	(0.116,0.117,0.118)	(0.142,0.140,0.138)	(0.171,0.171,0.172)	(0.210,0.214,0.217)	(0.138,0.140,0.142)	(0.173,0.175,0.177)	(0.158,0.160,0.161)	2
C_3	(0.080,0.081,0.081)	(0.039,0.039,0.039)	(0.048,0.048,0.047)	(0.035,0.035,0.035)	(0.030,0.030,0.029)	(0.028,0.028,0.027)	(0.042,0.043,0.044)	6
C_4	(0.121,0.122,0.123)	(0.083,0.084,0.086)	(0.175,0.175,0.176)	(0.131,0.129,0.127)	(0.197,0.200,0.203)	(0.179,0.180,0.182)	(0.147,0.148,0.150)	3
C_5	(0.114,0.115,0.116)	(0.109,0.110,0.112)	(0.178,0.179,0.180)	(0.070,0.071,0.072)	(0.113,0.110,0.108)	(0.128,0.130,0.131)	(0.118,0.119,0.120)	4
C_6	(0.103,0.104,0.105)	(0.071,0.072,0.073)	(0.154,0.154,0.154)	(0.063,0.064,0.065)	(0.076,0.077,0.078)	(0.092,0.090,0.088)	(0.093,0.094,0.095)	5

TABLE 13 Standard weight and ranking of factor layer for commissioning and acceptance of power supply department (MCS-AHP).

Indicator	D_1	D_2	D_3	D_4	wj	Rank
D_1	(0.692,0.689,0.688)	(0.574,0.575,0.575)	(0.792,0.793,0.793)	(0.544,0.542,0.540)	(0.649,0.650,0.651)	1
D_2	(0.104,0.104,0.105)	(0.088,0.087,0.086)	(0.039,0.039,0.040)	(0.124,0.127,0.129)	(0.088,0.089,0.090)	3
D_3	(0.113,0.114,0.115)	(0.288,0.289,0.289)	(0.132,0.131,0.130)	(0.259,0.259,0.260)	(0.197,0.198,0.199)	2
D_4	(0.091,0.092,0.092)	(0.048,0.049,0.051)	(0.036,0.037,0.037)	(0.073,0.072,0.071)	(0.062,0.063,0.064)	4

TABLE 14 Standard weight and total ranking of target layer (MCS-AHP).

Guideline level	w_{ij}	Factor layer	w_j	w_i	NI_n^σ (A)	Rank
A	(0.055,0.056,0.057)	A_1	(0.306,0.307,0.308)	(0.0168,0.0172,0.0176)	0.017 < 0.1	14
		A_2	(0.243,0.244,0.245)	(0.0134,0.0137,0.0140)		15
		A_3	(0.108,0.110,0.112)	(0.0059,0.0062,0.0064)		19
		A_4	(0.337,0.339,0.341)	(0.0185,0.0190,0.0194)		13
B	(0.192,0.194,0.196)	B_1	(0.046,0.047.0.048)	(0.0088,0.0091,0.0094)	0.081 < 0.1	17
		B_2	(0.113,0.114,0.115)	(0.0217,0.0221,0.0225)		12
		B_3	(0.134,0.135,0.136)	(0.0257,0.0262,0.0267)		10
		B_4	(0.309,0.310,0.311)	(0.0593,0.0601,0.0609)		7
		B_5	(0.393,0.394.0.395)	(0.0755,0.0764,0.0774)		5
C	(0.605,0.607,0.609)	C_1	(0.433,0.435,0.436)	(0.2620,0.2640,0.2655)	0.04 < 0.1	1
		C_2	(0.158,0.160,0.161)	(0.0956,0.0971,0.0980)		2
		C_3	(0.042,0.043,0.044)	(0.0254,0.0261,0.0268)		11
		C_4	(0.147,0.148,0.150)	(0.0889,0.0898,0.0913)		4
		C_5	(0.118,0.119,0.120)	(0.0714,0.0722,0.0731)		6
		C_6	(0.093,0.094,0.095)	(0.0563,0.0571,0.0579)		8
D	(0.141,0.142,0.143)	D_1	(0.649,0.650,0.651)	(0.0915,0.0923,0.0931)	0.071 < 0.1	3
		D_2	(0.088,0.089,0.090)	(0.0124,0.0126,0.0129)		16
		D_3	(0.197,0.198,0.199)	(0.0278,0.0281,0.0284)		9
		D_4	(0.062,0.063,0.064)	(0.0087,0.0089,0.0091)		18

TABLE 15 Pairwise comparison matrix of criterion layer (AHP).

Indicator	A	B	B	D	wj	Rank
A	1	0.258	0.131	0.281	0.056	4
B	3.875	1	0.262	1.656	0.195	2
C	7.625	3.813	1	5.435	0.608	1
D	3.563	0.604	0.184	1	0.141	3

place. The weight of power station equipment foundation construction is the fifth, and the weight of high-pressure protection and metering system installation is the sixth. Therefore, in the risk management of the entire construction schedule of the power supply and distribution project, the most important factors should be the control of materials and equipment procurement, production and arrival, installation of 10 kv high-voltage distribution cabinet, electrical acceptance and single commissioning, installation of low-voltage distribution cabinet and DC panel, equipment foundation construction of power station and installation of high-voltage protection metering system.

3.4 AHP determines the index weight

3.4.1 Construct a pairwise matrix and calculate the relative weights of each indicator

Based on the results of the expert questionnaire, fuzzy two-by-two comparison matrices were constructed for the guideline layer, the

TABLE 16 Pairwise comparison matrix of construction preparation factor layer (AHP).

Indicator	A_1	A_2	A_3	A_4	wj	Rank
A_1	1	1.479	2.583	0.750	0.300	2
A_2	0.676	1	2.250	0.844	0.246	3
A_3	0.387	0.444	1	0.316	0.110	4
A_4	1.333	1.184	3.165	1	0.345	1

TABLE 17 Pairwise comparison matrix of civil construction factor layer (AHP).

Indicator	B_1	B_2	B_3	B_4	B_5	wj	Rank
B_1	1	0.250	0.258	0.182	0.178	0.047	5
B_2	4.000	1	0.615	0.291	0.262	0.113	4
B_3	3.875	1.625	1	0.302	0.281	0.135	3
B_4	5.500	3.438	3.313	1	0.640	0.313	2
B_5	5.625	3.813	3.563	1.563	1	0.391	1

TABLE 18 Pairwise comparison matrix of installation construction factor layer (AHP).

Indicator	C_1	C_2	C_3	C_4	C_5	C_6	wj	Rank
C_1	1	3.938	5.688	3.750	4.000	4.375	0.435	1
C_2	0.254	1	3.625	1.688	1.313	1.875	0.161	2
C_3	0.176	0.276	1	0.278	0.270	0.305	0.044	6
C_4	0.267	0.592	3.597	1	1.813	1.938	0.147	3
C_5	0.250	0.762	3.704	0.552	1	1.375	0.118	4
C_6	0.229	0.533	3.279	0.516	0.727	1	0.096	5

construction preparation factor layer, the civil construction factor layer, the installation construction factor layer and the commissioning and power supply department acceptance factor layer, and the weights were calculated and ranked as shown in Tables 15–Tables 19 (to distinguish the results calculated by the MCS-AHP model, AHP was added to the table to indicate the results calculated by the AHP model):

3.4.2 Test of consistency

Since experts may have a large subjective deviation when scoring the schedule risk of power supply and distribution engineering, it is necessary to conduct a consistency test on all pairwise mutual judgment matrices. Firstly, the consistency test is carried out on the pairwise mutual judgment matrix of the criterion layer. The specific steps are as follows:

Consistency test of the pairwise matrix of criterion layer

Step 1. Eq. 23 can be used to calculate the maximum characteristic root λ_{max} of the matrix. of which,

TABLE 19 Pairwise comparison matrix of acceptance factor layer of commissioning and power supply department (AHP).

Indicator	D_1	D_2	D_3	D_4	wj	Rank
D_1	1	6.625	6.000	7.438	0.650	1
D_2	0.151	1	0.303	1.688	0.089	3
D_3	0.167	3.300	1	3.563	0.199	2
D_4	0.134	0.592	0.281	1	0.064	4

$$AW = \begin{bmatrix} 1 & 0.258 & 0.131 & 0.281 \\ 3.875 & 1 & 0.262 & 1.656 \\ 7.625 & 3.813 & 1 & 5.435 \\ 3.563 & 0.604 & 0.184 & 1 \end{bmatrix} \cdot \begin{bmatrix} 0.056 \\ 0.195 \\ 0.608 \\ 0.141 \end{bmatrix} = \begin{bmatrix} 0.226 \\ 0.805 \\ 2.545 \\ 0.570 \end{bmatrix}$$

$$= (0.226,\ 0.805, 2.545, 0.570)^T$$

$$\lambda_{max} = \sum_{i=1}^{n} \frac{(AW)_i}{nW_i} = \frac{1}{4}\left(\frac{0.226}{0.056} + \frac{0.805}{0.195} + \frac{2.545}{0.608} + \frac{0.570}{0.141}\right) = 4.098$$

Step 2. the consistency index can be calculated using Eq. 24.

$$CI = \frac{\lambda_{max} - n}{n-1} = \frac{4.098 - 4}{4-1} = 0.033$$

Step 3. the consistency ratio is calculated using Eq. 25, where the value of RI depends on the order of the matrix, and the pairwise matrix of the criterion layer has an order of 4. Checking the RI value (Chen, 2018) shows that when $n = 4$, RI = 0.89

$$CR = \frac{CI}{RI} = \frac{0.033}{0.89} = 0.037 < 0.1$$

Therefore, the pairwise matrix of the criterion layer passes the consistency test, and the weight calculated meets the requirements. The calculation steps of consistency test for each factor layer are the same. Due to space limitation, the calculation will not be carried out in detail.

According to the weights of each indicator calculated from Tables 15, 19 and the consistency ratios, the final weights can be calculated as shown in Table 20 below:

3.5 Discussion

From the target layer standard weight and Total Ranking (AHP) Table 20, it can be seen that the results calculated by the AHP model are as follows: C_1 ranks first in the weight of material and equipment purchased, production and arrival, C_2 ranks second in the weight of installation of 10 KV high voltage switchboard, and D_1 ranks the third in the weight of electrical acceptance and mono commissioning. C_4 installation of low-voltage PDC and DC panel ranks fourth, B_5 installation of power station equipment foundation ranks fifth, and C_5 installation of high-voltage protection and metering system ranks sixth. In preventing risks in the construction schedule of power supply and distribution engineering, these factors should be paid the most attention to.

According to the standard Weight and Total Ranking (MCS-AHP) Table 14 of the target layer, C_1 has the highest weight of material equipment purchase, production and arrival, which has the greatest

TABLE 20 Standard weight and total ranking of target layer (AHP).

Guideline level	w_{ij}	Factor layer	w_j	w_i	λ_{max}	CR	Rank
A	0.056	A_1	0.300	0.0168	4.021	0.008 < 0.1	14
		A_2	0.246	0.0138			15
		A_3	0.110	0.0062			19
		A_4	0.345	0.0193			13
B	0.195	B_1	0.047	0.0092	5.186	0.042 < 0.1	17
		B_2	0.113	0.0220			12
		B_3	0.135	0.0263			11
		B_4	0.313	0.0610			7
		B_5	0.391	0.0762			5
C	0.608	C_1	0.435	0.2645	6.204	0.033 < 0.1	1
		C_2	0.161	0.0979			2
		C_3	0.044	0.0268			10
		C_4	0.147	0.0894			4
		C_5	0.118	0.0717			6
		C_6	0.096	0.0584			8
D	0.141	D_1	0.650	0.0917	4.174	0.065 < 0.1	3
		D_2	0.089	0.0125			16
		D_3	0.199	0.0281			9
		D_4	0.064	0.0090			18

impact on the construction progress of power supply and distribution project and is the absolute factor that should be paid the most attention to. C_2 10 kv high voltage switchboard installation takes the second place, D_1 electrical acceptance and single commissioning takes the third place, and C_4 low voltage switchboard and DC panel installation take the fourth place, but these three have more overlapping weights and have a similar impact on the progress. They are all factors that should be paid attention to. The emphasis on electrical acceptance, unit commissioning and installation of low-voltage PDC and DC panel should not be lower than that of installation of 10 kv high-voltage PDC. The weight of B_5 power station equipment foundation construction is the fifth, and the weight of C_5 high-voltage protection and metering system installation is the sixth. There are many overlapping parts between the two, which should have the same impact on the schedule. Therefore, in the risk management of the entire construction schedule of the power supply and distribution project, the most important factors should be the control of materials and equipment procurement, production and arrival, installation of 10 kv high-voltage distribution cabinet, electrical acceptance and single commissioning, installation of low-voltage distribution cabinet and DC panel, equipment foundation construction of power station and installation of high-voltage protection metering system. There are many overlapping parts of weight between some factors, so it is not simple to sort a single process, which should be dealt with comprehensively.

In short, according to the final calculation results of the MCS-AHP model and the AHP model, the following conclusions can be drawn:

(1) The results calculated using the traditional AHP are consistent with those calculated by MCS-AHP, so the effectiveness of the improved AHP can be verified.
(2) The difference between the two methods is that the result calculated by traditional AHP is a specific value, while the result calculated by MCS-AHP is an interval. It can be concluded that risk factors are not simply ranked to judge the degree of impact on the schedule risk of power supply and distribution projects, and there may be much overlap between some factors. Therefore, the influence relationship between the two factors on the schedule should be considered comprehensively. If the traditional AHP is only used to single rank the schedule risk of power supply and distribution projects, It may ignore the degree of influence of some factors on the construction schedule. Therefore, the improved MCS-AHP is adopted to study the construction schedule risk of power supply and distribution engineering, which can effectively reduce the subjectivity and make the calculated weights and the relationship between them more scientific.

4 Conclusion

4.1 Conclusion

The following conclusions were drawn from a study of construction schedule risk factors for power supply and distribution projects.

(1) A complete evaluation index system for schedule risk management of power supply and distribution projects is constructed by determining 4 criterion layers and 19-factor layers to manage the schedule risk of this project in multiple dimensions and levels. With the fuzzy hierarchical analysis method as the general framework, the average distribution interval is used instead of specific values when constructing the two-two comparison matrix to reduce the subjective probability as well as to reduce the risk of people's fuzzy thinking during investigation and evaluation, which effectively solves the problem of greater subjectivity in the traditional fuzzy hierarchical analysis method, thus avoiding the influence on the results of the construction schedule risk evaluation index system of power supply and distribution projects and making the schedule The risk management is more scientific and reasonable.
(2) Taking a power-supporting Phase II project (construction) in Guangdong Province as an example, the results show that we should focus on controlling the procurement of materials and equipment, production and arrival of goods, installation of 10 kv high voltage distribution cabinet, electrical acceptance and single commissioning, installation of low voltage distribution cabinet and DC screen, equipment foundation construction of power station and installation of high voltage protection metering system. The results of schedule risk analysis are consistent with reality. The MCS-AHP model constructed has great significance for the risk analysis of power engineering and provides a reference for the risk analysis of other projects.

4.2 Limitations and prospects

Although this paper has made certain research results on the research of construction schedule risk management of power supply and distribution engineering, due to its own theoretical knowledge is not perfect. Therefore, there are limitations and shortcomings in the research results, which are manifested in the following aspects.

(1) Since the actual construction process of power supply and distribution engineering projects is more complex and changeable than the theoretical construction process, and there are certain other risk factors, the construction schedule evaluation index system of power supply and distribution engineering constructed is relatively rough and not comprehensive enough. In the future, we can consider adding some other dynamic risk factors to make the evaluation index system more perfect.
(2) This paper mainly adopts the Monte Carlo simulation method to improve the traditional AHP, using intervals instead of specific values to reduce the subjectivity of the evaluation, but does not consider that certain risk factors may affect each other in connection with each other, so in the future, we should adopt some quantitative methods to study the coupling relationship between risk factors to optimize the evaluation model, and can also adopt some newer research methods for power engineering projects.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding authors.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Conflict of interest

HX was employed by the company of State Grid Jiangxi Electric Power Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2022.1104007/full#supplementary-material

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Research on the pricing of PPP project ABS products based on the right of income of heating

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Introduction: The Public-Private Partnership (PPP) model has the advantages of enhancing the efficiency of social infrastructure construction and reducing the risk of government liabilities, and has been widely used and developed in China. In the current securitization of PPP project assets, the question of how to price them is key to whether the Asset-backed Securities (ABS) products can be issued successfully.

Methods: This study analyzes the pricing process and influencing factors of PPP project ABS in the context of PPP projects in China by collating the relevant literature on PPP project ABS products and collating the advantages and disadvantages of the static discounted cash flow (SCF), static spread (SS), and option-adjusted spread (OAS) methods. The study finds that the SCF and SS methods, primarily used in pricing PPP project ABS products, lack consideration of interest rate changes, early repayment rates, and multiple interest rate path options, leading to biased results. This study introduces the Monte Carlo simulation pricing method (MCSM) and conducts an empirical analysis based on the case of the Heating income right ABS of Huaxia Happiness PPP Project ABS.

Results: It is concluded that the Monte Carlo simulation method can more flexibly and accurately price PPP project ABS products with revenue rights as the underlying assets.

Discussion: This study has reference significance for the pricing of ABS products in future PPP projects and the construction of PPP projects in integrated energy service industrial parks, and can promote the development of new integrated energy service industrial parks, thereby helping to improve the energy consumption structure of enterprises in industrial parks, improve energy use efficiency, ensure the safety of energy use by enterprises, and further enhance the application of new energy by enterprises, thereby reducing their Greenhouse gas emissions.

KEYWORDS

PPP project, ABS pricing, Huaxia Happiness PPP project, option-adjusted spread, Monte Carlo simulation method

1 Introduction

The PPP model has been in development for more than a hundred years, and Lance Liebman. (1984) was the first to discuss how the role of government, as well as business, should be played in the PPP model and how governments and businesses should allocate their obligations and responsibilities, and made recommendations on these in his study of social capital in PPP projects. Doh and Ramamurti. (2003) found that governments often ignore the risk tolerance of social enterprises when cooperating, which may lead to social enterprises taking on more risks than they can bear. This can lead social enterprises to take on more risks than they can bear, including systemic risks such as interest rate and exchange rate risks, which is why many early PPP projects failed. Hoppe et al. (2013) shows that government-led PPP projects and inter-enterprise cooperation have better control over costs and are thus more efficient, making PPP projects more attractive than other forms of financing, attracting investment attention from society. Albalate et al. (2015) points out in her study that if the benefits in a PPP project are higher than the costs, the increase in profits will bring a great increase in motivation, and the relative cost of labor is also an essential factor. For the government, introducing social capital can significantly reduce the costs incurred, increase the efficiency of infrastructure development, and improve the delivery of public service functions, thereby requiring more ways to increase motivation. Spackman. (2002) argues that collaboration between the two parties can lead to higher benefits for both parties and that each can bring expertise to better support the project. The expertise of each party supported this project.

Asset-backed Securities (ABS) products first appeared in the United States in 1968 when the US Federal National Mortgage Association introduced the world's first ABS product. Since then, ABS has become widespread, and Gardener and Revell. (1988) defines it broadly as a means or process by which the borrower and the lender of funds can be matched in whole or in part in the capital markets. Frost. (1997) raises the issue of risk segregation and argues that ABS enables securitized and other risky assets to be segregated, thus avoiding some losses due to insolvency. This is done by utilizing a true sale of the underlying assets to a special institution in the ABS process, isolating the original beneficiary's other assets. Thus, even if the original underlying asset holder goes bankrupt, the underlying assets that have been sold are not covered by bankruptcy liquidation, so the investors in the ABS are not implicated by the bankruptcy of the original asset owner, thus avoiding the risk.

In their research on pricing methods, Dunn and McConnell. (1981) were the first to propose an option-adjusted spread method for mortgage securities, using historical data on the underlying assets to forecast cash flows and determine the likelihood of early repayment based on changes in interest rates. The option-adjusted spread method was also studied by Kalotay et al. (2004), which collates and modifies the option-adjusted spread method to extend its pricing scope and make the option-adjusted spread method more in line with the reality of capital markets. To address the issue of the drawdown rate, which has been mentioned in previous studies, McConnell and Singh. (1993) proposed an early paydown model based on reasonable assumptions, which indicates that issuers generally tend to liquidate early when the present index of the outstanding principal on the future interest rate path is greater than the refinancing cost and outstanding principal.

McConnell and Singh. (1994) used a Monte Carlo simulation pricing method to study the pricing of PPP ABS. The Schwartzblum model calculated the movement of claims and fixed interest rate. This study shows that even small changes in the early repayment rate can significantly impact on prices.

In the study of pricing influences, Ambrose and LaCour-Little. (2001) found an insignificant relationship between early repayment rates and loan maturity, but if there is a rise in discounting, the probability of early repayment increases. Dunsky and Ho. (2007) concluded that the basic method of determining price through ABS is to analyze the expected future cash flows of the project. The analysis of the evolution of the interest rate as a discount rate leads to the conclusion that the basic method of determining price through ABS is to analyze the expected cash flows to derive the net present value of the project. According to Fermanian. (2013), that the model is built by two lines, upper and lower, as per the characteristics of the price classification of securitized products.

At this stage, the theoretical basis of PPP project ABS and related industry practices (including market, issuance, trading, and regulatory aspects) are being explored in China, especially concerning pricing mechanisms and methods; however, pricing is a key step in the overall PPP projects ABS process. Pricing is the basis for the successful distribution and circulation of the product, allocation of profits between the issuer and investors, and link between assets and the market. Therefore, studying the pricing of PPP securitization products is of great practical importance.

As one of the first PPP projects ABS product in China and the first model project approved by the Ministry of Finance of China, the Huaxia Happiness Gu'an Industrial Park PPP heating tariff rights ABS products will be a good reference for future ABS projects of this kind. It will be a good reference and guide for the pricing of such PPP projects in the future, as well as for the pricing of PPP projects ABS product in other sectors.

2 ABS and pricing theory underlying PPP projects

2.1 PPP projects ABS process

The operational process of PPP project ABS is very complex. It needs to be coordinated with each other according to a strict process, which can be divided into the links in Figure 1: conducting due diligence, asset pool design, SPV construction, transfer of underlying assets, credit enhancement method selection, credit rating, asset-backed securities issuance, and follow-up management services and securities repayment.

2.2 Traditional pricing methods for PPP project ABS products

2.2.1 Static discounted cash flow method

Ordinary static cash flow is a method of discounting future cash flows generated by an asset at a fixed discount rate using a simple model without considering the effects of changes in interest rates and fluctuations in the early repayment rate.In asset securitization pricing studies, for the issue of cash flows, Dunsky and Ho. (2007) proposed to analyze the expected future cash flows that can be generated by the project and determine the discount rate at which the cash flows are discounted in order to obtain the net present value of the underlying project.

The static discounted cash flow method (SCF) method has the simplest expression, and the basic formula for this model is

$$P = \sum_{i=1}^{n} \frac{CF_i}{(1+r)^i}$$

In this model, the price of the securitized product is denoted by P, the number of periods of the product is denoted by n, CF is the expected cash flow in period i, and r is the discount rate.

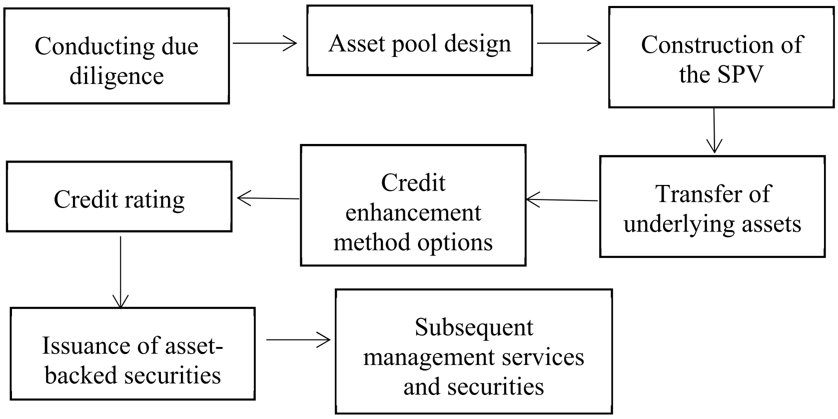

FIGURE 1
ABS process for PPP projects.

The biggest advantage of the static discounted cash flow method is that it is simple to use and easy to calculate to obtain the desired result quickly. However, this method also has the disadvantage that it does not consider any changes in interest rates in the best-case scenario, so the results obtained by this method may deviate significantly from the actual situation. In the actual pricing of PPP projects ABS product, changes in interest rates and early repayment rates are often considered. Thus, the pricing of PPP asset products obtained from this model can only be used as a basic reference and cannot be applied to the actual pricing of PPP projects ABS product.

2.2.2 Static spread method

The biggest optimization between the static spread (SS) method and the original static discounted cash flow method is that it considers the yield to maturity of treasury bonds. This method sets the discount rate as the yield of each maturity on the yield-to-maturity curve of Treasury bonds, plus a set fixed spread. The price of the bond is determined using this method as a measure of the entire yield-to-maturity curve.

The most concise formula for the Static Spread Method (SS) is:

$$P = \sum_{i=1}^{n} \frac{CF_i}{(1 + r_i + s)^i}$$

In this model, the product price is denoted by P, CF is the expected cash flow in period i, r is the yield of treasury bonds with different maturities, and S is the static spread.

The static and static cash flow methods do not differ significantly when cash flows are concentrated but can differ significantly when cash flows are more dispersed.

The static spread method considers the changes in yields to maturity of different treasury bonds and adds changes in interest rates to the application of the model, yielding more accurate results than the cash flow model. However, the spread model does not consider fluctuations in early repayment rates caused by different interest rate paths, which are not well addressed by the spread model because of the uncertainty of future cash flows in PPP projects ABS product and the refinancing interest rates may change, which will affect the pricing of the overall PPP projects ABS product. However, the static spread method does not consider these factors in the model and therefore does not accurately measure the price of the PPP projects ABS product.

2.2.3 Option-adjusted spread method

The option-adjusted spread (OAS) method is better than the static spread method, which considers early repayment of future cash flows from the underlying asset. This method combines the static cash flow method and static spread method and integrates interest rate risk by considering as many interest rate paths as possible, with the main paths utilized being the binomial tree pricing model interest rate path, Monte Carlo model interest rate path, and finite difference interest rate path.

Dunn and McConnell. (1981) predicted the likelihood of early repayment based on the movement of interest rates and proposed an option-adjusted spread method applied to mortgage-backed securities. Subsequently, they proposed an early repayment model based on the assumption of rationality in 2001. Researchers such as Kalotay et al. (2004), adapted and modified the method to broaden its pricing scope.

The option attribute in the OAS method applied in the pricing of PPP projects ABS product, in the concept of an option, for the purchaser of a call option, the purchaser has the right to buy a certain underlying amount at a price specified by the seller during the agreed period. For the buyer of a call option, the gain is derived from the increase in the price of the option due to an increase in the price of the underlying option and the gain from the exercise of the option. Still, if there is a fall in the price, the buyer's loss will only be the cost of buying the call option. By analogy with a debtor who raises money in capital markets, the risk of early repayment is treated as a call option.

The basic form of the option-adjusted spread (OAS) method model is

$$P = \frac{1}{T}\sum\nolimits_{T=1}^{T}\sum\nolimits_{S=1}^{S}\frac{CF_{S,T}}{(1 + R_{ST} + OAS)}$$

In this model, P refers to the price of the securitized product, R is the interest rate for period S under the Tth path, T is the total number

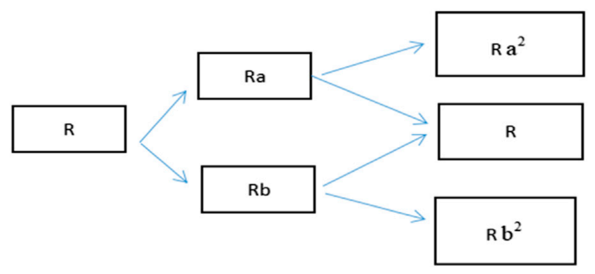

FIGURE 2
Interest rate binomial tree structure.

of bars in the simulated interest rate, and CF is the cash flow for period i under the *S*th path.

The key to this method is how to use the binomial tree model to determine the path of the interest rate, set to build a binomial tree where the value of the change is ∂, and the change at each time is the same as t. The interest rate is initially set to R, so if the interest rate rises, it is recorded as Ra; if the interest rate falls, it is recorded as Rb. If the interest rate decreases, then it is Rb, again, at the next moment, there are three possible scenarios Ra^2, R, Rb^2, and by analogy, there should be n+1 possible outcomes for the interest rate in the nth cycle of the subsequent binomial tree loop. Figure 2 shows the correspondence between interest rates of the binomial tree paths.

In its application, the OAS method can simulate early repayment and default behavior under different interest rate change paths and can obtain more reasonable forecasts of future cash flows in the pricing of PPP securitization products. The OAS model considers changes in early repayment rates and interest rates and is closer to reality than the static cash flow and static spread methods. The scenarios considered using this model are more complex, and thus, the requirements for the overall model are high, requiring the design of an option-adjusted spread model suitable for the operation of the product in the pricing of the product.

2.3 Monte Carlo simulation method

2.3.1 Reasons for introducing the Monte Carlo simulation method

The Monte Carlo model is currently widely used in finance as a representation of high value, and high flexibility in the field of finance, and the method was first applied to the pricing of financial securitization products by Paulier in 1977.McConnel and Singh. (1994) used a Monte Carlo simulation pricing method for fixed-rate and variable-rate mortgage bonds. In an exploration of PPP project financing, Yuan et al. (2011) constructed a Monte Carlo-based model for optimising the financing structure and analysed the main influencing factors and their mechanism of action.

Compared with other models, it is clear that the Monte Carlo model is more comprehensive in its consideration of factors, especially the choice of interest rates under multiple paths, and is more in line with changes in financial markets, making it highly applicable. The Monte Carlo model ensures independence of the predicted standard errors, and the results are more realistic.

In its current application, the Monte Carlo model relies heavily on computers to simulate several possible paths to obtain the value of the asset under the current path, and the risk-free rate can be applied to discount the current value of the entire asset.

2.3.2 The basic form of a Monte Carlo model

In the pricing of ABS products, it is the value at the moment T = 0 that is required, that is, the unconditional expectation of the discounted payment. The probability distributions of the parameter estimates calculated by Monte Carlo model simulations are complex; therefore, the workload of calculating the simulation parameter estimates using probability distribution methods is high, and in practice, the first-order moments of the discounted payments are generally used.

Paulier systematically described the methodology regarding the use of Monte Carlo models in the pricing of financial securitization products. The basic formula for the model is:

$$dP_t = rP_t dt + \sigma P_t dB(\mathrm{t})$$

Where P_t denotes the price of the underlying asset at time t, t denotes the time to maturity, r denotes the market risk-free rate, σ is the volatility of the underlying asset's return, and B(t) is Brownian motion under a risk-neutral measure.

2.3.3 Steps of the Monte Carlo simulation method

In the pricing of ABS products, it can be assumed that the ABS product's underlying asset is C, the risk-free interest rate is assumed to be a constant N, and this product pays out at the end of the period. We analyze the application of the Monte Carlo model to the pricing of PPP ABS products and calculate the present value of the product by following these steps.

1. Simulation of the stochastic process obeyed by all underlying assets of the PPP ABS product.
2. Calculate the price path of underlying asset C using a simple random sampling method.
3. The product value is calculated.
4. Steps 2 and 3 of the sampling cycle are repeated to obtain many samples.
5. Discount PPP ABS products through the risk-free rate.
6. The discounted sample mean is calculated, and following the law of large numbers, this sample mean is used as the point estimate of the limits of the securitized asset.
7. Confidence intervals at a given level of significance are obtained according to the central limit law to obtain interval estimates of the securitized asset's current index.

However, the Monte Carlo model also has great limitations, the main one of which is that the experimental difficulty is relatively large because Monte Carlo needs to perform a large number of simulation experiments; if it encounters complex securitization products, it will certainly increase the experimental difficulty substantially, and the processing of

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TABLE 1 Comparison of different pricing methods.

Pricing models	Static discounted cash flows	Static spread method	Option-adjusted spread method	Monte Carlo simulation method
Advantages	Simple calculations and easy to produce results	Adding changes in interest rates to the application of the model	Considers early repayment rates and changes in interest rates and is closer to reality than the static cash flow and static spread methods	The factors are more comprehensive, especially the choice of interest rates under multiple paths, which is more in line with the changes in financial markets and has strong applicability. The model is flexible in its construction and can be adjusted in time for large deviations, making it highly flexible
Disadvantages	This method does not consider all interest rate movements, so the results obtained by this method may deviate significantly from the actual situation	The spread model, however, does not consider the fluctuations in early repayment rates caused by different interest rate paths	The scenarios considered using this model are more complex, and thus the overall model requirements are high, requiring the design of an option-adjusted spread model suitable for the product run in the pricing of the product	The experiment is challenging, and the processing of the data is troublesome with the acquisition of more data
Price accuracy	Large errors	Small errors	Precise	Precise

TABLE 2 Basic project information.

Project name	Asset-backed special scheme for the right of income from Heat supply charges of the new Urbanization PPP project of Huaxia happiness Gu'an industrial park
Project purpose	Following the terms of the special scheme document, subscription funds are accepted from investors in asset-backed securities for the purchase of the underlying assets, and asset proceeds are paid to the purchasers of the securities assets with the proceeds generated from such assets
Asset-based securities	Sub-asset securities are classified as superior and subordinated and are classified into six classes: senior-1, senior-2, senior-3, senior-4, senior-5, and senior-6
Targeted fundraising scale for dedicated programs	The size of the senior asset-backed securities raised was RMB672 million, representing 95% of the total scheme, and the total target size of the entire special scheme was RMB706 million
Original interest holders	Gu'an Jiutongjiye Public Utilities Co.
Program Manager	China Merchants Securities Asset Management Limited
Lead Agency Promoter	China Merchants Securities Co.
Co-Agent Promoters	CITIC Capital Corporation Limited, Societe Generale Securities Company Limited, CITIC Securities Company Limited
Financial Advisors	Agricultural Bank of China Limited
Custodian	China Postal Savings Bank
Rating Agencies	China Chengxin Securities Valuation Limited
Acting Legal Adviser	Beijing Dacheng Law Firm
Accountants	Zhongxing Cai Guang Hua Accounting Firm
Par value participation price of asset securities	Rmb100
Asset-backed securities promotion targets	"Qualified investors in the People's Republic of China with appropriate financial investment and risk tolerance ability and full civil capacity" are the targets for the promotion of the senior securities of the Project
Listed Transfer Sites	Shanghai Stock Exchange

Source: Huaxia Happiness PPP, asset securities special program report.

obtaining more data is also more troublesome. Therefore, in response to this problem, scholars at home and abroad have made some improvements, most of which lie in the basic variance in the experiment, which commonly includes importance sampling, pairwise variables, and control variables.

2.4 Analysis of pricing model strengths and weaknesses

Regarding the four models for pricing PPP project ABS product, Table 1 provides a unified comparison of the advantages and disadvantages of these models.

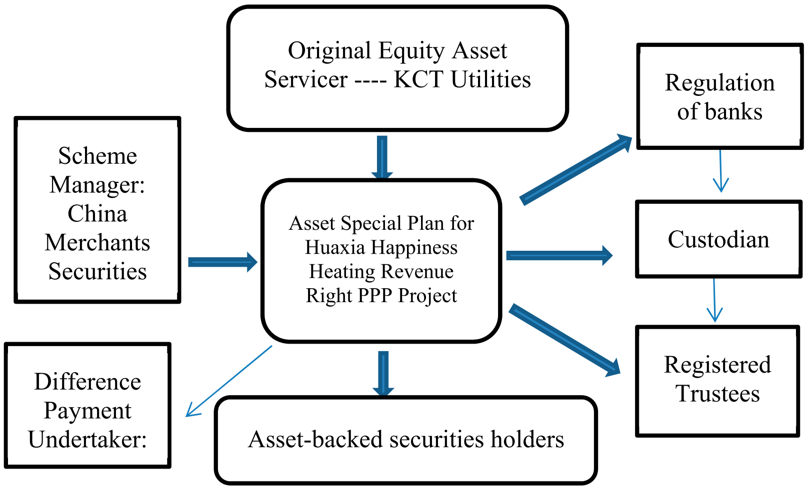

FIGURE 3
Diagram of the transaction structure.

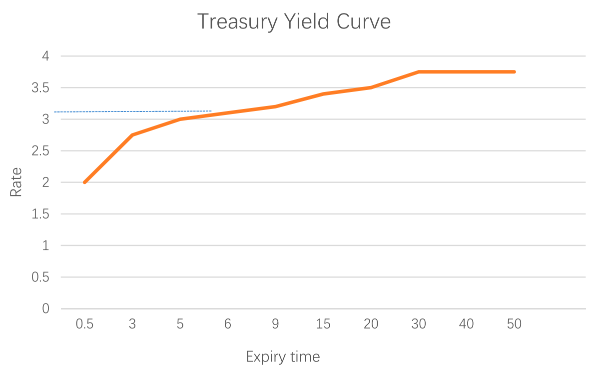

FIGURE 4
Treasury bond interest rate yields Source: China Bond Network.

In terms of the strengths and weaknesses of the above table and the accuracy of the results, it can be seen that the static cash flow method and the static spread method do not accurately determine the price of the PPP project ABS product, as these two models are not complete in their consideration of factors, particularly interest rate movements, and early repayment rates. For the option-adjusted spread method and Monte Carlo simulation method, both methods can accurately obtain the actual price of the product, but the two methods use different simulation paths and may yield different results.

3 Huaxia Happiness Heating Revenue Right PPP ABS project

3.1 Project overview

3.1.1 Basic information of the PPP ABS project of Huaxia Happiness Heating Revenue Right

As the first PPP ABS project in China, this project has good reference value for developing PPP projects in China and the ABS of PPP projects. Table 2 shows the basic information about this particular scheme.

3.1.2 Issuance of Huaxia's special schemes

Figure 3 shows the transaction structure of the special scheme.In the whole plan issue, the whole plan is proposed by China Merchants Capital Management as the initiator of the whole plan, the project is set up, Huaxia Happiness Party as the guarantor is providing external credit enhancement, and Jutong Public Utilities as the original equity owner and the service provider of the assets, which entrusts China Postal Savings Bank as the supervising bank to manage the funds for it, and Postal Savings Bank as the custodian, and China Merchants Securities Company.

As the first PPP ABS project issued in China, the overall transaction structure and issuance method of the asset securities of the Huaxia Happiness Gu'an PPP project, from the initial construction to the start of the issuance and finally identified as the first exemplary PPP ABS project in China, has high reference value for subsequent PPP ABS projects.

3.1.3 Asset-backed securities maturity and expected annual yield

The total target size of the Huaxia Happiness PPP ABS Special Programme is RMB 706 million. Table 3 provides basic information on this securities issue.The target size of senior asset-backed securities is RMB 672 million, representing 95% of the total size. The target size of Tier 1 asset-backed securities was RMB58 million, representing 8% of the total size; the target size of Tier 2 asset-backed securities was RMB 80 million, representing 11% of the total size; the target size of Tier 3 asset-backed securities was RMB 102 million, representing 14% of the total size; the target size of Tier 3 asset-backed securities was RMB 128 million, representing 18% of the total size; the Tier 5 asset-backed securities project size was RMB 143 million, accounting for 20% of the total size; and the target size of the Level 6 asset-backed securities project was RMB 159 million, accounting for 23% of the total size. The size of subordinated asset-backed securities raised was RMB 36 million, accounting for 5% of the total size.

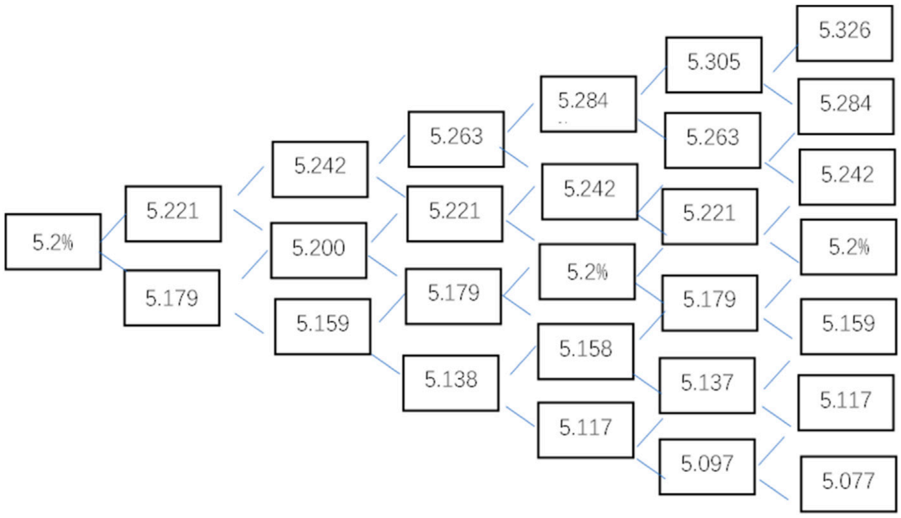

FIGURE 5
Binomial tree of interest rates Unit %.

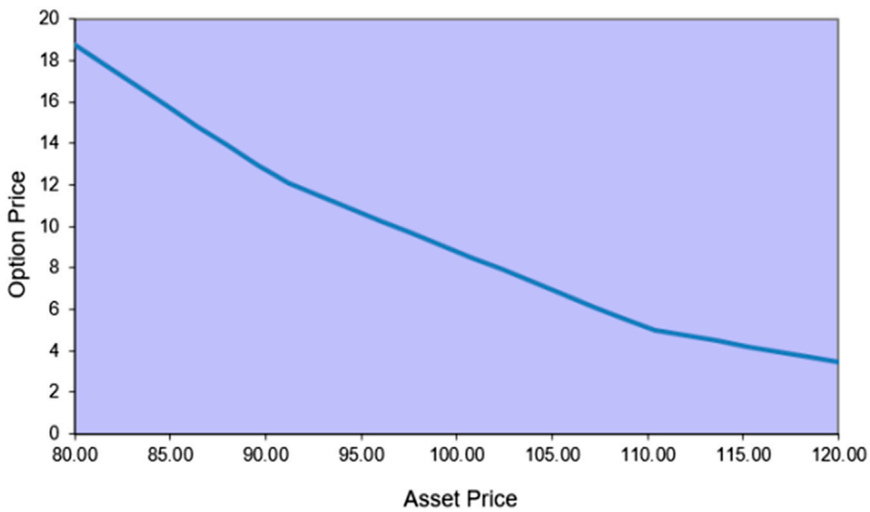

FIGURE 6
Asset price and option price curves. From: DerivaGem.

3.2 Analysis of underlying asset profile and cash flow projections

3.2.1 Information on the underlying assets

Throughout the special plan, the underlying assets are the rights of the original equity holders to collect heating charges from heating customers for a specific period as a result of the provision of heating services in the Gouan Industrial Park, which are allocated to the special plan by the original equity holders on the delivery date and are still recorded in the underlying asset documents.

In the Huaxia PPP project, according to the standard terms and conditions entered into, the underlying assets are the heat supply service provided by the original equity holders to the industrial park on the delivery date following the relevant documents and the heat supply fee income charged to the special plan, set for the period from 2017 to March 2023.

The PPP project heating tariff rights refer to the heating tariff revenue enjoyed by Jutong utilities for the provision of heating services under the PPP project.

After the project is put into operation, a fee agreement is signed with the residents in September-November each year, with cash or credit cards as the method of payment, and with the companies in September-December to collect the heating fee by transfer. According to the agreements signed and the negotiations with the authorities, the price per square meter of heat was 22 RMB for residents and 38 RMB per square meter for non-residents, looking for statistics Table 4 shows the from 2013 to 2016 before the project was signed.

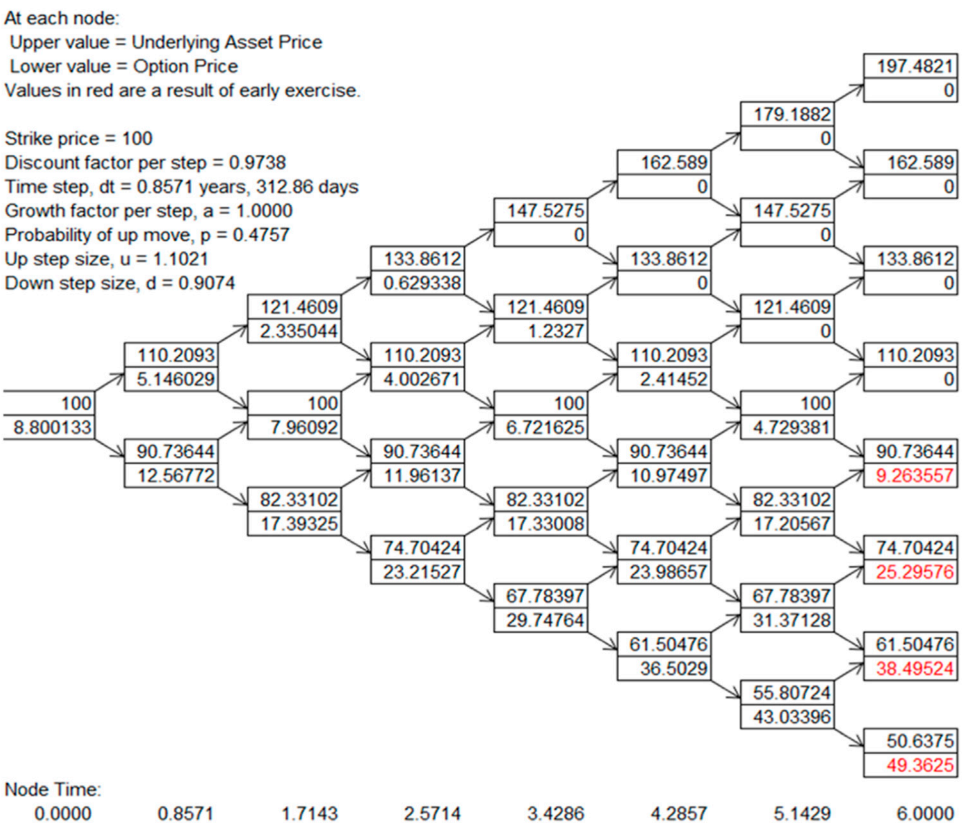

FIGURE 7
Interest rate binomial tree solving option prices. Data source: DerivaGem.

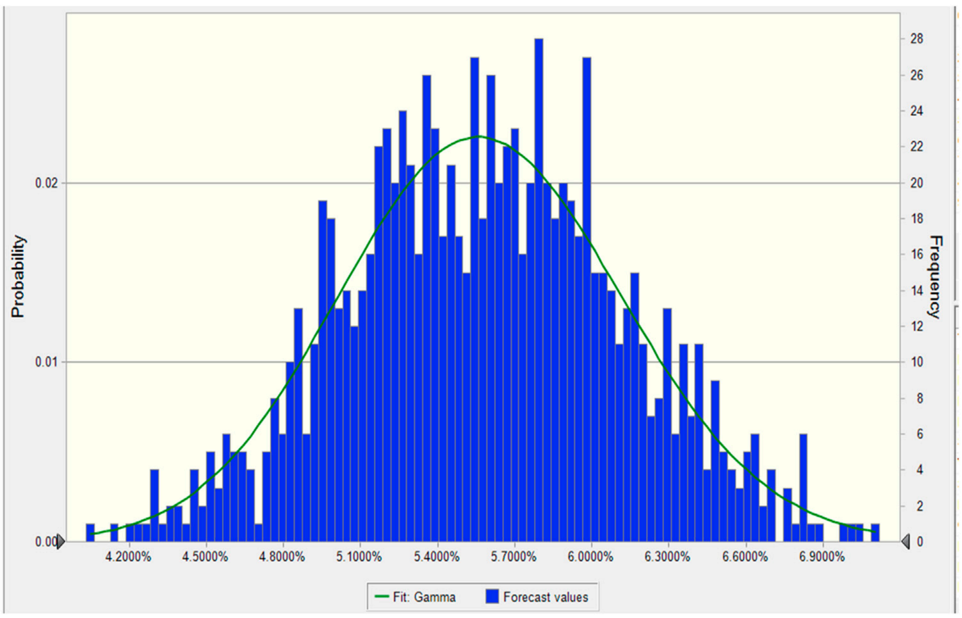

FIGURE 8
Yield Monte Carlo simulation results.

TABLE 3 Asset-backed securities issuance information.

Type of securities	Expected duration (year)	Payment date/ expected maturity date	Debt repayment method	Ratings	Expected rate of return	Size (RMB million)
Priority-1	1	9 March 2018	Annual interest payments and principal repayment on maturity	AAA	3.9%	5.800
Priority-2	2	9 March 2019	Annual interest payments and principal repayment on maturity	AAA	5.0%	8.000
Priority-3	3	9 March 2020	Annual interest payments and principal repayment on maturity	AAA	5.2%	10.200
Priority-4	4	9 March 2021	Annual interest payments and principal repayment on maturity	AAA	5.2%	12.800
Priority - 5	5	9 March 2022	Annual interest payments and principal repayment on maturity	AAA	5.2%	14.300
Priority - 6	6	9 March 2023	Annual interest payments and principal repayment on maturity	AAA	5.2%	15.900
Subordinated asset-backed securities	6	9 March 2023	---	AAA	No expected rate of return	3.600

TABLE 4 Overview of heating in JWT utilities 2013–2016.

Indicators	User	2013	2014	2015	2016
Total area of the tender section	Residents	9.478E+02	1.577E+03	2.389E+03	2.876E+03
	Growth rate	-	66%	51%	20%
	Companies	2.747E+02	3.982E+02	6.556E+02	7.864E+02
	Growth rate	-	45%	65%	20%
Heating rate	Residents	63%	75%	69%	73%
	Companies	100%	100%	100%	100%

Units: Thousand sqm.

3.2.2 Cash flow projections for the underlying assets

Based on statistical information, as well as the project's publicly available accounting reports, the forecast assumptions are divided into two segments for residents and businesses and are assumed separately when making the forecast.

The main factors underlying projections regarding future cash flows for residents are the total area of residential heating bids, heating rates, and tariffs. The main assumptions regarding cash flow projections are as follows.

1. No legal risks are associated with the right to receive proceeds and the entire valuation base date.
2. The plan for the entire campus will be to add 14,359,667 square meters of heating bids in 2017, 5,677,775 square meters in 2018, and 1,363,130 square meters in 2019, and is expected to remain the same overall for 2020-2022.
3. The heating rate will be used as a baseline for the entirety of the previous 2013-2016 period and is expected to increase by 3% per year in 2017–2019 at the time of the assumptions and remain consistent with assumption two in 2020–2022, assuming no overall change.
4. The payback rate will be set to the ideal state of 100% for the entire set period of 2017–2022.
5. Lastly, it does not consider national policy changes, industrial policies, and other unavoidable factors.

The final overall resident projection assumption assumes that 80% of the completed homes are occupied and under contract in the current year, with the remaining 20% expected to contract the next year. The total forecast resulted in a combined cash flow of RMB551,443,500 from 2017 to 2022.

For enterprise heating, the main elements considered are the total area of the tender section and the tariff, where the main factors that will have an impact on the tariff are local GDP, local fiscal revenue, the number of enterprises in the park, and the amount of fixed asset investment completed in the park. The following assumptions are made for enterprise cash flow.

1. No legal risks are associated with the right to receive proceeds and the entire valuation base date.
2. The heating rates were assumed to be 100% and remained the same from 2017 to 2022.

TABLE 5 Resident and companies income.

Source of income	Indicators	2017	2018	2019	2020	2021	2022	Total
Residents	Total area of the tender section(sqm)	4.024E+06	4.766E+06	5.970E+06	6.242E+06	6.242E+06	6.242E+06	3.349E+07
	Heating rate	70%	73%	76%	76%	76%	76%	
	Heating area (sqm)	2.817E+06	3.479E+06	4.537E+06	4.744E+06	4.744E+06	4.744E+06	2.507E+07
	Charges (yuan/sqm/year)	22	22	22	22	22	22	
	Payback ratio	100%	100%	100%	100%	100%	100%	
	Projected return (RMBmillion)	6.197E+01	7.654E+01	9.981E+01	1.044E+02	1.044E+02	1.044E+02	5.514E+02
Companies	Total area of the tender section (sqm)	9.830E+05	1.209E+06	1.463E+06	1.741E+06	2.037E+06	2.342E+06	3.349E+07
	Heating rate	100%	100%	100%	100%	100%	100%	
	Heating area (sqm)	9.830E+05	1.209E+06	1.463E+06	1.741E+06	2.037E+06	2.342E+06	9.795E+06
	Charges (yuan/sqm/year)	38	38	38	38	38	38	
	Payback ratio	100%	100%	100%	100%	100%	100%	
	Projected return (RMB)	3.736E+07	4.595E+07	5.539E+07	6.654E+07	7.778E+07	8.901E+07	3.722E+08
Total revenue	(RMB)	9.933E+07	1.225E+08	1.554E+08	1.709E+08	1.822E+08	1.934E+08	9.237E+08

Data source: Huaxia Happiness PPP, project asset-backed securities unique plan book.

TABLE 6 Cash flows under normal conditions.

Year	Projected cash flow (RMB)	Total principal and interest (RMB)	Coverage multiplier
2017	9.933E+07	9.063E+07	1.100
2018	1.225E+08	1.099E+08	1.110
2019	1.554E+08	1.281E+08	1.210
2020	1.709E+08	1.491E+08	1.150
2021	1.822E+08	1.578E+08	1.150
2022	1.934E+08	1.668E+08	1.160

3. Its payback ratio is set at 100% to remain unchanged for future years.
4. The remittance rate is set at 100% from 2017-2022.
5. Compound growth assumption of 27% for the heating tender area.
6. Free from any other force majeure factors.

Using the above assumptions on the total surface of the impact factors of the heating section of the enterprise, the weights are assigned to 20% of the regional GDP, 15% of the amount of fixed asset investment, 35% of the fiscal revenue, and 30% of the number of enterprises in the park. The data are adjusted and collated for events that are highly likely to have an impact. Table5 shows the income forecasts for residents and companies.

It is possible to see the totals for 2017–2022 for the overall income of residents and businesses for 2017–2019, which can then be used as a reference for pricing products when pricing assets.

3.2.3 Cash flow forecasting and stress testing of underlying assets

Based on the overall project analysis, the cash flow projections for the PPP projects under normal circumstances are made into a chart from 2017-2022, as shown in Table 6 below.

Conduct a first test cash flow analysis of a simulated scenario stress situation.

In this scenario, cash flow is projected to be under pressure if there is an increase in yield, and the cash flow is projected to continue from year four to year 6, with the expected yield increasing by 10 BP based on each additional year of the measured yield according to the issue term, on which the measured yield increases by 50 BP per tranche, as shown in Table 7 below.

As seen from the Table 7 above, in this scenario, all the underlying assets generate cash flows to cover each tranche of senior asset-backed securities a multiple of one time or more to pass the stress test.

Conducting a simulated scenario stress situation in the second test cash flow analysis.

Changes in heating cash flow income may be affected by changes in the total heating tender area, heating charges, heating tariffs, and payback rates.

For the changes in the total residential heating bid area, the residential heating area for 2017-2022 will be increased according to the average of the annual increase in heating area from 2013-2016, and the bid area will not be increased after 2020.

TABLE 7 Cash flow under stress scenario 1.

Year	Projected cash flow (RMB)	Total principal and interest (RMB)	Measuring yield (%)	Coverage multiplier
2017	9.933E+07	9.488E+07	5.2	1.050
2018	1.225E+08	1.139E+08	5.3	1.080
2019	1.554E+08	1.316E+08	5.4	1.180
2020	1.709E+08	1.521E+08	5.5	1.120
2021	1.822E+08	1.601E+08	5.6	1.140
2022	1.934E+08	1.681E+08	5.7	1.150

TABLE 8 Combined heating rate scenarios 2017–2022.

		2017	2018	2019	2020	2021	2022
	Heating rate (%)	Area share (%)	Area share (%)	Area share (%)	Area share (%)	Area share (%)	Area share (%)
1 year	61	10.830	16.730	13.360			
2 years	74	25.070	11.600	18.300	13.360		
3 years	77	22.770	20.150	9.520	18.300	13.360	
4 years	79	24.070	18.300	16.530	9.520	18.300	13.360
5 years	80	8.940	19.350	15.020	16.530	9.520	18.300
6 years	80	0.00	7.19	15.880	15.020	16.530	9.520
7 years	80	8.320	0.000	5.900	15.880	15.020	16.530
8 years	80	0.000	6.690	0.000	5.900	15.880	15.020
9 years	80	0.000	0.000	5.490	0.000	5.900	15.880
10 years	80				5.490	0.000	5.900
11 years	80					5.490	0.000
12 years	80						5.490
Combined heating rate		75.410	75.310	75.850	78.490	79.400	79.850

Data source: Huaxia Happiness PPP, project asset-backed securities special plan book.

For businesses, another criterion is used to increase their heating area from 2017-2022 to in increments of 1.1 times the average annual increase in heating area from 2013-2016.

Another important influence is in the adjustment of the heating rate, through the statistics for past historical data, as the heating rate increased in the first 5 years and has remained stable since then, Table 8 shows the cash flow measurement.

The heating fee collection rate refers to historical data, both residential and non-residential heat are 100%, combined with the heating rate change scenario, it is reasonable to assume that the heating fee collection rate is 97%, assuming that the special plan continues to survive from the fourth to the sixth year, the expected yield is increased by 10BP for each additional year of the issue term, and a new cash flow forecast Table 9 is made for comparison.

The calculations based on the above table and various assumptions made in the current stress environment result in the following Table 10 of cash flows.

3.3 Empirical analysis data

In project pricing, the issuer of the project uses cash flow forecasting and stress testing to demonstrate the viability of the project's returns and prices the product using a static discounted cash flow method, to which the option-adjusted spread method and Monte Carlo simulation method will be added in this study. Based on the data from Table 3 to Table 10, the underlying cash flow forecasts used are extracted, Table 11 shows the main relevant data used in the subsequent pricing methodology.

4 Empirical analysis of ABS product pricing for Huaxia Happiness PPP projects

4.1 Option-adjusted spread method pricing

4.1.1 Construction of a binary tree interest rate path

The Huaxia Happiness Heating Revenue PPP Asset Securitisation Project, based on the cash flow forecast from 2017 to 2022, the project

TABLE 9 Scenario 2 with 2017–2022 Ninth Avenue utilities heating revenue.

Source of income	Indicators	2017	2018	2019	2020	2021	2022	Total
Residents	Total area of the tender section(sqm)	3.518E+06	4.161E+06	4.803E+06	5.446E+06	5.446E+06	5.446E+06	2.882E+07
	Heating rate	75.410%	75.310%	75.850%	78.490%	79.400%	79.850%	
	Heating area(sqm)	2.653E+06	3.134E+06	3.643E+06	4.275E+06	4.324E+06	4.349E+06	2.238E+07
	Charges(RMB)	22	22	22	22	22	22	
	Payback ratio	97%	97%	97%	97%	97%	97%	
	Projected return (RMB)	5.662E+07	6.687E+07	7.774E+07	9.122E+07	9.228E+07	9.280E+07	4.775E+08
Companies	Total area of the tender section(sqm)	9.928E+05	1.199E+06	1.406E+06	1.612E+06	1.818E+06	2.025E+06	9.052E+06
	Heating ratio	100%	100%	100%	100%	100%	100%	
	Heating area(sqm)	9.928E+05	1.199E+06	1.406E+06	1.612E+06	1.818E+06	2.025E+06	9.052E+06
	Charges(RMB)	38	38	38	38	38	38	
	Payback ratio	97%	97%	97%	97%	97%	97%	
	Projected return(RMB)	3.659E+07	4.420E+07	5.181E+07	5.941E+07	6.702E+07	7.463E+07	3.337E+08
	Total(RMB)	9.321E+07	1.111E+08	1.296E+08	1.506E+08	1.593E+08	1.674E+08	8.112E+08

TABLE 10 Cash flows under scenario two.

Year	Projected cash flow (RMB)	Total principal and interest (RMB)	Measuring yield (%)	Coverage multiplier
2017	9.257E+07	9.153E+07	4.7	1.018
2018	1.108E+08	1.108E+08	4.8	1.002
2019	1.290E+08	1.290E+08	4.9	1.005
2020	1.500E+08	1.500E+08	5.0	1.004
2021	1.586E+08	1.586E+08	5.1	1.005
2022	1.673E+08	1.673E+08	5.2	1.001

Under scenario 2, cash flow income is expected to cover the principal and interest of the dedicated plan, and the test can be passed.

TABLE 11 The main data used in the empirical evidence.

Year	2017	2018	2019	2020	2021	2022
Residents total area of the tender section (sqm)	2.817E+06	3.479E+06	4.537E+06	4.744E+06	4.744E+06	4.744E+06
Residents heating rate	70%	73%	76%	76%	76%	76%
Companie total area of the tender section (sqm)	9.830E+05	1.209E+06	1.463E+06	1.741E+06	2.037E+06	2.342E+06
Companie heating rate	100%	100%	100%	100%	100%	100%
Payback ratio	100%	100%	100%	100%	100%	100%
scenario 2 Payback ratio	97%	97%	97%	97%	97%	97%
Residents charges (yuan/sqm/year)	22	22	22	22	22	22
Companie charges (yuan/sqm/year)	38	38	38	38	38	38
Projected cash flow (RMB million)	9.933E+07	1.225E+08	1.554E+08	1.709E+08	1.822E+08	1.934E+08
Scenario 1 cash flow (RMB million)	9.933E+07	1.225E+08	1.554E+08	1.709E+08	1.822E+08	1.934E+08
Scenario 2 cash flow (RMB million)	9.26E+07	1.11E+08	1.29E+08	1.50E+08	1.59E+08	1.67E+08
Expected rate of return	3.90%	5.00%	5.20%	5.20%	5.20%	5.20%

issue is expected to arrive at the interest rate in 2018–2023. This project issue has a senior-1 interest rate of 3.9%, a senior-2 rate of 5.0%, and the senior 3–6 rate of 5.2%; from this information, we can see that senior-1 and senior-2 are the first 2 years of interest payment rate; the project does not open for an interest rate adjustment, repurchase, and sale back until the end of the third year, so with a target interest rate of 5.2% for the project, the overall term of the project is 6 years.

The 6-year Treasury yield in the bond market is the underlying factor for the risk-free rate in the model, with an average rate r of approximately 3.1%, as shown in Figure 4 below.

The volatility of interest rates was used in the research of Lin Hai and Zheng Zhenlong, which set the volatility of interest rates at 0.4%, that is, $\partial = 0.4\%$ in the model, and the upward multiplier of interest rate changes was obtained as u = 1.004008 and d = 0.996008 according to $u = e^{\sigma\sqrt{\Delta t}}$, which resulted in a binomial tree of interest rates. Set the time T for each segment to 1 year, for 6 years. This is depicted in the Figure 5.

4.1.2 Binomial tree solver product prices

From this, it can be seen that, under multiple interest rate paths, the interest rate on each path is obtained by adding the interest rate changes and plotted in Figure 6. There are 64 interest rate paths in total. The asset-backed security price volatility is set to 10.5% of the corporate bond volatility index using the DerivaGem software designed explicitly for option pricing,and plotted in Figure 6.

The value of the option at the zero moment is calculated, and the cash flows are discounted separately for each period to obtain the theoretical price on each path, call option price, and put option price. And the binomial tree of option prices is drawn based on the interest rate binomial tree as shown in Figure 7.

From the binomial tree model of option prices, the price under 64 paths can be obtained, with the second cell on the graph representing the price of the lookalike option. The posting limit for the option was found to be RMB 105.63 using arithmetic averaging. The previous pricing theory on ABS, which is equivalent to a call option for project redeemers, so the final price of the ABS product = the discounted value of the expected future cash flows - the option value of the early repayment by the originator. Therefore, the final price of the ABS product is 105.63–8.8 = 96.83.

Compared to the issue price of RMB 100 for the Huaxia Happiness PPP ABS project, the price of RMB 96.83 obtained using the option-adjusted spread method is less than that of RMB 100.

4.2 Monte Carlo simulation method

4.2.1 Parameterization of price influencing factors

In the Monte Carlo simulation method, the underlying idea is to build a probabilistic model or stochastic process first, such that its parameters are equal to the solution of the problem. The statistical characteristics of the stochastic parameters were then computed by observation and random sampling of the model or process, and an approximation of the solution was obtained. The newly developed software Oracle-Crystal Ball was used to obtain a better experiment structure.

Based on the data in the previous section on cash flow projections and factors affecting the pricing of ABS products for PPP projects, changes in the total area of heating bids, heating fees, heating tariffs, and payback ratios may affect changes in heating cash flow revenue, according to the plan for the whole park will be 1,435,967 square meters of new heating bids in 2017, 5,67,775 square meters in 2018 square meters in 2017, 5,67,775 square meters in 2018, and 136,310 square meters in 2019, and is expected to remain the same overall for 2020–2022. The heating rates will be used as a baseline for the entirety of the previous 2013-2016 period and are expected to increase by 3% per annum in 2017–2019 at the time of the assumptions and remain consistent with assumption 2 in 2020–2022, assuming no change overall. The rate of return will be set to the ideal state, that is, 100% for the entire set period of 2017–2022, and no consideration will be given to national policy changes, industry policies, and other unavoidable factors. This led to the construction and derivation of the model. The hypothetical parameter estimation was performed as shown in Table 12.

4.2.2 Mathematical model construction

Based on the actual situation of the Huaxia PPP Project heating project, a mathematical model was constructed to determine the required hypothetical parameters and the variables affecting the final expected rate of return. The specific equations are as follows:

Operating income in a year, N = monthly heating income per square meter × heating area × number of heating months per year × payback rate × heating rate.

Heating revenue per square meter in year N: business and residential weights set at 25% and 75%

$$\begin{aligned} I_N &= 22{*}0.75 + 38{*}0.25 = 26 \\ &= 26.0{*}1.1 \\ &= 26.0{*}1.1{*}1.1 \\ &= 26.0{*}1.1{*}1.1{*}1.1 \\ &= 26.0{*}1.1{*}1.1{*}1.1{*}1.1 \\ &= 26.0{*}1.1{*}1.1{*}1.1{*}1.1{*}1.1 \end{aligned} \tag{1}$$

Overall heating area per year.

S_N = (residential heating area × heating rate + corporate heating area × heating rate) × (1 + growth rate),

$$S_N = (2653148{*}75\% + 992772{*}100\%){*}(1+g_a)^{n-1}$$
$$S \leq 4551064,\ n = 1, 2, 3, ...6 \tag{2}$$

Year N cost = depreciation + heating cost, year N heating cost per square foot.

$$D_N = 21.5{*}(1+g_b)^{n-1}\ (n = 1, 2, 3 \ldots .6) \tag{3}$$

Depreciation expense in year N.

$$F_N = D_N{*}0.082 \tag{4}$$

Total profit in year N.

$$T_N = (I_N - D_N - F_N){*}S_N \tag{5}$$

Discounted net profit in year N.

$$P_N = \frac{T_N}{(1+R)^N} \tag{6}$$

As can be seen from the above equation, for annual discounting, the overall price of the project is influenced by the average annual growth rate of heating using g_a, growth rate of costs g_b, and discount rate R, which were assumed in the previous parameter settings. The analysis was performed using Crystal Ball software, based on the model listed and parameter settings.

TABLE 12 Basic information on each parameter.

Projects	Data	Remarks
Issue amount of Huaxia Happiness PPP heating rights income securitization project	706 million	As issued
Timing of project securitization proceeds	6	2017–2023
Government subsidies	0	The project is self-funded
Heating charges	Residents RMB22/sqm Companie RMB38/sqm	According to the PPP Project Securities Support Report
Price adjustment range	0	According to the project report, no price adjustment will occur
Heating usage	Projected heating area of 3,787,365 square meters by 2023	Based on data in the cash flow forecast
Average annual growth rate of heating use	Set at 0.74%	Based on data in the cash flow forecast
Heating costs	21.5 per square meter	Extrapolation regarding the percentage of revenue in the financial statements
Depreciation	8.2%	Based on financial reports
Annual growth rate of heating costs	3%	Estimates based on follow-up reports
Discount rate	2.7%	According to the relevant reports
Payback rate	100%	According to the relevant reports

Source: Huaxia PPP, project securities special programme prospectus.

4.2.3 Model pricing process and results

Simulations were conducted using Crystal Ball software, and the entire model was set to run 1,000 times, with the rate of return for the time interval of the PPP securitization project obtained in each simulation. Table 13 shows the set variables, the quantities that may change in each simulation are the average annual growth rate of heating use g_a, growth rate of costs g_b, and discount rate R. The probability functions for the three impact factors were obtained as random numbers and were introduced into the model.

The model was imported into the software, and each parameter was assigned a value corresponding to the rate of return, and the process was repeated 1,000 times. The assumptions regarding the probability variables are as follows: Monte Carlo simulations are performed using the software, and the entire process is run 1,000 times and plotted using EXCELL. The results are shown in Figure 8

The results of the Crystal Ball data are as shown in Figure 9.

From the arithmetic results report, the fundamental values were collated, found, and collated as shown in Table 14.

As can be seen from the Figure 10 above, the mean value of the return is 5.5754%, and its deviation of 0.0174% is greater than zero, indicating that this result has a heavy tail on the right-hand side and the distribution is right-skewed. The right-hand side is more concentrated, and the result is feasible based on the numerical results, as well as the cumulative probability distribution of the model.

4.3 Analysis of results

4.3.1 Analysis of empirical results

Combining the information in Table 14, with Figures 8, 9, 10 the analysis of the statistical results following the Monte Carlo simulation leads to the following conclusions.

1. Combining Table 14 with Figures 8, 9, it can be seen that the maximum value of the heating tariff yield for this PPP project is 7.89%, the minimum value is 3.33%, and the mean expectation of the yield is approximately 5.5754%, which provides a selected range of yields for the entire PPP ABS project. Compared to the actual rate of 5.2% achieved in the actual issue, the mean yield of 5.5754% obtained from this simulation was greater than the actual issue result.
2. The probability of the interval for this simulation experiment is shown in Figures 8, , where the probability of a return between 3.9% and 7.1% reaches 100%, indicating that the return values are selected within it. A further careful division in which the probability between 4.8% and 6.0% is 70% and the probability of 5.1%–5.7% in the figure is 51% over 50%, which after analysis, gives an accurate idea of the probability of each return.
3. Based on the results of the above analysis, it can be concluded that the results of this simulation can effectively match the yield of the ABS product of the Huaxia happiness PPP project. The actual issue had three yields from senior-1 to senior-6 of 3.9%, 5.0%, and 5.2%, respectively. All the yields are within the determined range, so the Monte Carlo simulation method has implications for the pricing of PPP ABS products. From the results of this experiment, an expected mean value of 5.5754% can be used as the basis for pricing the issued products, and the selected yield range is between 3.9% and 7.1%.
4. The comparison between the results of this experiment and those obtained by the option-adjusted spread method and the actual issue of the product is the same, indicating that the experimental results of the two pricing methods are isotropically verifiable.

4.3.2 Analysis of the reasons for deviations between empirical results and actual prices

The pricing results obtained through the option-adjusted spread method and the Monte Carlo simulation method are both lower than

Statistics:	Forecast values
Trials	1000
Base Case	5. 5991%
Mean	5. 5754%
Median	5. 5783%
Mode	–
Standard Deviation	0. 5510%
Variance	0. 0030%
Skewness	–0. 0031
Kurtosis	3. 23
Coeff. of Variability	0. 0988
Minimum	3. 3305%
Maxmum	7. 8945%
Range Width	4. 5640%
Mean Std. Error	0. 0174%

FIGURE 9
Monte Carlo simulation data results.

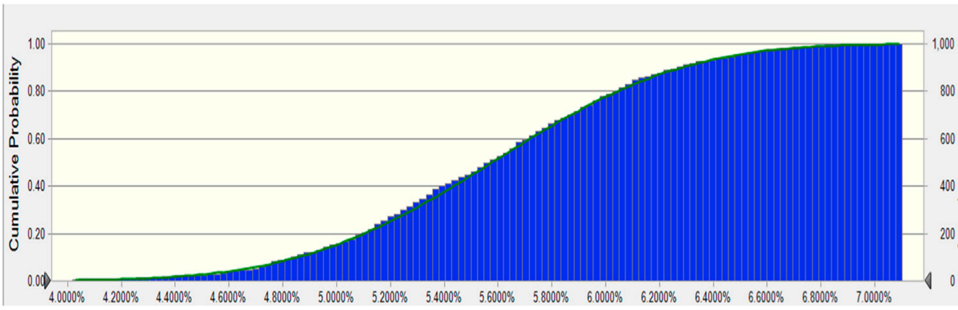

FIGURE 10
Cumulative probability diagram.

TABLE 13 Corresponding probability functions for the factors.

Factor	Corresponding probability functions
Average annual growth rate of heating use g_a	Mean 0.74% is and standard deviation of 0.2% normal distribution
Growth rate of costs g_b	Normal distribution with a mean of 3% and standard deviation of 0.5%
Discount rate R	Normal distribution with a mean of 2.7% and a standard deviation of 0.5%

the actual issue price; that is, the yield of the empirical results is higher than that of the actual issue product. For this reason, the reasons for this situation are analyzed in the context of the basic situation of the Huaxia Happiness PPP project as follows.

1. Project assets are of superior quality, which reduces the risk of default. The Huaxia Happiness PPP project was repaid by the right of return on heat supply, and Gu'an Jiutong and the government signed a stable exclusive heat supply agreement. According to the agreement, the probability of default risk is low during the offering and repayment of the ABS products of this project, and this project has a relatively stable cash flow; therefore, the actual yield of the final issue is lower.
2. Project senior/subordinated layering mechanism with tiered issuance. When the ABS products of the Huaxia Happiness PPP ABS project were

TABLE 14 Monte Carlo simulation data.

Projects	Simulated data
Number of simulations	1,000
Average value	5.575%
Median	5.578%
Maximum number	7.895%
Minimum number	3.331%
Standard deviation	0.551%
Variance	0.003%
Range width	4.564%
Deviation	0.017%

issued, they were divided into senior and subordinated products, where the senior securities products were further divided into senior-1, senior-2, senior-3, senior-4, senior-5, and senior-6, each with a 1-year maturity based on time. The model time used in the experiment was selected as the overall project time of 6 years, which reduced the product issuance repayment risk, increased the liquidity of the product, and improved the actual price valuation so that the actual issue ended up with a lower pricing rate.

3. The original equity holders' differential payment and third-party institution guarantee a mechanism. The multiple project support guarantees that the Huaxia PPP project has a better credit profile and the risk of default is further reduced, so it will finally cause the actual issue price to be higher than the experiment and the yield to be lower.

4.4 Implications of the empirical results for the pricing of ABS products

4.4.1 More flexible pricing for project products

When securitizing assets, the projection of cash flows is subject to more risk factors; therefore, it is necessary to measure the annual risk factors when forecasting cash flows. The use of Monte Carlo simulation in pricing such projects allows for flexibility in modifying risk factors according to project circumstances and changes, allowing for better adaptation to changes in project cash flows.

4.4.2 More reasonable pricing yields for project products

The use of Monte Carlo simulation to price the ABS products of the heating yield class can yield a more reasonable price range, as can be seen from the ABS products of the Huaxia Happiness PPP project, which have a senior/subordinate classification and issue several senior products with different yields, fluctuating from 3.9% to 5.2%. The use of Monte Carlo simulation can accurately predict a reasonable range of prices and obtain a yield that is suitable for the current situation of the project within a reasonable range. The overall pricing to obtain a more reasonable yield meets the requirements of the characteristics of the heating revenue rights class of projects. Therefore, the Monte Carlo simulations have a high reference value.

5 Discussion

Currently, the pricing of ABS products issued in the market mainly adopts the static discounted cash flow method and the static spread method. The underlying assets of ABS are mostly real estate, receivables and credit assets, unlike traditional ABS products, the underlying assets of PPP projects ABS products are mostly future income, and the traditional method does not accurately price them. Scholar Guo introduced the option-adjusted spread method for analysis, but it cannot be applied to all PPP projects ABS products. By introducing the Monte Carlo simulation method and conducting a comparative analysis of the empirical results, this study argues that the option-adjusted spread method and the Monte Carlo simulation method should be applied to different projects.

5.1 Items to which the option-adjusted spread method applies

The traditional option-adjusted spread method determines the price of a product by simulating the interest rate path through a binomial tree, relying on an analysis of cash flow forecasts to determine the specific price. If the cash flow forecast of the project is adjusted, it will affect the subsequent interest rate path as well as the final price determination; therefore, projects with less grading and fixed interest rates for the issuance of securities and projects with stable cash flows are more suitable for the option-adjusted spread method.

According to the PPP projects that have been implemented, the road, bridge, and tunnel projects have a stable cash flow for various reasons, such as government funding and social participation, so the use of the option-adjusted spread method for such projects can more accurately obtain the product price and yield.

5.2 Monte Carlo simulation applicable items

From the first PPP ABS projects issued in China so far, such as the Huaxia Happiness Heating Revenue Right PPP Project, New Water Source Sewage Treatment Revenue Right PPP Project, Shougang Sewage Treatment Revenue Right PPP Project, and Luyuan Sewage Treatment Revenue Right PPP Project, the ABS projects using heating and sewage treatment revenue rights as underlying assets have multi-grade senior securities with a wide choice of interest rates A typical one is the First Creation Sewage Treatment PPP Project with 18 graded rates.

A major reason for such graded projects is that there are more risk factors for cash flows to be received, so making cash flow forecasts requires setting multiple assumption parameters, which can effectively reduce the risk of default and the impact of cash flow changes.

Monte Carlo simulation modeling allows flexibility in adjusting the model to obtain a suitable price range, which is helpful for senior/subordinated types of PPP ABS products. Therefore, these types of wastewater treatment and heating revenue rights projects are well suited to pricing using Monte Carlo simulations.

This study uses a single case for empirical analysis, which can be expanded to include more cases for empirical analysis to improve the operability and accuracy of the methodology. This study can solve the financial problems in the construction of integrated energy service industrial parks, better help enterprises to solve energy use problems, promote the use of new energy in industrial parks, and help energy saving and emission reduction.

6 Conclusion

This study introduces four different methods of pricing PPP projects ABS products and analyzes their advantages and disadvantages. Based on the case of the Huaxia Happiness PPP ABS project, two methods–the option-adjusted spread method and the Monte Carlo simulation method–are selected for empirical research. A comparative analysis based on the research results concludes that the Monte Carlo simulation method is more suitable for pricing the PPP projects ABS products where the underlying asset is the right to income of heating. The Monte Carlo simulation method in such projects allows for accurate product pricing and the flexibility to adapt the model to financial market changes to obtain an appropriate price for the product.By successfully issuing ABS products based on the right of return on heat supply, it can help the construction of new energy industrial parks, provide integrated energy services for enterprises and residents, improve energy security and efficiency while achieving economic and sustainable profitability, and increase the application and development of new energy technologies to meet the needs of residents for low-carbon living and enterprises for energy conservation and emission reduction.

This study is based on the case of the Huaxia Happiness PPP ABS project to study the pricing method of the product, and the conclusions obtained have some reference value for and similar PPP projects with heating revenue rights as the underlying assets. However, the empirical results examine PPP project ABS products where the underlying assets are future income rights, and whether this applies to ABS projects where the other underlying assets are real estate, loan contracts and receivables cannot be accurately concluded from the empirical results alone. A large number of empirical tests are needed to correct the results and conclusions. Due to the limitations of this paper, a large number of cases have not been tested empirically, so further research and exploration is needed to analyse the applicability of the conclusions.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

This article was jointly completed by ZD and YZ. ZD was responsible for the paper construction and model processing, while YZ was responsible for data collection and peer review.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The impact of managerial competence on corporate carbon performance: An empirical study based on Chinese heavy polluters

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Climate risk to human survival and progress can no longer be disregarded, nor can the reduction of carbon emissions be postponed. How can economic progress and carbon emission reduction be reconciled? This research studied the relationship between managerial skill and carbon emission performance. We used the Shanghai and Shenzhen A-shares data of Chinese heavy polluters from 2014 to 2019 to assess the impact of managerial competency on business carbon emission performance using a temporal and individual fixed effects model. We discovered that management competency can greatly contribute to the enhancement of carbon emission performance inside corporations. The stepwise regression technique was then utilized to examine the mediating influence of financing limitations and financial status. This study validated the threshold effect of internal pay equity among corporate managers using a threshold regression model.

KEYWORDS

carbon performance, managerial competence, financing Constraints, financial position, pay equity

1 Introduction

The average global temperature has grown by 1.1°C since the beginning of the industrial revolution. And the temperature of the Earth continues to rise. Environmental pollution poses a grave threat to human existence and progress, according to the Intergovernmental Panel on Climate Change (IPCC), which forecasts that the Earth's temperature will rise by 1.5°C by 2052 compared to pre-industrial revolution levels (Ginglinger and Moreau, 2019). The EU was one of the early organisations to focus on the issue, and they launched a series of early programmes to promote the transformation of the industry (Streimikiene et al., 2022). As the largest emitter of carbon in the world and a responsible power, China has been actively involved in carbon reduction. At the 75th session of the United Nations General Assembly, President Xi Jinping established a target for China to reach "peak carbon" by 2030 and "carbon neutrality" by 2060. The Fifth Plenary Session of the 19th Central Committee of the Communist Party of China advocated for speeding green and low-carbon development, and the 20th National Congress of the Communist Party of China proposed once again to pursue "carbon peaking" and "carbon neutrality" aggressively. Carbon emissions are primarily caused by carbon dioxide emitted during human production and daily life, and are intimately tied to economic growth. While establishing the goals of "carbon peaking" and "carbon neutrality," we should not suffocate on them and consider economic growth. Carbon reduction requires the involvement of all aspects of society (Stankuniene et al., 2020). As the core of the economy, firms are responsible for achieving the "carbon peaking" and "carbon neutrality" goals through lowering emissions at their source. The coordination of economic development and carbon emission reduction is consistent with the national goal of sustainable development and plays a crucial role in the green transformation of businesses.

The Chinese government and official organizations have initiated a series of environmental protection measures. The Chinese government issued the Announcement on Corporate Environmental Information Disclosure in 2003 to encourage corporations to disclose environmental information voluntarily. And in 2012, the CBRC issued the Green Credit Guidelines, urging financial institutions to strengthen credit management of corporate pollution and requiring lending companies to strengthen environmental information disclosure. To promote the green development of the financial system, the Bank of China, the Ministry of Finance, and other departments issued the "Guidelines for Building a Green Financial System" in 2016. In 2016, the Industrial and Commercial Bank of China led the way in conducting environmental risk stress tests based on the thermal power and cement industries, followed by the Bank of China, China Construction Bank, and additional financial institutions. In 2021, Bank of China became an official TCFD supporting institution.

Concerning the calculation of carbon emission performance, neoclassical economic theory employs SBM-DEA to calculate total factor productivity from the perspective of supply and output, with total factor productivity becoming an increasingly significant indicator of economic development (Young, 1995). To compensate and repair the ecological damage caused by environmental pollution, however, a certain level of capital and human input is required; therefore, total factor productivity without environmental pollution consideration would overestimate the level of economic development (Xiao-yu and Zi-xuan, 2022). Green total factor productivity is a more precise indicator of production efficiency. Later, Afsharian and Ahn, 2015 subdivided pollutants into carbon dioxide emissions and utilized this information to calculate the carbon performance of companies.

However, for calculation and data collection purposes, academics typically base their calculations on regions and rarely consider microeconomic enterprises. Based on a country-level analysis of 88 economic agents from 1975 to 2013, Bai et al. (2019) determined that developed countries have significantly higher carbon emission performance than developing countries. Li and Wang (2019) conducted an empirical study utilizing regional data and discovered that the carbon emission performance of cities in central and western China grew more slowly than that of developed eastern coastal provinces and cities. In contrast, Dong et al. (2018) conducted an empirical study from 1992 to 2012 using data from China's construction industry and other industries to identify industries with relatively low carbon emission intensity. Ioanna et al. (2022) also base their projections on national and regional levels. Due to the limitations of carbon emission detection technology, measuring the carbon emissions of businesses is indeed challenging. However, abandoning the research would result in a dearth of microeconomic agent-level literature. More reasonable measurement methods can help government departments to introduce adaptive policies and the business sector to choose viable development strategies (Sebos et al., 2020). Therefore, this study will examine the carbon emission performance of individual businesses from the perspective of microeconomic agents. What factors affect the performance of carbon? The process of economic development generates carbon emissions invariably, but once the economy reaches a certain size, both society and the individual economy have the motivation and capacity to reduce carbon emissions (Zhao et al., 2020). Even more literature exists on the effect of technological innovation on carbon emission performance. Technological innovation can enhance a company's carbon performance by transforming its carbon assets (Liu et al., 2023). Technological innovation can improve the efficiency of energy use to reduce carbon emissions from the demand side in terms of energy consumption (Xu et al., 2021). On the output side, technological innovation can reduce carbon emissions and increase profits (Gu and Su, 2018). Current research on the economic repercussions of managers focuses on corporate finance, investment and financing, and the quality of corporate accounting data. Strong managers typically have a clear understanding of the company's financial situation and can avoid tax risks to some extent (Koester et al., 2017). With information asymmetry, managers may also engage in surplus management for private gain, resulting in degraded accounting information for the company (Call et al., 2014). Managers with strong competencies also integrate the company's resources effectively, mitigating underinvestment caused by information asymmetry (Chen S. et al., 2021). However, how does managerial competence affect a company's carbon performance? There is an absence of pertinent research. This study will investigate the impact of managerial capability on the carbon performance of firms, as well as the transmission mechanism in terms of the degree of external financing constraints and the internal financial position of firms.

The first part is an introduction. The second part is a literature review. The third part introduces the theory used in this paper and formulates the hypothesis, while the research design is then based on the research hypothesis. The fourth part is the empirical analysis. Part V is further research. The sixth part is the conclusion.

Due to the requirements of the DEA calculation method for balanced panel data and the lack of certain data in the China Statistical Yearbook, the sample for this study was comprised of Chinese Shanghai and Shenzhen A-share heavy polluters from 2014 to 2019. After testing, we employed individual and time dual fixed effects models to examine the association between manager competency and carbon emission performance. The transmission pathway between the degree of external financing constraints and the internal financial position of firms was then validated using a series of tests. The incentive effect of internal pay equity was finally examined using threshold regression.

The following are the marginal contributions of this study: 1) this study proposed a method to measure corporate carbon performance based on prior research; 2) this study is the first to examine the role of corporate managers' ability on carbon performance, thereby enriching the literature on carbon performance; and 3) this study took the degree of external financing constraints and internal financial status as the transmission path, thereby expanding the scholars' understanding of the carbon emission performance transmission mechanism.

2 Review of the literature

2.1 Measurements of carbon performance and influencing factors

2.1.1 Measurement of carbon emission performance

When measuring relative efficiency using multiple inputs and multiple outputs, scholars mostly use data envelopment analysis (DEA). Traditional DEA models include CCR and BBC models, which are measured from both radial and angular directions (Chen W. et al., 2021). Tone and Sahoo (2004) conducted data envelopment analysis from non-radial and non-angular directions and proposed SBM model, which takes into account the variation of the relaxation degree. As for the application to carbon emission performance, Zhou et al. (2012) defined carbon emission performance as the ratio of potential carbon emission intensity to actual carbon emission intensity. And Zhang and Choi, 2013 considered CO2 as a non-desired output and used the non-radial Malmquist index to calculate carbon emission efficiency. While the Malmquist index cannot have intersection with the production Frontier surface along the direction of the direction vector in period t+1, the problem of infeasible solution appears. Pastor and Lovell (2005) proposed Global Malmquist to solve it. In this study, the SBM-DDF model is used to calculate the carbon performance of a firm by combining the Global Malmquist index, where labor, capital and energy are considered as inputs and operating income and CO2 emissions are considered as outputs.

2.1.2 Factors influencing carbon performance

What factors affect the performance of carbon? Innovation in technology is one of them. Technological innovation can help firms increase their productivity (Wang et al., 2021; Desalegn and Tangl, 2022; Li J. et al., 2022), and when firms have more advanced technology, they can often obtain higher returns with fewer inputs of production materials, thereby increasing the output desired by their business activities (Sun et al., 2021). As for green technology innovation, green technology innovation requires more investment on the short term (Acemoglu et al., 2012). By utilizing clean energy and green innovation technologies, businesses can optimize their energy mix and reduce carbon emissions at the source (Liu et al., 2022a; Yang and Nie, 2022). Even if firms continue to use non-clean energy after the introduction of green technology, the energy use efficiency is improved, which indirectly reduces the firm's carbon emissions (Liu et al., 2022b), thereby reducing the undesirable output of the firm's production activities. Secondly, the economic situation. The unstable financial situation of businesses will cause panic among stock market investors, and the cost of using capital will rise as a result of the "financial accelerator" resulting in a vicious cycle of increasing external financing constraints and escalating financial difficulties (Candian and Dmitriev, 2020). As a result, firms' business decisions may change, and they may become "short-sighted" in selecting projects with high short-term returns in order to signal good business on the capital market (Chiarini et al., 2022; Nicolas, 2022). As for technological innovation, it is difficult to have positive feedback on short-term financial performance (Acemoglu et al., 2012), and even if it is in line with sustainable development and can contribute to the achievement of the "carbon peaking" and "carbon neutrality" goals, companies will to some extent ignore it in their actual operations. Therefore, the financial market can be expanded to improve the financial situation of businesses in order to promote innovation in green technology (Liu et al., 2022c). Third, the regional situation. If there are a large number of "zombie enterprises" in the economic environment surrounding enterprises that rely on debt to continue operations, their carbon emission performance may be affected. Because the "pool of capital" is limited, "zombie enterprises" occupy an excessive amount of capital in the financial market for an extended period of time, but their output is less efficient, which can "crowd out" the financial market (Du and Li, 2019). Businesses that could have used these funds for technological innovation would have missed out on the chance to reduce their carbon emissions. Fourthly, the government's policy guidance will affect businesses' carbon performance. Improving the carbon performance of businesses will affect their pursuit of benefits in the short term, but the production and operation of businesses must be subject to the rules of society, and businesses must obtain "legitimacy" by complying with mandatory rules (Chen et al., 2022). After the government enacts relevant laws and regulations, enterprises will actively pay for the policy and regulations in order to gain social reputation in order to adhere to the law. As is the case with the pursuit of carbon performance, the purpose of businesses is to obtain profits. However, because the negative effects of pollution are socially shared, businesses could have ignored the carbon emission situation. However, under the pressure of stakeholders and government concern, businesses will focus on their own social ethical situation and assume a degree of social responsibility by reducing carbon emissions (Luo and Tang, 2021).

2.2 Managerial competence and carbon emission performance

The role of managers in the production and operation of businesses is not "homogeneous," but rather varies based on the internal and external environments in which they operate. So that various managers make varied decisions (Kathuria and Porth, 2003). Due to the bias of managers' personal interests and external capital market pressures, firms may become myopic from the perspective of technological innovation (Mishra et al., 2022). In other words, technological innovation with a lengthy payback period is not favored by firms that are overly risk-averse. However, competent managers also have a tendency to be forward-looking and immune to short-term vested interests (del Mar Alonso-Almeida et al., 2017). In order to achieve a balance between the company's current performance and its sustainable development. They recognize the impact of advanced technology on the enterprise's overall growth over time. Therefore, in the context of "dual carbon," capable managers will choose to support carbon reduction while ensuring the enterprise's smooth operation in the current period. In terms of corporate capital flow, managers with strong capabilities are frequently able to integrate the available or potential resources in an efficient manner (Yakob, 2020). These businesses are frequently better able to respond to threats, seize opportunities, and maintain sufficient cash flow to ensure their survival and growth. Indicating

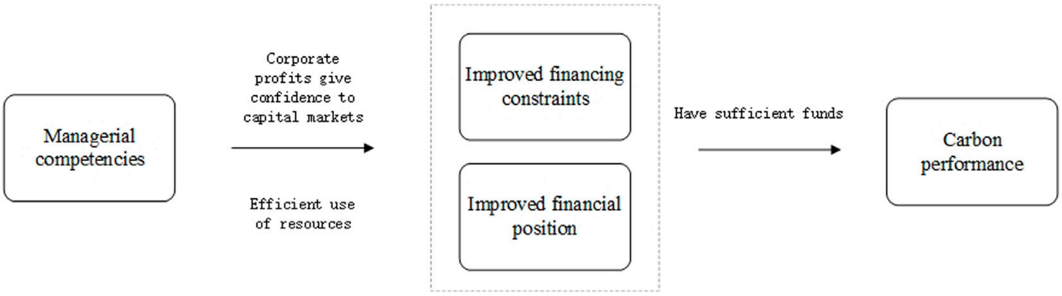

FIGURE 1
Mechanism conduction diagram.

that the company has prospects, managers who respond effectively to threats and opportunities can also give the capital market a "cardiac stimulant." Thus relieving the company of its financial constraints (Freel et al., 2014.; Park and Ryu, 2022). From an active social responsibility perspective. Under China's "carbon peaking" and "carbon neutrality" objectives, improving the carbon performance of enterprises is a requirement of the Chinese government, a requirement of the enterprises' stakeholders, and the enterprises' own responsibility. If businesses take responsibility for reducing carbon emissions, they can obtain political resources like tax incentives (Lin, 2021). And build a positive corporate image so that they can obtain more benefits in the future from their stakeholders (Godos-Díez et al., 2011). In contrast, corporate managers with only operational rights may also prioritize social responsibility in their business decisions for the purpose of enhancing their personal image and social standing (Galaskiewicz, 1997). That is, utilizing their talents to assist businesses in enhancing their carbon performance and societal standing.

3 Hypothesis and research design

3.1 Theoretical analysis and research hypothesis

Figure 1 is a mechanistic transmission diagram of the impact of managerial competencies on corporate carbon performance.

3.1.1 Managerial competence and carbon emission performance

After the separation of the two powers, the owners of the company hire individuals with specific competencies to serve as managers, and these managers assume operational control. Upper Echelons Theory posits that managers' knowledge of the market is necessarily limited due to the environment's complexity, and the decisions they make at this time will vary depending on the manager (Hambrick and Mason, 1984). This study categorizes outputs into desired and undesirable outputs when measuring carbon performance, allowing the effect of managerial competence on a company's carbon performance to be studied separately for these two aspects. Greater managerial competence contributes positively to a company's operating income (Herrmann et al., 2003). Managers with strong competencies can integrate the necessary resources for the company's growth in a more timely manner. They are able to capitalize on potential opportunities and avoid potential threats within the organization. Regarding the reduction of carbon emissions, managers are also conscious of the problems caused by their own production and emissions (Esmaeilifar et al., 2020). Capable managers are aware of the damage to the company's reputation and other aspects of the temporary carbon emission issue. They will be able to balance the investment in carbon emission reduction with the company's normal production growth. Therefore, we propose the first hypothesis.

H1: Other things being equal, good managerial competence can help firms improve their carbon performance.

3.1.2 The mediating role of external financing constraints and firms' financial performance

With the widespread danger of global warming and the political orientation of "carbon peaking" and "carbon neutrality," the concept of carbon reduction is deeply ingrained in people's minds, and according to the expectation theory, businesses have sufficient motivation to take social responsibility (Tsai et al., 2016). Even if they have the desire to be socially responsible, they must consider their actual capabilities. In the short term, firms that invest in carbon reduction activities do not experience immediate revenue growth, putting pressure on their cash flow and posing a threat to their survival (Tsai, 2008). Effective management skills can signal the market and inspire investor confidence to alleviate external financing constraints (Peng et al., 2022). And business managers who run their companies more effectively will also benefit from a stronger financial position. Generally, organizations with greater cash flow achieve superior operating results. A sufficient cash flow can assist businesses in weathering unforeseeable crises. In the event of opportunities, adequate cash flow enables businesses to make the necessary production adjustments in a shorter period of time (So and Zhang, 2022). With sufficient cash flow, businesses can make decisions with lower short-term returns but long-term benefits for society and the business, and they can increase their cash investments in projects that contribute to "carbon reduction" with confidence (Safiullah et al., 2021). The following hypothesis is therefore proposed.

H2a: All else being equal, good managerial capacity can enhance the carbon performance of firms by alleviating the degree of external financing constraints.

H2b: bOther things being equal, good managerial competencies can enhance firms to improve their carbon performance by improving their internal financial position.

3.1.3 Threshold effect of key managers' compensation

Being involved in social responsibility and assisting other businesses in enhancing their carbon performance has a significant impact on the company's reputation. However, it may not be particularly beneficial for the managers themselves. Especially when the manager has no strong ties to the company, the owner's ability to rehire the manager frequently depends on the profitability of the company. Currently, the manager will prioritize the company's earnings. Regarding the company's reputation, managers may not be concerned. Optimal Salary Contract Theory posits that an increase in managerial compensation can enhance the manager's sense of belonging to the organization, and that higher compensation can increase the manager's commitment to assisting the organization in making decisions (Stevens and Thevaranjan, 2010). However, the company's resources are limited, so their allocation should be based on the contributions of each manager. When individuals make decisions, the contractual reference effect considers the impact of the difference between actual profit and loss and expected value (Kahneman, 1979). According to the Pareto principle, corporate decisions are frequently made by a small number of managers, and if they are distributed equally, regardless of each manager's contribution, it will result in the inefficiency of key managers (Carnahan, 1979). We therefore proposed the third hypothesis.

H3: All other things being equal, the higher the proportion of key managers' compensation, the more significant the effect of managers' competence on corporate carbon performance

3.2 Research design

We have included at the end of the text a brief explanation of the variables that appear in the article, with the range of values for the variables shown in the descriptive statistics in 4.1.

3.2.1 Data selection

This study utilizes data from 2014 to 2019 for Chinese heavy polluters listed on Shanghai and Shenzhen A-shares. Because using the SBM-DDF model in conjunction with the GML index necessitates balancing the panel data, which will result in a substantial loss of samples, the sample interval for this study is 2014–2019. Matlab 2020 was used to calculate the carbon emission performance from 2015 to 2019, after which pertinent financial data from the China Economic and Financial Research Database were selected (CSMAR). As for heavy polluters, China's State Environmental Protection Administration proposed 13 categories of heavy polluting industries in 2003. While there have been some changes to China's industry classification standards since then, the following industry codes will be considered heavy polluters: B6, B7, B8, B9, B10, B11, C15, C17, C18, C19, C22, C25, C26, C27, C28, C29, C30, C31, C32, and D44.

China Stock Market & Accounting Research Database (CSMAR), China Statistical Yearbook, and China Environmental Statistical Yearbook provided the data for this study. In addition, some indicators were manually compiled and calculated using EXCEL 2021, Matlab 2020, and Stata17, and data analysis was conducted using Stata17. The information was analyzed using Stata17. In addition, we performed a 10% winsorization to mitigate the impact of extreme values.

3.2.2 Variable selection

Please see Table 1 for the main variables used in this paper.

3.2.2.1 Explained variables

Utilizing labor, stock capital, and energy consumption as input variables and regional GDP and pollution levels as output variables, scholars measure carbon emission performance at the province or city level (Liu et al., 2021). Fewer scholars assess firm-level carbon emission performance. This study utilizes Wang et al. (2021) to measure carbon emission efficiency. 1) The number of employees at the end of the year is utilized as the labor input variable. 2) The firm's fixed asset stock is taken as the capital input variable, and the calculation formula is $K_t = (1-\delta)K_{t-1} + \frac{I_t}{P_t}$. Where K_t denotes the capital stock in period t; I_t denotes the new fixed assets in period t,; P_t is the price index of fixed asset investment in the province. 3) After converting the enterprise's energy consumption into standard coal as the energy input variable, the enterprise's energy consumption is multiplied by the industry's energy consumption using the ratio of the enterprise's operating cost to the industry's operating cost as the coefficient. 4) Consider the enterprise's income as the expected output. 5) The pollution produced by the enterprise as unanticipated output, using the same method as the enterprise's energy measurement. Combined with GML and the SBM-DDF model to evaluate the enterprise's carbon emission performance.

3.2.2.2 Explanatory variables

There are some discrepancies between the financial statement requirements in China and international standards, which may cause some difficulties in the calculation of managerial competency indicators. We improved the managerial competency measure proposed by Demerjian et al. (2012) in the context of Chinese reality. Firstly, sales revenue ($Sales$) as the output variable, and the main operating cost ($CoGS$), selling expenses and administrative expenses ($SG\&A$), fixed assets (PPE), net intangible assets ($Intan$), R&D expenditures ($R\&D$) and goodwill ($Googwill$) as input variables. Then the productivity of the firm is measured by data envelopment analysis (DEA).

$$MAX(\theta) = \frac{Sales}{v_1 CoGS + v_2 SG\&A + v_3 PPE + v_4 OpsLease + v_5 Intan + v_6 Googwill} \tag{1}$$

The Tobit model is also used to regress measured firm productivity on firm size, market share, free cash flow, years on the market, and business complexity to obtain residuals as an indicator of firm managerial competency, with larger residuals indicating greater managerial competency. In order to reduce the

TABLE 1 Variable definitions.

	Symbols	Definition	Measurements
Explained variables	CP	Carbon performance of companies	See previous article, using the SBM-DDF model combined with the GML index measure
Explanatory variables	ME	Managerial competencies	Measured using DEA-Tobit method
Intermediate variables	KZ	Degree of external financing constraints	KZ Index
	OScore	Internal Financial Position	Drawing on Ohlson's (1980) model of financial distress
Threshold variables	SG3	Key management compensation	The proportion of the top three corporate managers' compensation in the total compensation of corporate executives
Control variables	size	Enterprise size	Natural logarithm of business assets
	age	Business Age	Time since the establishment of the company
	cash	Cash Flow Position	Cash flow from operating activities/total assets
	top1	Shareholding Concentration	Shareholding ratio of major shareholders
	board	Board Size	Natural logarithm of the number of board members
	stock	Institutional shareholding ratio	Shareholding of institutional investors

TABLE 2 Descriptive statistics.

Variable	N	SD	Mean	Min	p50	Max
CP	3,625	0.433	1.143	0.409	1.080	3.932
CPR	3,625	0.529	1.154	0.297	1.070	4.002
ME	3,625	0.219	−0.024	−0.800	−0.003	0.590
KZ	3,625	1.943	1.152	−4.721	1.299	6.573
OScore	3,625	2.431	−8.761	−17.606	−8.573	−2.476
SG3	3,625	0.138	0.476	0.232	0.458	0.913
size	3,625	1.311	22.572	19.684	22.386	26.315
age	3,625	6.242	14.328	3.710	14.833	26.080
cash	3,625	0.260	−0.032	−0.900	−0.009	0.937
top1	3,625	0.151	0.348	0.000	0.327	0.750
board	3,625	0.200	2.148	1.610	2.197	2.708
stock	3,625	0.234	0.464	0.008	0.489	0.922

impact of firm-level factors such as firm size on the measurement of managerial capability, we also control for industry and year fixed effects. Individual and annual clustering effects are also used to control for cross-sectional and temporal correlations.

$$\theta = \alpha + \beta_1 \mathrm{Size} + \beta_2 \mathrm{Marketshare} + \beta_3 \mathrm{FCF} + \beta_4 \mathrm{Age} + \beta_5\ \mathrm{HHI} + \varepsilon \tag{2}$$

3.2.2.3 Control variables

To mitigate potential endogeneity issues associated with omitted variables, this study included firm size, firm age, and cash flow status as financial control variables. Additionally, we include equity concentration, board size, and institutional shareholding, which are control variables for corporate governance characteristics.

3.2.3 Model construction

For hypothesis 1, this study constructs the following model. If β_1 is significant as positive, it means that stronger managerial competencies can significantly contribute to the carbon performance of firms.

$$CP_{i,t} = \alpha + \beta_1 ME_{i,t} + control + \sum firm + \sum year + \varepsilon_{i,t} \tag{3}$$

For hypothesis 2, this study uses a stepwise test to examine the mediating role of the degree of external financing constraints and the firm's own financial position.

$$KZ_{i,t} = \alpha + \beta_1 ME_{i,t} + control + \sum firm + \sum year + \varepsilon_{i,t} \tag{4}$$

$$CP_{i,t} = \alpha + \beta_1 KZ_{i,t} + \beta_2 ME_{i,t} + control + \sum firm + \sum year + \varepsilon_{i,t} \tag{5}$$

$$OScore_{i,t} = \alpha + \beta_1 ME_{i,t} + control + \sum firm + \sum year + \varepsilon_{i,t} \tag{6}$$

$$CP_{i,t} = \alpha + \beta_1 OScore_{i,t} + \beta_2 ME_{i,t} + control + \sum firm + \sum year + \varepsilon_{i,t} \tag{7}$$

4 Empirical study

4.1 Descriptive statistics

The descriptive statistics for this study are shown in Table 2. Carbon performance (CP) has a mean value of 1.143 and a median value of 1.080, which is less than the mean. Indicating that a small number of companies with high carbon performance account for the majority of the data. CP has a minimum value of 0.409 and a

TABLE 3 Correlation analysis.

	CP	ME	KZ	OScore	Lev	roa	Cash	top1	Board	Stock
CP	1									
ME	0.170***	1								
KZ	−0.004*	−0.090***	1							
OScore	−0.035**	−0.110***	0.782***	1						
lev	0.033**	0.164***	−0.018	0.029*	1					
roa	0.083***	−0.075***	0.141***	0.124***	0.235***	1				
cash	−0.087***	0.016	−0.022	−0.097***	−0.079***	0.190***	1			
top1	0.002	0.071***	−0.117***	−0.091***	0.346***	0.006	0.005	1		
board	−0.001	0.054***	0.002	0.040**	0.304***	0.158***	0.031*	0.049***	1	
stock	0.065***	0.046***	−0.055***	−0.026	0.515***	0.368***	0.018	0.505***	0.235***	1

TABLE 4 Variance inflation factor.

Variable	VIF	1/VIF
stock	1.900	0.526
size	1.530	0.653
top1	1.460	0.685
age	1.310	0.765
board	1.130	0.885
cash	1.060	0.940
ME	1.050	0.956
Mean VIF	1.350	

TABLE 5 Benchmark regression.

	(1)	(2)	(3)	(4)
	CP	CP	CP	CP
ME	0.583***	0.595***	0.580***	0.589***
	[0.068]	[0.068]	[0.068]	[0.067]
account	no	yes	no	yes
manage	no	no	yes	yes
firm	yes	yes	yes	yes
year	yes	yes	yes	yes
_cons	0.996***	−2.121	0.306	−1.363
	[0.013]	[1.595]	[0.188]	[1.425]
N	3,625	3,625	3,625	3,625
adj. R-sq	0.134	0.151	0.151	0.161

Standard errors in brackets.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Robustness Tests.

maximum value of 3.932, despite a standard deviation of 0.433. The mean and average values of ME are both less than 0, indicating that these companies need to improve their managerial capacity. Consistent with Campbell et al.'s research, there is a great deal of variation in the financing constraints faced by various businesses (2021). The descriptive statistics of the financial situation illustrate the substantial disparities between the financial situations of various businesses.

4.2 Correlation analysis

In this study, correlation tests were conducted on the relevant variables, and the results are shown in Table 3. A significant positive correlation exists between managerial competence (ME) and corporate carbon performance (CP), and hypothesis H1 was initially tested. Table 2 demonstrates that managerial competence (ME) is significantly and negatively related to firms' external financing constraints (KZ) and internal financial position (OScore), and that the latter is significantly and negatively related to firms' carbon performance (CP). Hypothesis H2a and hypothesis H2b are initially tested.

The results of the variance inflation factor test are displayed in Table 4 of this study. Each of the swelling factors is below 10. At first, it is determined that there is no covariance issue. The Hausman test was followed by the use of individual and time fixed effects, which can mitigate the endogeneity issue caused by the difference between groups.

4.3 Benchmark regression

Table 5 presents the baseline regression test for hypothesis H1 in this study. The coefficient of the effect of managerial competence (ME) on firm's carbon performance (CP) is 0.583, which is significant at the 1% level, according to the results of the test conducted without the inclusion of control variables, as shown in column 1). The results of the test including firm size, firm age, and firm cash flow position, which are financial control variables, are displayed in column 2. The results of adding equity concentration, board size, and institutional shareholding, which are control

TABLE 6 Robustness tests.

	(1)	(2)
	CP	CP
ME	1.151**	0.723***
	[0.454]	[0.075]
Underidentification test	0	
Kleibergen-Paap rk Wald F	23.375	
Stock-Yogo 10%	16.38	
account	yes	yes
manage	yes	yes
firm	yes	yes
year	yes	yes
_cons		−3.313**
		[1.497]
N	3,625	3,625
adj. R-sq	−0.266	0.126

Standard errors in brackets.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE 7 Intermediary effects.

	(1)	(2)	(3)	(4)	(5)
	CP	KZ	CP	OScore	CP
KZ			−0.012*		
			[0.007]		
OScore					−0.024***
					[0.008]
ME	0.589***	−0.498***	0.550***	−1.138***	0.562***
	[0.067]	[0.121]	[0.068]	[0.144]	[0.067]
account	yes	yes	yes	yes	yes
manage	yes	yes	yes	yes	yes
firm	yes	yes	yes	yes	yes
year	yes	yes	yes	yes	yes
_cons	−1.363	12.48**	−0.622	−3.352	−1.442
	[1.425]	[6.162]	[1.475]	[5.947]	[1.406]
N	3,625	3,517	3,514	3,625	3,625
adj. R-sq	0.161	0.045	0.152	0.094	0.166

Standard errors in brackets.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

variables relating to firm management characteristics, are displayed in column 3. The test results of adding the previously mentioned control variables are displayed in column 4). The addition of control variables can mitigate the endogeneity issue caused by variables that were omitted. According to Table 5, the model's explanatory power (adj. R-sq) is enhanced by the addition of control variables, and the coefficient of the effect of managerial competence (ME) on carbon performance (CP) ranges between 0.580 and 0.595, all of which are statistically significant at the 1% level. It indicates that competent management can assist businesses in enhancing their carbon performance, thus confirming hypothesis H1.

4.3.1 Endogeneity test

This study employs two-order least squares (2sls) in conjunction with a GMM dynamic panel model to test the endogeneity of the benchmark regression results in order to mitigate the endogeneity issue. As the instrumental variable, the regional mean of managerial competency (ME) of other companies was chosen (Li, 2016). The outcomes are shown in column (1) of Table 6. Existence of a significant positive relationship between the independent and dependent variables can be observed. The Under identification test has a p-value of 0. There is no weak instrumental variable, as the Kleibergen-Paap rk Wald F is 23.375 and the Stock-Yogo 10% is 16.38. Regarding adj. R-sq, it is less than 0 because, in conjunction with the GMM dynamic panel model employing two-order least squares (2sls), it does not require much consideration (Sribney et al., 2005). Passing the test for endogeneity.

4.3.2 Substitution of variables

We defaulted to variable scaled payoffs when calculating carbon performance (CP). This study replaced the explanatory variables in the robustness test calculation while maintaining the scale payoffs. The test results for robustness are displayed in column 2 of Table 6. At the 1% significance level, managerial ability (ME) remains significantly and positively associated with firm carbon performance (CP) after controlling for the explanatory variable.

5 Further Analysis

5.1 The mediating role of financing constraints and financial position

Table 7 displays the test for the mediating effect. In this study, the measure of external financing constraints (KZ) is a positive indicator, meaning that the greater the value of KZ, the more severe the firm's financing constraints. Table 7 columns (2) and (3) illustrate the effect of external financing constraint on mediation (KZ). Stronger managerial capability can significantly mitigate the external financing constraint (KZ), while external financing constraint (KZ) partially mediates the relationship between managerial capability and corporate carbon performance (column 3) (CP). In this study, the selected measure of the firm's internal financial position (OScore) is a negative indicator, i.e., a higher OScore value indicates that the firm's financial position has deteriorated. Table 7's columns (4) and (5) illustrate the mediating impact of internal financial position (OScore). A stronger managerial capability can significantly improve the internal financial position (OScore), as shown in column 4, while the internal financial position (OScore) partially mediates the relationship between managerial capability and corporate carbon performance, as shown in column 5 (CP). Considering that equity markets around the world have become cautious in the wake of the financial crisis (Li T. et al.,

TABLE 8 Threshold value test.

		Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
ME	Single	0.240	500.518	0.173	15.04	0.010	8.886	10.677	14.64
	Double	0.578	503.117	0.174	70.67	0.000	17.871	24.141	37.021
	Triple	−0.231	499.728	0.173	4.58	0.797	16.902	19.178	28.867
SG3	Single	0.492	786.148	0.272	22.61	0.007	11.845	14.921	20.676
	Double	0.510	786.114	0.272	0.12	1.000	13.155	16.285	20.917

2022), firms' access to capital has been significantly constrained as a result. Good managerial capabilities can enhance the carbon performance of firms by alleviating financing constraints and improving their financial position. The H2a and H2b hypotheses are supported.

5.2 Threshold Effect

This study utilized a threshold regression with the independent variable managerial competency (ME) as the threshold variable to investigate the extent to which an increase in managerial competency (ME) produces a qualitative change that results in a change in the impact of managerial competency (ME) on corporate carbon performance (CP). The tests assuming managerial competence (ME) as the threshold variable are shown in Rows one through three of Table 8. When managerial competency (ME) is the threshold variable, the *p*-value of the double threshold effect is significant at the 1% level, whereas it is not significant when a triple threshold effect is assumed. Thus, we concluded that there is a double threshold effect when the threshold variable is managerial competency (ME). As for the threshold test with internal equity in compensation (SG3) as the threshold variable, Table 8 rows four and five display the results of its threshold test, which indicates that there is currently a single threshold effect.

The threshold regression test with managerial competence (ME) as the threshold variable is displayed in column (1) of Table 9. When it reaches 0.240 and 0.578, the effect of managerial competence (ME) on the firm's carbon performance (CP) increases significantly (the coefficient increases from 0.271 to 0.724 and then to 1.584 after reaching the second threshold). The threshold regression test with internal pay equity (SG3) as the threshold variable is displayed in column (2) of Table 9. It can be seen that once the level of internal pay equity (SG3) reaches the threshold value, the manager's bond with the firm strengthens and the manager's motivation to improve the firm's carbon performance (CP) increases. The H3 hypothesis is confirmed.

5.3 Discussion

The manager of a firm under separation of powers controls the production and business decisions of the firm, when managerial characteristics influence the behaviour of the firm (Benmelech and Frydman, 2015). Aggressive managers may favour projects with high risks and benefits when making decisions, while conservative managers will be more shy of riskier projects. Therefore, managers with strong competencies tend to be able to improve the carbon performance of their companies while ensuring smooth operations with an eye on the long-term development of the company. This hypothesis has been confirmed by empirical analysis. We empirically analyse the pathways through which managerial capability affects the carbon performance of firms. Previous scholars have tended to study the carbon performance of firms from the perspective of Science and Technology Innovation (Sun et al., 2021). We consider the impact of financial status on firms' decisions and conduct hypotheses and empirical analysis from this perspective. This can expand the path of research on corporate carbon performance and offer educational opportunities of long-lasting learning to relevant scholars.

6 Summary, recommendations and limitations

6.1 Summary

Governments are enacting regulations to combat carbon dioxide emissions, which contribute to global warming and pose a threat to human survival and development. This study examined firms as microeconomic agents to determine their contribution to global warming. Using a sample of Chinese heavy polluters from Shanghai and Shenzhen A-shares, this study investigated the impact of managerial competence on carbon performance and drew the following conclusions.

(1) Greater managerial competence has a significant impact on the carbon emission performance of businesses. Managers with greater competence can ensure the enterprise's normal production and operation and increase the desired output - operating income. And managers with strong capability have a propensity to be forward-thinking; they can see the harm that carbon emissions cause to the economy, society, and the enterprise itself. They are capable of effectively reducing the undesirable output of the business—carbon emissions.
(2) External financing restrictions and internal financial conditions serve as a moderating factor. While it is common knowledge that a company's reputation can be enhanced by being socially responsible and reducing carbon emissions, a company cannot improve its technology and management structure without sufficient cash flow. In this study, we discovered that competent management can reduce external financing constraints and improve internal financial conditions, thereby improving the carbon performance of businesses.

TABLE 9 Threshold effects.

	(1)			(2)	
	CP			CP	
	ME < 0.240	0.240 < ME < 0.578	ME > 0.578	SG3<0.492	SG3>0.492
ME	0.271***	0.724***	1.584***	0.419***	0.873***
	[0.046]	[0.105]	[0.134]	[0.061]	[0.076]
account	yes			yes	
manage	yes			yes	
firm	yes			yes	
year	yes			yes	
_cons	−1.504**			−2.892***	
	[0.673]			[0.850]	
N	3,625			3,625	
adj. R-sq	0.033			0.008	

Standard errors in brackets.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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(3) A threshold effect exists between managerial competency and internal pay equity. This study found that when managerial competency surpasses the threshold twice, it will have a qualitative effect on the carbon performance of the firm. When the proportion of key managers' compensation exceeds the threshold, the bond between the key managers and the company strengthens, and managers with greater competence will pay more attention to the company's reputation and work more diligently to improve the company's carbon emission performance.

6.2 Recommendations

What sort of policies can the government implement to assist businesses in enhancing their carbon performance? To expect businesses to forego their economic benefits and assume their social responsibility to reduce carbon emissions is unrealistic. To reduce carbon emissions, businesses are motivated by their social standing and their aversion to risk. Under the policy guidance, stakeholders will become increasingly supportive of carbon emission reduction, and businesses may cater to the needs of their stakeholders to meet their expectations.

Investors should be aware of the contribution of competent management to the carbon performance of a company. Competent managers are able to ensure the company achieves adequate business results while reducing its carbon footprint. In this way, the company's reputation on the capital market is safeguarded, its market value has the potential to rise steadily, and investors' interests are safeguarded.

Companies should recognize the importance of key managers to their operational growth. If conditions permit, the company should increase the remuneration of key managers in order to increase the degree of bonding between key managers and the company and to meet their psychological expectations, so that managers are more committed to balancing business operations and carbon reduction.

6.3 Limitations

Due to the fact that the relevant data in the China Statistical Yearbook are not disclosed after 2020 and the calculation of carbon emission performance requires balanced panel data, this study selected enterprises that have been continuously operating from 2014 to 2019. These businesses have been continuously operating for at least 6 years and may have unique characteristics in some aspects of business management. From this perspective, scholars of future studies can improve this study.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Author contributions

ZZ: Conceptualize the idea of this study. Responsible for data collection, model design and paper writing. PW: Collect literature and be responsible for part of the literature review. Cover the costs associated with this study.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Appendix A.

TABLE A1 Variable definitions.

Variable	Description
CP	Carbon performance of companies, variable default size payoff. Using the SBM-DDF model combined with the GML index measure
CPR	Carbon performance of companies, no change in default size payout. Using the SBM-DDF model combined with the GML index measure
Number of people employed	Number of people employed at the end of the year
Fixed asset stock	Stock of fixed assets at the end of the year of the enterprise using the method in section 4.2.1. Unit: ten thousand CNY
Energy consumption	Converts the energy consumption of a business into standard coal. Unit: tonnes
Income	The total revenue of the enterprise for the year. Unit: ten thousand CNY
Carbon emissions	Co2 produced by the enterprise during the year. Unit: tonnes
ME	Indicators to measure the capacity of managers. Measured using DEA-Tobit method
Sales	Sales revenue from the enterprise's main business for the year. Unit: CNY
CoGS	The enterprise's main operating costs for the year. Unit: CNY
SG&A	Cost of sales and administrative expenses of the enterprise for the year. Unit: CNY
PPE	Book value of fixed assets at the end of the year of the enterprise. Unit: CNY
Intan	Net book value of intangible assets at the end of the year of the enterprise. Unit: CNY
R&D	R&D expenditure invested by the enterprise during the year. Unit: CNY
Goodwill	Value of goodwill at the end of the year of the enterprise. Unit: CNY
Size	The natural logarithm of the enterprise's total book assets at the end of the year
Marketshare	The percentage of the enterprise's main business revenue for the year as a percentage of the industry's revenue for the year
FCF	The natural logarithm of the enterprise's cash flow at the end of the year
Age	The time since the business was established. Unit: year
HHI	Herfindahl-Hirschman Index, a higher index indicates a more competitive market
KZ	Degree of external financing constraints. KZ Index
OScore	The internal financial position of the business for the year. Drawing on Ohlson's (1980) model of financial distress
SG3	The remuneration of key managers of the company as a percentage of the remuneration of all managers in that year
cash	Cash flow from operating activities/total assets
top1	Shareholding ratio of major shareholders
board	Natural logarithm of the number of board members
stock	Shareholding of institutional investors

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Prediction of return on equity of the energy industry based on equity characteristics

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We take the return on equity of energy enterprises as the research object to predict it. Our research adopts a new framework to solve multivariable time series problems. Compared to a single regression model, this model focuses more on the results of the regression equation rather than the coefficients of each indicator. Compared to the single machine learning regression method, this model can use the two-way encoder representation of the Transformers model to embed text data into the data, and then use the XGBoost model for regression model processing after PCA dimensionality reduction processing, thereby improving the accuracy of model prediction. Comparative experiments have verified that the method we use has advantages in terms of prediction accuracy.

KEYWORDS

energy industry, equity, return on equity, XGBoost, predict

1 Introduction

The energy industry, which belongs to the basic industry of the national economy, is an important field of enterprise reform. At this stage, the equity operation matters faced by energy enterprises are gradually increasing, which puts forward higher requirements for the ability and level of equity management of such enterprises. In the actual operation process of energy enterprises, equity factors are at the forefront of several factors affecting the return on equity (ROE).

Energy enterprises are very interested in predicting the performance of the next year based on the previous annual performance and taking it as the basis for the prediction and decision making. As an important indicator of enterprises, it is very important for energy enterprises to be able to predict and correct. As an indicator to measure the operating efficiency of energy enterprises, the ROE reflects not only a simple number but also the problems reflected behind it through the superficial meaning of the number. Therefore, this article proposes a prediction model to achieve the aforementioned situation.

Judging whether a company's operation is good or bad depends on its return on net assets, not on the growth of earnings per share. At the moment, there are several aspects in the study of enterprise performance. With the growth of enterprises and the complexity of ownership structure, there is a gradual study of performance from the aspect of equity.

When we talk about time series modeling, we usually refer to ARIMA, VAR, LSTM, and other models. The aforementioned models can usually achieve good results in dealing with single-variable time series problems, but they often perform poorly in the face of multivariable modeling. From the data analysis, we can see that this task is not a typical time series problem, but a multivariable time series problem. In order to make eXtreme Gradient Boosting (XGBoost) (Chen and Guestrin, 2016) available for time series prediction, the time series dataset should be first transformed into a supervised problem so that the time series dataset can also be used for supervised learning.

In the process of model construction, this model uses the XGBoost model as the main support and combines the main body with Bidirectional Encoder Representations of Transformers (BERT) to solve the following three problems: 1) Realizing accurate prediction of the future economic data trend of the enterprise. Of course, this part of prediction is based on the sustainable operation of energy enterprises, excluding the performance fluctuations of energy enterprises caused by force majeure. 2) Solving the problem of text variables being used in the model. To improve the prediction accuracy of this model, we select as many variables as possible, including text variables. 3) This model is not only applicable to ROE prediction of energy enterprises but also universal and can be reasonably used with other types of enterprises.

2 Literature review

The relationship between equity and performance has always been the focus of research. At present, in terms of equity research, there is a close relationship between equity and performance. Zhou (2018) examined the internationalization strategy of hybrid state-owned enterprises (SOEs). Nar et al. (2018) examined the relationship between corporate governance and dividend policy of Nepalese enterprises. The contribution of Bhattarai (2018) was to examine the relationship between firm strategy and sustainability of financial performance of Nepalese Enterprises. Matuszak and Szarzec (2019) aimed to analyze SOEs in 11 post-socialist Central–Eastern European (CEE) countries. Chazova and Mukhina (2019) analyzed the structure of enterprises and organizations by forms of ownership in Russia. This study was conducted to determine empirical evidence of the influence of company characteristics and ownership structure on tax avoidance in SOEs listed on the Indonesia Stock Exchange (BEI) in 2013–2016 (Arviyanti and Muiz, 2020). Taking the mixed ownership reform of Chinese SOEs as the research object, Gao and Song (2021) analyzed the impact of management ownership on the performance of mixed ownership enterprises. The objective of the work of Men and Hieu (2021) was to identify the relationship between different variables affecting profitability of the firms in the oil and gas sector in Vietnam. The objective of the work of Roffia (2021) was to provide new evidence on the relationship between family involvement and financial performance in small- and medium-sized enterprises (SMEs). Other influential studies include the study of Wang and Zhao (2021).

As far as the ROE of enterprises is concerned, the research shows diversification. The linear regression method is often used in the study of quantitative relationship. Using performance analysis, So et al. (2018) examined the cooperation between SOEs and their suppliers. Otekunrin et al. (2018) used multiple regression analysis which is limited to the use of data taken from the selected financial statement. Vlčková et al. (2019) examined the SMEs in the Czech Republic from the perspective what makes them to adopt telework using the financial indicators. The aim of the work of Farooq (2019) was to investigate the effect of inventory turnover on firm profitability. The subject of the work of Irfan Sauqi et al. (2019) was to determine the financial effect proxy through current ratio, debt equity ratio, ROE, return on investment, and net profit margin against stock price of the company and the like mentioned in BEI. Decomposition of ROE after return on assets (ROA), return on sales (ROS), total assets turnover (TAT), and equity multiplier (EM) provides an analytical framework appropriate for observing factors that make and influence profitability (Bielienkova, 2020). The subject of the work of Tho Do (2020) was to empirically investigate the relationship between capital structure and firm performance using a sample of Vietnam material enterprises. The research by Petruk et al.(2020) considered the influence of the capital structure on the efficiency of communal enterprises of passenger land transport, and also, they (Ji and Kim, 2020) identified employment in social enterprises in terms of its quantity and quality. Taking the mixed ownership reform of Chinese SOEs as the research object, Gao and Song (2021) analyzed the impact of management ownership on the performance of mixed ownership enterprises.

In recent years, the XGBoost model has been widely used in various fields and has performed well. Yang et al. (2022) aimed to explore the influence of road and environmental factors on the severity of freeway traffic crash and establish a prediction model toward freeway traffic crash severity. XGBoost, AdaBoost, and Bagging were the employed soft computing techniques (Shen et al., 2022). The research by Ullah et al. (2022) used four different ensemble machine learning (EML) algorithms: random forest, XGBoost, categorical boosting, and light gradient boosting machine, for predicting EVs' charging time. Mao et al. (2022) developed a stacked generalization (stacking)-based incipient fault diagnosis scheme for the traction system of high-speed trains. In order to improve the problem of inaccurate results in non-contact heart rate detection due to a series of movements of the subject such as breathing, blinking, facial expressions, and noise generated by changes in ambient light, the signal is processed in advance using normalization and wavelet denoising, and then, an XGBoost algorithm based on a Gaussian process (GP)-based Bayesian optimization method is introduced (Gao et al., 2022). Sanyal et al. (2022) presented a novel hybrid ensemble framework consisting of multiple fine-tuned convolutional neural network (CNN) architectures as supervised feature extractors and XGBoost trees as a top-level classifier, for patch-wise classification of high-resolution breast histopathology images. Other influential works include those of Nguyen et al. (2022), Srinivas and Katarya (2022), Zhou et al. (2022), and Zhang et al. (2022).

In the study of performance, this article mainly uses the ROE as a measurement index. In terms of model, the regression model is usually used for analysis. Regression analysis is usually used to study the relationship between equity and performance. The advantages of the regression model are obvious: it can show the significant relationship between independent variables and different dependent variables and show the influence intensity of multiple independent variables on a dependent variable. Regression analysis also allows comparing and measuring the interaction between variables of different scales, which is convenient for constructing the regression model.

This article will try to use XGBoost to model time series. XGBoost is an effective implementation of gradient lifting for classification and regression problems. It is fast and efficient. It can get good performance in a wide range of prediction modeling tasks. It can be used to solve time series problems. In order to make XGBoost available for time series prediction, the time series dataset needs to be first converted into a supervised learning problem. Here, the problem is transformed into a supervised problem by using the sliding time window so that the time series dataset can also be applicable to supervised learning. The specific idea of constructing the dataset is as follows: using the data of the first n years of the enterprise as the feature to predict the ROE in the N + 1 year. In this way, we can transform the time series problem into a traditional regression problem. The text data in the dataset are embedded with the BERT model, processed with PCA dimensionality reduction, and then, processed with the XGBoost regression model.

3 Model building

3.1 Data processing

The purpose of missing value supplement processing is to retain the existing data as much as possible in the case of insufficient data samples. However, when making up the data, it should be noted that it is conditional for the existing data to be insufficient for the missing value. Equity ratio, separation rate of two rights, net profit growth rate, and other indicators are continuous in time, and various indicators will not have major changes under the normal operation of the enterprise, so they can be supplemented. Therefore, the K-means clustering method is used to fill in the adjacent missing data. Because the selected data have strong consistency in time arrangement, the missing values can be processed to a certain extent. The missing value processing method selected in this article is the k-nearest distance method.

The specific method is as follows: first, the Euclidean distance method or correlation analysis method is used to collect and calculate the K sample values closest to the missing points, and then, the weighted average of K numbers is used to estimate the missing data. The same mean interpolation is a single-value interpolation. The difference is that the hierarchical clustering model is used to predict the missing variables, and then, the average value is used for interpolation.

By setting the training sample ψ, there are m numbers in the dataset and in $\psi^{(i)}$ and $\psi^{(j)}$, i and j represent the i th and j th numbers. Each dimension contains H_p defined as

$$H_p\left(\psi^{(i)}, \psi^{(j)}\right) = \left(\sum_{k=1}^{m}\left|\psi_k^{(i)} - \psi_k^{(j)}\right|^p\right)^{\frac{1}{p}}; p \geq 1, \tag{1}$$

when $p = 2$, and it represents the Euclidean distance.

$$H_p\left(\psi^{(i)}, \psi^{(j)}\right) = \left(\sum_{k=1}^{m}\left|\psi_k^{(i)} - \psi_k^{(j)}\right|^2\right)^{\frac{1}{2}}. \tag{2}$$

In fact, the selection of k value has a great impact on making up the missing items. Generally, the value of k is small. The classification decision rule in the k nearest neighbor method is often majority voting, so the misclassification rate should be minimized.

By setting the classification function as: $f: R_n \rightarrow C_1, C_2, \ldots, C_K$. Then, the misclassification probability is

$$P(\sigma \neq f(\psi)) = 1 - P(\sigma = f(\psi)). \tag{3}$$

Then, the misclassification rate I is

$$\frac{1}{k}\sum_{\psi_i \in N_k(\psi)} I = 1 - \frac{1}{k}\sum_{\psi_i \in N_k(\psi)} I = (f_i = c_i), \tag{4}$$

where, $N_k(\psi)$ A is the set of k-nearest neighbor training instance points and c_i is the $N_k(\psi)$ area category. Then, the missing data are supplemented by constructing a KD tree and searching the KD tree, and the supplemented dataset is recorded.

The maximum age length of the data selected in this article is 18; that is, the time span of the annual limit is 18 years. All empty data should be filled after statistics to ensure the maximum rational use of data. In this data sample, it is classified according to the securities code and filled with the data of the same company's adjacent years according to the aforementioned method. For information similar to equity, if the company does not publish it, it will be treated as unchanged.

3.2 Word embedding

When dealing with text non-data information, word embedding is usually needed. Word embedding is a numerical representation of text information. Generally, the text will be mapped to a high-dimensional vector (word vector) to represent the text. Generally speaking, the text will be transformed into data form. The mapped label encoding uses a dictionary to associate each category label with an increasing integer, that is, to generate a label named class the index of the instance array of.

In all data, industry types have great text characteristics. In this article, the BERT model is used to obtain the feature expression of the corresponding text.

With a highly pragmatic method and higher performance, BERT has attracted much attention because of its most advanced performance in many natural language processing (NLP) tasks. BERT has advantages over models such as Word2Vec because although each word has a fixed representation under Word2vec, regardless of the context in which the word appears, the word representation generated by BERT is dynamically represented by the surrounding words.

The BERT model can be expressed as follows:

The language model of Markov hypothesis (n-gram language model) is introduced. If n = 1, there are

$$P(w_1, w_2 \ldots\ldots w_n) = P(w_1)P(w_2 \mid w_1)P(w_3 \mid w_2)\ldots\ldots P(w_n \mid w_{n-1}). \tag{5}$$

The conditional probability is obtained by maximum likelihood estimation.

$$P(w_n \mid w_{n-1}) = \frac{C(w_{n-1}, w_n)}{C(w_n - 1)}. \tag{6}$$

We set the objective function as

TABLE 1 Scores of the BERT model.

Model	Score	Douban	ChnSentiCorp	LCQMC	TNEWS (CLUE)	iFLYTEK (CLUE)	OCNLI (CLUE)
RoBERTa-Tiny	72.3	83	91.4	81.8	62	55	60.3
RoBERTa-Mini	75.7	84.8	93.7	86.1	63.9	58.3	67.4
RoBERTa-Small	76.8	86.5	93.4	86.5	65.1	59.4	69.7
RoBERTa-Medium	77.8	87.6	94.8	88.1	65.6	59.5	71.2
RoBERTa-Basel	79.5	89.1	95.2	89.2	67	60.9	75.5

$$\min \prod_{w \in C} p(w \mid V(w)), \tag{7}$$

where C represents the corpus and C (W) represents the context of word W. Let each text generate three vectors Q, K, and V, and then, the initialization formula is

$$D(R, K, \mathrm{V}) = S\left(\frac{RK^T}{\sqrt{d_k}}\right)V. \tag{8}$$

The S function means Soft-max.

In $R = X\theta^R$, $K = X\theta^K$, and $V = X\theta^V$, X is the formal length of text data and θ is the weight matrix. Recalculate score is given by

$$score = RK. \tag{9}$$

We normalize

$$\xi = S\left(\frac{RK}{\sqrt{d_k}}\right). \tag{10}$$

By increasing the attention of text recognition through matrix multiplication,

$$D = \xi V. \tag{11}$$

Since the Common Language Specification (CLS) of BERT is not very effective as the expression of phrase, and the next sentence task is canceled in the later unofficial version, the mean pooling strategy is adopted as the expression of phrase.

- First, the output vector of CLS position is directly used to represent the vector representation of the whole sentence
- Second, the mean strategy calculates the average value of each token output vector to represent the sentence vector
- Third, the max strategy takes the maximum value of each dimension of all output vectors to represent the sentence vector

The data are quoted here to highlight the advantages of using the BERT model. This time, the pre-training model open source by the Tencent UER-py team is used to code short sentences to obtain embedded information.

The following is the performance of the model in several different tasks (Table 1). It should be noted that RoBERTa here is an optimized version of the BERT model, which is basically a replica version of BERT, so it is usually classified as BERT. Because BERT's CLS is not very good as a phrase and the later unofficial versions cancel the task of listing the next sentence, the mean pooling strategy is used as a phrase.

TABLE 2 Pooling strategy score.

Pooling strategy	NLI	STSb
MIN	80.78	87.44
MAX	79.07	69.92
CLS	79.8	86.62

Pooling strategy: SBERT adds a pooling operation to the output of BERT/RoBERTa to generate a fixed-size sentence embedding vector. Three pooling strategies were adopted in the experiment for comparison.

1. Directly using the output vector of CLS position to represent the vector of the whole sentence.
2. MEAN strategy: The average value of each token output vector is calculated to represent the sentence vector.
3. MAX strategy: The maximum value of each dimension of all output vectors is taken to represent the sentence vector. Specific values are given in Table 2.

Then, principal component analysis (PCA) was used for analysis. PCA is a common data analysis method, which is often used to reduce the dimension of high-dimensional data, and can be used to extract the main feature components of data. For industry types, the pre-trained BERT model is used to embed the text, and then, PCA is used to reduce the dimension.

3.3 PCA dimensionality reduction

Dimensionality reduction of high-latitude data can avoid the high complexity of the model caused by excessive data dimensions. Especially for some cases of insufficient sample data, the final trained model will have poor generalization. Removing the collinearity between data attributes can optimize the model, reduce the complexity of the model, reduce the training time of the model, and improve the robustness and generalization of the model. For PCA, this process is essentially a lossy feature compression process, but it is expected to lose as little accuracy as possible and retain the most original information in the compression process.

By setting text dataset ω, the feature after dimensionality reduction is A. $(A) = \frac{1}{m}\sum_i^m (a_i - \mu_a)^2$, and the larger the value, the better. μ_a is the mean value of characteristic A. By setting the data sample as $\omega = \begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \vdots & \vdots \\ a_m & b_m \end{bmatrix}$, the covariance matrix is $\frac{1}{m}\omega^T\omega = \begin{bmatrix} \frac{1}{m}\sum_i^m a_i^2 & \frac{1}{m}\sum_i^m a_i b_i \\ \frac{1}{m}\sum_i^m a_i b_i & \frac{1}{m}\sum_i^m b_i^2 \end{bmatrix}$; by setting Γ for raw data, the data after PCA meets the requirements $\Gamma = P\ \Gamma c$ and c corresponding matrix:

$$\Gamma_c = \frac{1}{m}\Gamma^T\Gamma\frac{1}{m}(\omega P)^T\omega P = \frac{1}{m}P^T X\omega^T\omega P = P^T\left(\frac{1}{m}\omega^T\omega\right)P = P^T\omega_c P. \tag{12}$$

Because this task contains many influencing factors and the sample data are time series data, this task does not belong to a typical time series problem but should be classified as a multivariable time series problem. In this article, the existing problems will be transformed into supervised problems by using sliding time window so that the time series dataset can be suitable for supervised learning. The text data in the data are embedded with the BERT model, processed with PCA dimensionality reduction, and then, processed with the XGBoost regression model.

In the process of dimensionality reduction, the data after dimensionality reduction do not represent the advantages and disadvantages of the data after dimensionality reduction but reflect the distance of relevant industries. The reason is that this step extracts the more important components or key parts of the original data and maps them to another space. Currently, the performance of the data is not directly related to the original data, so there are positive and negative situations. The original data are compressed and transformed in the original space and mapped to a new space. In essence, it is the original data, but the form of expression is also different.

At this time, the dataset after defect filling, word embedding, and dimension reduction is recorded as X; then, $X = \{X, \Gamma\}$.

3.4 Data scaling

To prevent the model accuracy from being affected by abnormal data in the data, this article scales the data and limits the ROE to - 1–1.

$$\eta = \frac{\tau(Q)}{v(Q)}, \tag{13}$$

where Q is the rate of ROE $\tau(Q) = \zeta - \zeta_{\min} v(Q) = \zeta_{\max} - \zeta_{\min}$, η is a new feature of ROE, and $\zeta_{\min}$ and $\zeta_{\max}$ is the minimum and maximum value before being scaled by the feature, respectively. ζ is the original eigenvalue. Minmaxscaler can convert each element (feature) into a given range of values. The estimator scales and transforms each feature separately so that it is within a given range of the training set such as in the interval [0, 1].

The conversion method is

$$X_{\text{std}} = \frac{(X - X_{\min}(axis = 0))}{(X_{\max}(axis = 0))} - X_{\min}(axis = 0), \tag{14}$$

$$X_{\text{scaled}} = \frac{X_{\text{std}}}{(\max - \min)} + \min.$$

This transformation is often used as an alternative to zero mean, unit variance scaling. The task is not a typical time series problem, but a multivariable time series problem. By using sliding time window representation, time series datasets can be suitable for supervised learning. The idea of building a dataset is as follows:

First, the "securities code" column is used as the basis for grouping.

Second, the grouped data are sorted using "deadline."

Third, the data of the previous n years are used to predict the "ROE in the N + 1 year."

3.5 Feature selection

By selecting *K* Best, all features except the *K* features with the highest score are removed, and the function returns the variable score and *p* value. The calculation formula of *p* value is as follows:

$$Z_0 = \frac{(x - np_0)}{\sqrt{(np_0(1 - p_0))}}. \tag{15}$$

In inferential statistics, hypothesis testing is a very important link. Through the statistical analysis of SAS and SPSS, it is found that *p* value (*p* value, probability, PR) is another important basis for testing.

P value is used to reflect the possibility of an event in the actual situation. The *P* value is obtained through the significance test. Generally, $P < 0.05$ is the statistical difference, $P < 0.01$ is the significant statistical difference, and $P < 0.001$ is the extremely significant statistical difference. It means that the probability of the difference between the samples caused by sampling error is less than 0.05, 0.01, and 0.001. However, the *P* value cannot assign any importance to the data and can only indicate the probability of an event. The statistical results show $Pr\ > F$, which can also be written as $Pr(> F), P = P\{f_{(0.05)} > F\}$ *or* $P = P\{f_{(0.01)} > F\}$.

3.6 ROE model

The ROE model is essentially the XGBoost model. XGBoost is a tree-based model. It can stack as many trees as possible, and each additional tree tries to reduce the errors of the previous tree set. The general idea is to combine many simple and weak predictors to build a powerful predictor.

XGBoost is an addition formula composed of multiple decision trees, which is expressed as follows:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F, \tag{16}$$

where the estimated y_i is the predicted value, x_i is the eigenvector, $f_k(x_i)$ is the value calculated for each tree, and K is the total number of trees. $f_t(x_i)$ is the *t*th lifting tree, n is the number of decision trees, and the initial value $f_0(x) = 0$.

Therefore, for each tree, the XGBoost model is essentially an additive model. We observe $f(k)$ to know how to calculate the tree score to determine which function to use. The loss function represents the loss value of each tree, and the loss function $L^{(t)}\ L(t)$ is expressed as

$$L^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i). \tag{17}$$

The objective function of a given XGBoost is

$$L_{(\phi)} = \sum_i l(\hat{y}_l + y_i) + \sum_k \Omega(f_k), \quad (18)$$

where $\Omega(f) = \Upsilon T + \frac{1}{2}\lambda\|w\|^2$ is the regular term used to express the complexity of the model and Υ, λ is the penalty coefficient in the penalty term. The loss function is proved to be convex and differentiable, and the latter term is the regular term of system complexity, that is, the penalty coefficient. The significance of this coefficient is to prevent overfitting of the model. In the regular term of the latter term, it actually includes the sum of the square of the number of leaf nodes of each decision tree and its node score, which is used to judge the quality of decision making and optimize the calculation.

Since the objective function is difficult to solve at this time, the Taylor formula can be used for an approximate solution.

$$\mathcal{L}^{(t)} \simeq \sum_{i=1}^{n}\left[l\left(y_i, \hat{y}^{(t-1)}\right) + g_i f_t(X_i) + \frac{1}{2}h_i f_t^2(X_i)\right] + \Omega(f_t), \quad (19)$$

where g_i is the first partial derivative of l, h_i is the second-order partial derivative of l, and the expression is

$$g_i = \partial_{\hat{y}(t-1)} l\left(y_i, \hat{y}^{(t-1)}\right), h_i = \partial^2_{\hat{y}(t-1)} l\left(y_i, \hat{y}^{(t-1)}\right). \quad (20)$$

After removing the constant term in the objective function, the simplified approximate function is obtained.

$$\tilde{\mathcal{L}}^{(t)} = \sum_{i=1}^{n}\left[g_i f_t(X_i) + \frac{1}{2}h_i f_t^2(X_i)\right] + \Omega(f_t). \quad (21)$$

The previous formula is to calculate the loss for each sample x_i and then calculate the sum of all sample losses. The sample accumulation operation is converted into leaf nodes, and the sample set on each leaf node j is defined as $I_j = i|q(x_i) = j$.

$$\begin{aligned}
\Delta^{(t)} &\simeq \sum_{i=1}^{n}\left[g_i f_t(x_i) + \frac{1}{2}h_i f_t^2(x_i)\right] + \Omega(f_t), \\
&= \sum_{i=1}^{n}\left[g_i w_{q(x_i)} + \frac{1}{2}h_i, w_{q(x_i)}^2\right] + \gamma T + \lambda\frac{1}{2}\sum_{j=1}^{T} w_j^2, \\
&= \sum_{j=1}^{T}\left[\left(\sum_{i\in I_j} g_i\right)w_j + \frac{1}{2}\left(\sum_{i\in I_j} h_i\right)w_j^2\right] + \gamma T + \lambda\frac{1}{2}\sum_{j=1}^{T} w_j^2, \\
&= \sum_{j=1}^{T}\left[\left(\sum_{i\in I_j} g_i\right)w_j + \frac{1}{2}\left(\sum_{i\in I_j} h_i + \lambda\right)w_j^2\right] + \gamma T, \\
&= \sum_{j=1}^{T}\left[G_j w_j + \frac{1}{2}(H_i + \lambda)w_j^2\right] + \gamma T, \quad (22)
\end{aligned}$$

$$w_j^* = -\frac{G_j}{H_j + \lambda} = -\frac{\sum_{i\in I_j} g_i}{\sum_{i\in I_j} h_i + \lambda},$$

where w_j^* is the optimal solution of leaf weight. The optimal solution is brought into the objective function to obtain the optimal objective function.

$$\tilde{\Delta}^{(t)} = -\frac{1}{2}\sum_{j=1}^{T}\frac{G_j^2}{H_j + \lambda} + \gamma T = -\frac{1}{2}\sum_{j=1}^{T}\frac{\left(\sum_{i\in I_j} g_i\right)^2}{\sum_{i\in I_j} h_i + \lambda} + \gamma T. \quad (23)$$

Since the loss function is convex, the partial derivative of the objective function can be obtained to find the minimum value point in the interval, which represents the case of minimum loss. After calculation, the expression of $\min(L)$ of the minimum loss value is

$$\min(L) = -\frac{1}{2}\sum_{j=1}^{T}\frac{\left(\sum_{i\in I_j} g_i\right)^2}{\sum_{i\in I_j} h_i + \lambda} + \Upsilon T. \quad (24)$$

The formula is used to measure the quality of decision tree. Based on the given loss function, after pruning the decision tree, we observe whether the value of the loss function decreases to judge whether pruning should be performed.

The forward step-by-step algorithm is used for model optimization, and the objective function is

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t). \quad (25)$$

According to the XGBoost document, the equation is as follows: $f_t(x) = w_{q(x)}, w \in R^T, q\colon R^d \to \{1, 2, \ldots, T\}$.

$q(x)$ attributes the feature x to a specific leaf of the current tree t. $wq(x)$ is the current feature of the tree which is the score of t and the current feature of x.

In determining where each decision tree forks, the exact greedy algorithm is adopted.

$$\varpi = L_{\text{split}} = \frac{1}{2}\left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda}\right] - \gamma. \quad (26)$$

Here, ϖ means gain and represents split income $G_i = \sum_{i\in I_j} g_i, H_i = \sum_{i\in I_j} h_i$.

Since the exact greedy algorithm affects the calculation efficiency when the sample size is large, the approximate algorithm can be used. Global and local methods can be used to determine the split point.

Global indicates that the candidate splits are calculated before the spanning tree. This method does only one operation in the whole calculation process. The candidate segmentation points that have been calculated in advance are used in the subsequent node division; local calculates the candidate segmentation points only when each node is divided. Experiments show that if the two methods want to achieve the accuracy of approaching the exact greedy algorithm, we need to take more candidate segmentation points to improve the accuracy. Because local needs to be calculated every time the node is divided, in some cases, the amount of calculation is very close. The use of the two methods is also different, which is suitable for taking a large number of segmentation points; local is more suitable for deep tree structures.

In order to avoid the unreasonable definition of candidate cut points by simple statistical indicators, the weighted quantile sketch is introduced.

Dataset $D_k = \{(x_{1k}, h_1), (x_{2k}, h_2), \ldots, (x_{nk}, h_n)\}$ represents the set of the kth eigenvalue $(x_n k)$ and the second derivative $(h_n k)$ of each sample.

Ranking function $r_k(z) = \frac{1}{\sum_{(x,h)\in D_k} h}\sum_{(x,h)\in D_{k,x<z}} h$ indicates the proportion of the kth eigenvalue less than z in the dataset.

Then, candidate points are selected according to the following formula:

$$\left|r_k\left(s_{k,j}\right) - r_k\left(s_{k,j+1}\right)\right| < \varepsilon, s_{k1} = \min_i X_{ik}, s_{kl} = \max_i X_{ik}. \quad (27)$$

TABLE 3 Variable classification table.

Variable classification	Variable name
Ownership structure	State-owned equity ratio
	Shareholding ratio of top ten shareholders
	Separation rate of two rights
	Proportion of actual controller with control right of listed company
	Total remuneration of the top three management
	Shareholding ratio of management
Profitability	Proportion of minority shareholders' equity
	Return on equity
	Operating gross profit margin
	Return on assets (ROAs)
	Total asset net profit margin
Operation	Total asset turnover
	Growth rate of administrative expenses
Financial situation	Asset liability ratio
	Long-term debt ratio
Business performance	Proportion of profits from financial activities
	Retained earnings ratio
	Growth rate of main revenue
Solvency	Long-term capital liability ratio
	Ratio of long-term loans to total assets
Development capacity	Capital accumulation rate
	Growth rate of administrative expenses
	Net profit growth rate
Ratio structure	Cash asset ratio
	Ratio of working capital to current assets
	Proportion of net profit to comprehensive income
Other variables	Industry type
	Total assets

In terms of sparse values, the model can automatically learn the default division direction for the missing data. In each segmentation, the missing value is segmented to the left node and the right node. By calculating the score value and comparing which of the two segmentation methods is better, an optimal default segmentation direction will be learned for the missing value of each feature.

In a word, once the model is trained, the prediction simply boils down to identifying the correct leaves of each tree according to the characteristics and summarizing the value of each leaf, which becomes the most difficult part of the problem.

XGBoost is an optimal allocation gradient lifting program for efficiency, flexibility, and convenience. Based on gradient boosting, a machine learning method based on gradient boosting is completed. XGBoost provides a parallel tree structure (also known as GBDT, GBM) that can quickly and accurately deal with a large number of data science problems. XGBoost is an implementation of gradient lifting integration method for classification and regression problems. In this task, the sliding time window representation is used to make the time series dataset suitable for supervised learning.

3.7 Effect evaluation

The goodness of fit test of this model adopts the external data verification method; that is, the simulation test is carried out with the data not participating in the training in the sample data to verify the accuracy and stability of the model prediction. The data used to evaluate the link account for about 50% the total sample data.

TABLE 4 Classification of energy enterprises.

Classification	Industry
Traditional energy	Coal chemical industry
	Coal concept
	Fuel ethanol
	Natural gas
	Shale gas
	Energy conservation and environmental protection
	Energy saving lighting
New energy	Green power
	Wind power generation
	Photovoltaic concept
	Nuclear power
	Alkylene oxide
	Power exchange concept
Energy reserves	Fuel cell
	Lithium battery
	Sodium ion battery
	Graphite electrode
	Graphene
	Pumped storage
	Energy savings

After the XGBoost model is constructed, the model is scored with the data of the training set. Here, we need to pay attention to the scoring standard R^2. XGBregressor is used for the score. Since it is a regression model, the scoring standard of the regression model should be selected.

$$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=0}^{n_{\text{samples}}-1}(y_i - \hat{y}_l)^2}{\sum_{i=0}^{n_{\text{samples}}-1}(y_i - \bar{y}_l)^2}. \tag{28}$$

Under this scoring standard, when the model is better, $R^2 \to 1$ and when the model is worse, $R^2 \to 0$.

4 Experimental process

4.1 Data source

The data in this article are from the Guotai'an database. A total of 12,072 corresponding indicators of 1,084 Chinese energy enterprises from 2003 to 2021 are selected for analysis. The selected variables are shown in Table 3.

According to the industry type, energy companies are divided into traditional energy, new energy, and energy reserve according to the energy type. The specific classification is shown in the table as follows.

The data are preliminarily screened, and descriptive statistics are carried out. The software is SPSS. The descriptive statistics of the data is given in Table 4.

It can be seen from Table 5 that the minimum value of the core explanatory variable enterprise performance ROE is −28.2046, maximum value is 204.6869, mean value is 0.04, and standard deviation is 2.11727, indicating that there are individual outliers, but the overall volatility is small and the data are relatively concentrated. The difference between the maximum and minimum values of the equity ratio of SOEs, long-term debt ratio, total asset turnover rate, retained earnings ratio, and the equity ratio of the top ten shareholders is less than 10, and the standard deviation is less than 1, indicating that its numerical distribution is uniform and concentrated, with little fluctuation. For the normal operation of the model data, this article first removes the enterprises with state-owned equity ratio of 0 before regression and removes the extreme values of other control scalars.

4.2 Missing value supplement

The purpose of making up the missing values is to retain as much sample data as possible for the training of datasets. Once the missing values are not handled well, the analysis results may be unreliable and fail to achieve the purpose of analysis. However, not all data can be supplemented, and the supplemented data are not the real value of the data sample, but based on other existing fields, the missing field is predicted as the target variable, so as to obtain the most possible complement value.

For example, in Figure 1, in the missing value statistics, there are 1,283 missing data values of the variable "retained earnings rate," and the missing values of the variable are in the middle of the 18-year time span, which has a strong regularity. This depends on the nature of the variable itself. In terms of profit distribution, many enterprises distribute profits due to established strategies, in the development period or quota. Therefore, the index data will show the same value for many years, with strong regularity and in line with the continuity of time. Therefore, the k-value complement method can be used to supplement the data.

Thus, the sample data can be retained as much as possible to realize the full application of the sample data, so as to form a complete data record for subsequent data processing and analysis.

4.3 Word embedding

Word embedding for text types: The main idea of word embedding is to transform the text into a vector representation of lower-dimensional space. There are two important requirements for this transformed vector: lower-dimensional space and minimizing the sparsity of the encoded word vector. This article uses the BERT model for word embedding. The BERT model used in this article is shown in Figure 2.

4.4 PCA dimensionality reduction

The data obtained after word embedding are high-latitude data, so PCA is used for analysis. PCA is a common data analysis method, which is often used to reduce the dimension of high-dimensional

TABLE 5 Descriptive statistics.

	N	Min	Max	Mean value		Variance
	Statistics	Statistical value	Statistical value	Statistical value	Standard error value	Statistical value
Two-weight separation rate (%)	11571	−4.54	42.9311	4.905435	0.072431	60.704951
Return on equity	11965	−28.204643	204.689594	0.054139	0.019583	4.588664
Total assets	12069	0	2.73E+12	1.87E+10	9.00E+08	9.77E+21
Turnover rate of total assets	12058	0.000001	8.601021	0.611893	0.004158	0.20844
Asset liability ratio	12068	0.001725	178.345473	0.511475	0.015763	2.998402
Long-term debt ratio	12066	0	0.962461	0.195723	0.001753	0.037075
Growth rate of main business income	11585	−28.58916	3107.432182	1.111996	0.299991	1,042.588701
Retained earnings ratio	10786	−78.272724	1	0.685335	0.009888	1.054563
Return on assets A	12068	−29.288039	11.006162	0.041977	0.004077	0.200606
Operating gross margin	12061	−4.030042	0.991165	0.23568	0.001328	0.021281
Ratio of long-term borrowings to total assets	12068	0	0.729697	0.061888	0.000907	0.009933
Long-term capital liability ratio	12068	−63.470481	107.416845	0.169899	0.011032	1.468617
Capital accumulation rate	11977	−140.022595	56.256959	0.234004	0.015604	2.916331
Net profit growth rate	9897	−4541.72768	45174.35609	3.180794	4.649705	213970.6914
Growth rate of administrative expenses	11278	−3.85294	117.788749	0.217024	0.014245	2.288687
Return on assets A	12068	−29.288039	11.006162	0.041977	0.004077	0.200606
Return on total assets (ROAs) A	12068	−30.958697	10.400923	0.023135	0.004158	0.208691
Return on equity A	11965	−28.204643	204.689594	0.054168	0.019583	4.58866
Operating gross margin	12061	−4.030042	0.991165	0.23568	0.001328	0.021281
Proportion of control right of the listed company owned by the actual controller	11609	0	99.005	40.385572	0.150803	264.006052
Separation rate of two rights of the actual controller	11604	−49.4249	60.3231	4.898207	0.073583	62.828658
Total remuneration of the top three management	11993	0	6.61E+07	1.97E+06	2.01E+04	4.83E+12
Management shareholding ratio	11644	0	100	10.87922	0.173118	348.967633
Cash asset ratio	12051	−0.059826	71.545313	0.150407	0.006028	0.43792
Working capital to current assets ratio	12067	−491.839301	0.991409	−0.048636	0.068556	56.714714
Proportion of minority shareholders' equity	12068	−48.689484	2.254116	0.065877	0.004187	0.211597
Proportion of profits from financial activities	12069	−168.68566	169.066139	0.25977	0.032408	12.67588
Proportion of net profit and comprehensive income	9734	−186.28428	130.281312	0.953985	0.03128	9.523818
Number of effective cases (listed)	6842					

data, and can be used to extract the main feature components of data. For industry types, the pre trained BERT model is used to embed the text, and then, PCA is used to reduce the dimension.

PCA is essentially a lossy feature compression process, but it is expected to lose as little accuracy as possible and retain the most original information in the compression process. In this model, the variable "industry type" belongs to text variable, which cannot be quantified intuitively. Therefore, we build the BERT model to embed text words into the classified variable "industry type," so as to obtain a large number of high-dimensional data. PCA is used to reduce the dimension of the obtained high-dimensional data. Treatment results are given in Table 6. The corresponding scatter diagram is shown in Figure 3.

The data in the aforementioned chart represent the distribution of industries. The sign does not represent the advantages and disadvantages of the data, but reflects the distance of relevant

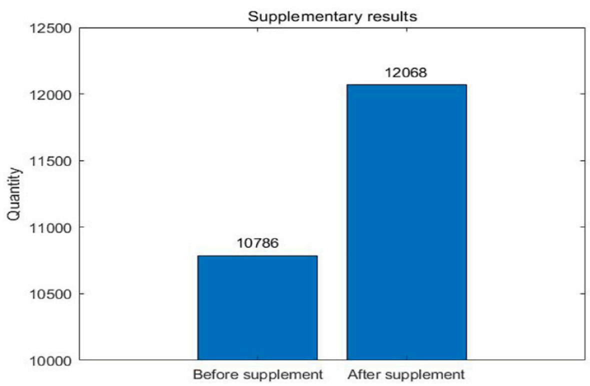

FIGURE 1
Supplementary effect drawing of retained earnings.

industries. The reason is that after extracting the more important components or key parts of the original data in this step, they are mapped to another space. At this time, the performance of the data is not directly related to the original data, so there are positive and negative situations. The original data are compressed and transformed in the original space and mapped to a new space. In essence, they are the original data, but the form of expression is different.

4.5 Data zoom

The multi-index comprehensive evaluation method is scientific and reasonable to evaluate things. It combines multiple indexes describing different aspects of a thing to get a comprehensive index and evaluates and compares the thing through it. Due to different properties, different evaluation indexes usually have different

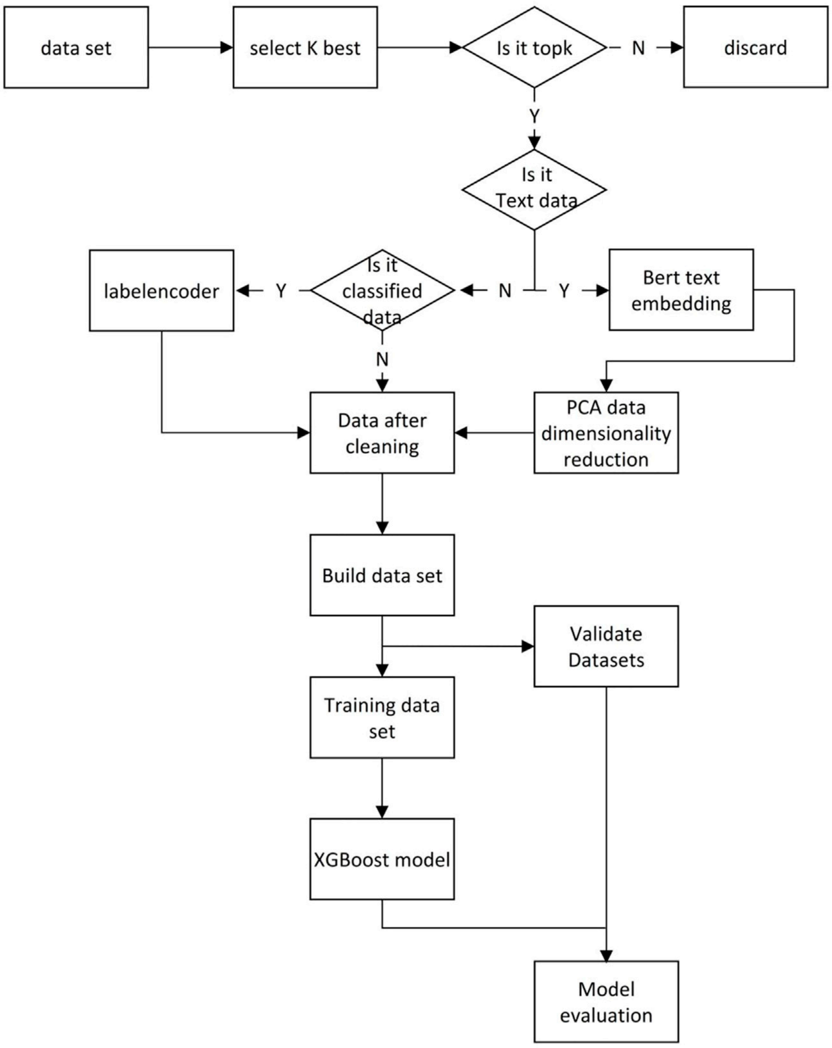

FIGURE 2
Flow chart of the BERT model.

TABLE 6 PCA data dimensionality reduction result.

Classification	Number	Name	PCA dimensionality reduction
Traditional energy	1	Coal chemical industry	−0.6997
	2	Coal concept	−0.7345
	3	Fuel ethanol	2.5851
	4	Natural gas	−0.0543
	5	Shale gas	−2.5140
	6	Energy conservation and environmental protection	1.5466
	7	Energy saving lighting	−2.9614
New energy	8	Green power	−0.9272
	9	Wind power generation	−0.1071
	10	PV concept	−1.2262
	11	Nuclear power	−0.5171
	12	Alkylene oxide	1.4380
	13	Power exchange concept	−1.1772
Energy reserves	14	Fuel cell	2.6068
	15	Lithium battery	−0.3903
	16	Sodium ion battery	1.4123
	17	Graphite electrode	−1.1713
	18	Graphene	−1.2262
	19	Pumped storage	−1.5915
	20	Energy savings	3.5715

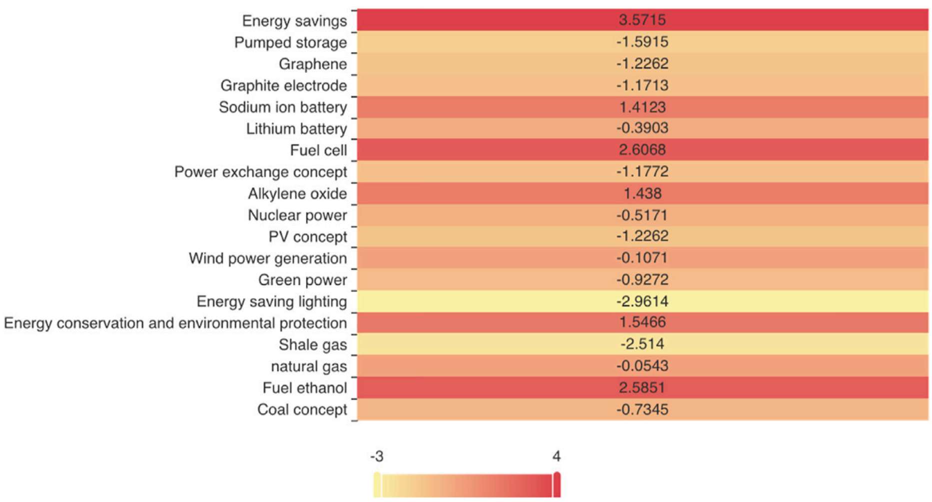

FIGURE 3
Scatter diagram of dimension reduction results of PCA.

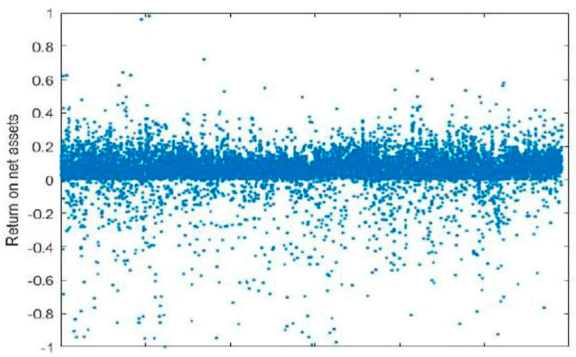

FIGURE 4
Scatter chart of return on equity scaling results.

TABLE 7 Statistical table of *p* value score.

Field	Score	*p* value
Separation rate of two rights	1.3276	7.97E-06
Long-term debt ratio	1.2905	4.86E-05
Growth rate of main revenue	7.7499	1.80E-136
Retained earnings ratio	7.7380	1.08E-08
Industry type	1.4507	1.08E-08
Growth rate of administrative expenses	1.3646	2.67E-04
Separation rate of two rights of actual controller	1.2533	2.67E-04
Total remuneration of the top three management	1.7982	5.14E-18
Shareholding ratio of management	1.7788	1.81E-17

dimensions and orders of magnitude. When the indexes differ greatly, if the original index value is directly used to calculate the comprehensive index, the role of the index with larger value in the analysis will be highlighted and the role of the index with smaller value in the analysis will be weakened.

Data scaling, in statistics, means that the original data are converted according to a certain proportion through a certain mathematical transformation method, and the data are placed in a small specific interval. The purpose is to eliminate the differences of characteristic attributes such as characteristics and quantity between different samples and convert them into a dimensionless reactive value. The characteristic quantity values of each sample are in the same order of magnitude.

As shown in Figure 4, after excluding the extreme value, this article scales the ROE to $[-1, 1]$. This step can not only further remove the extreme value and realize the prediction accuracy of the model but also eliminate the difference of dimension and order of magnitude between the evaluation indexes and ensure the reliability of the results.

4.6 Eigenvalue selection

Eigenvalue selection is very important. Some scholars believe that in most machine learning tasks, features determine the upper limit of model effect, and the selection and combination of models are only infinitely close to this upper limit.

Feature selection can reduce the number of features, prevent dimension disaster, and reduce training time. The generalization ability of the model is enhanced, and overfitting is reduced; the understanding of features and eigenvalues is enhanced. Specific data are given in Table 7. In this article, the eigenvalues are selected according to the *p* value, and the results are as shown in Figure 5.

The smaller the score in the aforementioned table, the better it can reflect the correlation between independent variables and dependent variables. Among the top ten of the aforementioned eigenvalues, the impact of equity specific factors is the first, which means that equity factors play an important role in the prediction of ROE.

It can be seen from the aforementioned table that the score of the two rights separation rate is the lowest, so the cash capital ratio has

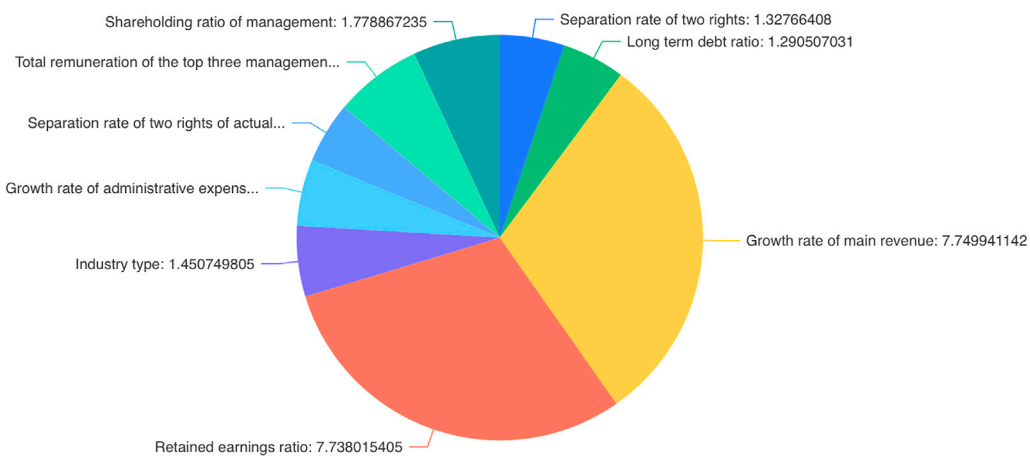

FIGURE 5
Variable score pie chart.

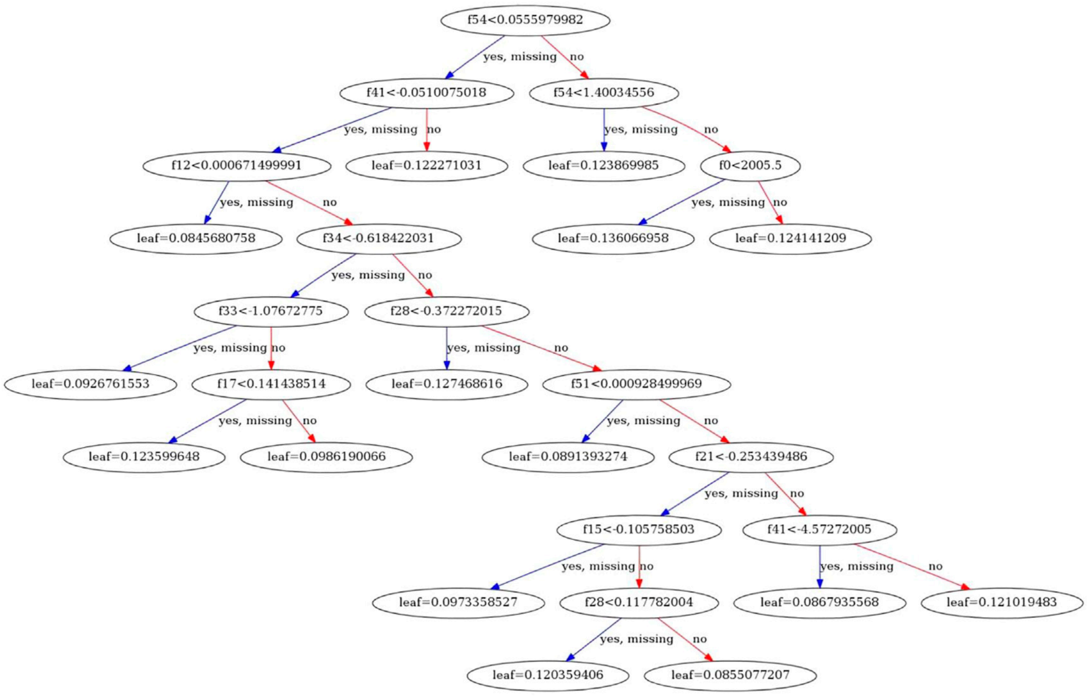

FIGURE 6
Schematic diagram of the XGBoost model.

TABLE 8 Model score comparison.

Model	R^2 score
XGBoost	0.9460
Decision tree regression model	0.9210
BP neural network model	−0.0071
Stochastic forest model	0.8610

the lowest impact on the ROE, and the two rights separation rate has the greatest impact on the ROE.

It can be seen from the aforementioned pie chart that the *p* value of the separation rate of the two rights is the highest, and the equity factors stand out among several other factors, which has the greatest impact on the prediction rate of the ROE.

4.7 Construction of the equity net asset return model

The ROE equity model is essentially the XGBoost model. XGBoost is a tree-based model. It can stack as many trees as possible, and each additional tree tries to reduce the errors of the previous tree set. The general idea is to combine many simple and weak predictors to build a powerful predictor.

After construction, the results of the equity net asset income model are as shown in Figure 6.

The model is the final result of the collection of multiple decision trees. The red line is the branch reduction direction of the decision tree, and the blue line is the decision direction of the decision tree.

4.8 Model evaluation

The goodness-of-fit test of this model adopts the external data verification method; that is, the simulation test is carried out with the data not participating in the training in the sample data to verify the accuracy and stability of the model prediction. The data used to evaluate the link account for about 50 percent of the total sample data.

After the XGBoost model is constructed, the model is scored with the data of the training set. Here, we need to pay attention to the scoring standard R^2. XGBregressor is used for score. Since it is a regression model, the scoring standard of the regression model should be selected. Under this scoring standard, when the model is better, $R^2 \rightarrow 1$ and when the model is worse, $R^2 \rightarrow 0$.

Finally, under this scoring standard, through the evaluation of the model, the final score of the model is

$$R^2 \text{ score} = 0.9460.$$

The score shows that the independent variable of this model has a good explanation for the dependent variable, so the ROE predicted 435 by this model is reliable.

4.9 Model comparison

After the previous experiments and conclusions, this section will now conduct comparative experiments and compare R2 scores of different machine learning model methods.

The datasets that have been processed are brought into the decision tree regression model, the BP neural network model, and the random forest regression model, and the R2 scores of each model operation are obtained as shown in Table 8, with the scores of 0.921, −0.0071, and 0.861. This value is less than 0.946 of the model R2 in our model. Therefore, among these models, the model built in this article has the highest accuracy.

5 Conclusion

Using the XGBoost model, this article constructs the net asset income model of energy enterprises based on the characteristics of ownership structure through missing value supplement, word embedding, PCA dimensionality reduction, and model evaluation. After evaluation, the data accuracy of the N + 1 year predicted by the model based on the data of the previous n years is about 95%, and the prediction effect is good.

Under the background of carbon neutralization and carbon peak, the operation status of energy enterprises is gradually remarkable. With the rapid development of energy enterprises, the ownership structure is becoming more and more complex. Taking energy enterprises as the research object and based on the XGBoost model, this article constructs the ROE equity model to realize the accurate, scientific, and timely prediction of the ROE and can reasonably modify and allocate the equity structure of energy enterprises through the predicted ROE, so as to play the role of prediction and early warning for the next business cycle of enterprises. The timeliness of the prediction of the ROE of this model can reasonably avoid the lag of the ROE and play a positive role in the equity planning and future development of energy enterprises.

At present, the relationship between equity and ROE generally tends to be inter-industry research, which is not subdivided into different types in a specific industry. In addition, the existing research is more inclined to analyze the existing results, that is, to analyze the connection in the existing data at a certain time node, which has a certain lag effect, which is caused by the lag of the ROE itself.

The aforementioned research ideas are not scientific in predicting the future business performance level, and the test cycle of the conclusions is long. To sum up, this article abstracts the problem into a multivariable time series problem by using the thought and method of deep learning, analyzes it under various indicators, scientifically and effectively predicts the operation effect of the next cycle in this business cycle, and modifies the equity proportion and rights by predicting the ROE, so as to achieve a more ideal and reasonable level.

ROE is the most important financial indicator in the business process of an enterprise, and it is also the benchmark to judge whether the business is healthy or not. Many enterprises hope to achieve the performance indicators, so the research on ROE has always been the favorite of different scientists. Based on XGBoost, this article uses missing value supplement, PCA dimensionality reduction, and the BERT model to process text information, uses the R^2 score method to evaluate the model, takes energy enterprises in multiple industries as samples to process and predict multivariate time series data, and adds comparative experiments. The experiment shows that the prediction accuracy of this model is higher than that of other machine learning models, and the dataset can be directly applied to this model after adding text variables, which increases the range of variables compared with other machine learning models, and can better predict the ROE of energy enterprises. In addition, this model is not only limited to predicting the ROE of energy enterprises but also applicable to other types of enterprises. Compared with the traditional regression model, this model has certain advantages, mainly focusing on two points: first, the focus is different. Traditional regression models pay more attention to the coefficient relationship between various indicators and ROE, that is, the change trend; the model in this article is more direct to get the predicted value, and the data are more secure because they come from a lot of learning. Second, the traditional regression model is not good at dealing with text information. This model takes this factor into account and is not bound by reasonable text variables. Third, the model proposed in this article has more advantages for processing large amounts of data and seeing the general changes of the whole industry.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Materials, further inquiries can be directed to the corresponding author.

Author contributions

YY: data analysis, writing, and formal analysis. ZW: validation and methodology.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The impact of product and process innovation on abandoning fossil fuel energy consumption in low and middle income countries: consent towards carbon neutrality

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The study used a sample of 43 low and middle-income countries for the time span of 14 years, i.e., from 2005 to 2018 with the objective to analyze the global fossil fuel market. The novelty of the study lies in its variable product and process innovation, study sample as well as the methodology adopted by the System GMM model. The fossil fuels demand in terms of Domestic material consumption of fossil fuel is regressed against 4 Energy and innovation, social and economic variables. The study employed System GMM model for estimation of results and FMOLS for robustness check. The results reveal that estimates for lag fossil fuels consumption, fossil fuel price and GDP are statistically significant and positive while estimates for patents are negative. The study suggests that low and middle income countries' Government should focus on product and process innovation as a critical element while structuring their policy for climate change mitigation.

KEYWORDS

fossil fuel, product and process innovation, carbon neutrality, low and middle income countries, system GMM

1 Introduction

The world is experiencing climate change at a drastic level. According to the (World Meteorological Organization 2019), 2014–2019 are the record hottest 5 years on earth. The root cause of global warming is CO2 emission from the burning of fossil fuels in the energy sector (Aziz et al., 2013; Ahmad et al., 2022). The world has acknowledged the fact that reduction in energy consumption (EC) is foremost important for climate change mitigation (Zaharia et al., 2019). In 2015 the United Nations introduced a sustainable development strategy "The 2030 Agenda". A set of 17 goals were documented for sustainable development among which number 7"Affordable and clean energy" directly referred to the energy sector. Since the industrial revolution, the use of carbon-intensive energy has put the planet further away from its climate goals thus policymakers shifted their focus to technological development and innovation in the energy sector as a remedy for the rapidly growing problem of CO2 emission (Grafström, 2017). As it is widely known that global warming has severe consequences, policymakers stress technological change in the field of renewable energy as one of the foremost solutions.

In this context, technology can bring hope for sustainable life on earth. It can be a source for overcoming most of the hardest challenges faced by our society, which can be climate change disease, and/or scarcity. Innovation is a powerful tool for advancing economic development and a better life for human beings (Schumpeter, 1942). The threat of climate change resulting from the increased use of energy and accumulation of large-scale greenhouse gases can be avoided through the development of advanced carbon-free technologies on a priority basis (Stern and Stern, 2007). Technology increases efficiency by increasing the level of production with a given amount of inputs as well as reducing the emission level. In other words, technology can comparatively lower the emission level of GHGs at the current consumption level or can increase the consumption level without altering the emission level of GHGs. (Del Río, 2004). According to the research conducted by (Choudhry et al., 2015), EC can be reduced by 10%–20% with operational improvement it can be further boosted up to 50% or more by investing in energy efficiency technologies. The development of low carbon or carbon-free technologies is one of the ways to limit the emission of GHGs and protect the climate (Stern and Stern, 2007). To achieve the goal of climate protection Governments are required to adopt a portfolio of policies to foster Technological innovation (TI) as well as the adoption of advanced technologies on a large scale at all levels including governments, firms, and individuals (Rubin, 2011). According to the report of the UN Economic and Social Council, there is significant progress in increasing renewable energy use in electricity. The renewable energy share in total EC increased from 16.4% in the year 2010% to 17.1% in the year 2018. The renewable energy capacity of developing countries increased by 7% over the year 2019. Thus, in the recent arena, most scientists are focusing on technologies as the most obvious solution toward carbon neutrality. Various firms and industries are investing in TI in all fields of life including energy, food and health.

Keeping in view the above discussion this paper aims at investigating the role of product and process innovation in fossil fuel demand. Since the world is transforming its energy sources from fossil fuel to low carbon energy it is a dire need to find out what role the product and process innovation play in moving the country toward a Carbon neutral nation. Nations are efficiently putting efforts to develop such technologies that can reduce fossil fuel usage and GHG emission from fossil fuels. There is an emerging trend of renewable energy which is a major substitute for fossil fuel energy. With an increasing demand for renewable energy or low carbon energy, a significant effect on the demand for fossil fuel energy. Most of the work done in earlier literature exposed several factors that have causal relationship with energy demand. To the best of the researcher knowledge product and process innovation has not been considered by the previous studies as an influencing factor for fossil fuel demand. The novelty of the study lies in its variable product and process innovation and study sample of 43 low and middle-income countries for 14 years, i.e., from 2005-to 2018 as well as the methodology adopted by the System GMM model. For a more detailed in-depth analysis, the study also conducted regional basis anatomy. The low and middle-income countries are divided into 6 regions to get more comprehensive results. The core objective of this study is a macroeconomic analysis of the fossil fuel market in LMICs. This study is in its true sense an evaluation step for finding out whether the efforts made by research development and innovation to reduce fossil fuel EC and climate change mitigation are successful or whether there exists any gap between the desired objectives and actual state. The results of the study will help policymakers, especially in low and middle-income countries to transform their energy sector or industrial sector and formulate policies for the industrial sector that contribute towards achieving the goal of carbon neutrality and thus improving the country's status in terms of carbon-neutral nation.

The remainder of the study is organized in the following manner. The review of previous literature is given in the second section, the third section describes the methodology adopted to achieve the objectives of the study fourth section provides the results and discussion over the finding of the study at the last recommendations suggested by the authors are narrated.

2 Literature

Analysis of previous literature for this study can be classified into two categories. Firstly, the work done in the field of energy demand is analyzed and secondly, the role of innovation in energy demand is discussed.

2.1 Literature in the field of energy demand

Among the earlier studies, (Pesaran et al., 1998), pointed out that one of the extensively researched areas in the field of energy economics has been the estimation of energy demand. The accurate estimate for energy demand is the key input for future analysis of EC and policy making. Energy demand estimation is popular due to its wide range of applications for important policy issues in the energy sector (Barker et al., 1995). Using the panel data set for the period 1998–2008 (Chaudry, 2010) attempted to estimate energy demand in Pakistan at the firm and economic levels. His findings showed a positive significant relation between income and electricity demand while a negative relationship between price and electricity demand. A significant relationship between income variation and EC is found by (Asafu-Adjaye, 2000) for India, Indonesia, the Philippines, and Thailand. Similarly, (Aqeel and Butt, 2001), stated that there is a significant positive impact of a country's economic growth on the level of petroleum consumption of a country. Ahmad, et al. (2021) found a significantly positive relationship between economic progress and intensity of energy use. Rehman et al., 2021 and Khan et al. (2021) found a constructive linkage between ecological footprint and trade, globalization and GDP growth for Pakistan. Dagar et al., 2022 found that industrial production, total reserve and financial development adversely affect environment in case of OECD countries. Cao et al., 2022 found stock market, financial development, economic growth and electricity consumption all contribute to the emission of carbon dioxide in OECD countries in long as well as in short run. In the study conducted by (Mielnik and Goldemberg, 2002) a sample of 20 developing countries was taken for investigating the role of financial development on energy intensity. Financial development was measured through FDI and found to have a significant negative relation with energy intensity. Çoban and Topcu, (2013) used financial development, energy prices, and economic progress as influencing variables to study EC for EU27 countries. Their results revealed that for old member countries with a higher level of financial development there is an increasing trend of EC as compared to the new member countries with the less developed financial system; Rehman et al., 2022 studied Pakistan economy and found that economic progress of Pakistan is significantly and positively related with fossil fuel energy, GDP *per capita*, renewable energy usage and CO2 emission; Wang et al. (2019) used panel data on 186 countries for analyzing the impact of GDP, energy prices, and urbanization on EC between the years 1980–2015. The finding revealed an inverse relationship between energy prices and EC in low-and medium-income countries; Gorus & Aydin, (2019) investigated eight MENA countries for the existence of causal relationship between economic growth, energy consumption and carbon dioxide emission for the period 1975–2014. They found no casual relation between economic growth and CO2 emission and recommended conservation policies for these countries; Aydin, M. (2019) found bidirectional causality between non-renewable electricity consumption and economic growth for 26 OECD countries; Noor et al. (2023) found a negative effect of nonrenewable energy on sustainable development; Aydin, M. (2018) found a significantly positive long run relationship between natural gas consumption and economic growth for top 10 natural gas–consuming countries from 1994 to 2015; Zaharia et al. (2019) assessed the energy determinants for (EU28) intending to achieve sustainability in the energy sector. The study covered various aspects of sustainable development including social, economic, and environmental aspects. According to the results GHG emissions, GDP, oil prices, research and development expenditure, labor growth, and population are positively related to EC while feminine population increase, energy taxes, and expenditure on healthcare have a negative relation with EC.

2.2 Literature on role of innovation in energy demand

In recent times many countries of the world and organizations have committed terms of their contribution to the elimination of GHGs emissions. It has focused on the almost complete conversion of the energy system in at least 3 decades. With the help of innovation, the world is transforming archaic technologies in the energy sector into clean energy technologies. Innovations in the energy sector make electrical power a more reliable source of energy as well as provide solutions that are more consumer-oriented with more distributed resources. This attracts new investors to the market which puts more pressure on product and process innovation. Product innovation refers to the execution of a good or service that has significantly better features or desired uses (Oslo Manual §156). On the other hand, process innovation refers to the execution of significantly improved and new methods of production and/or delivery (Oslo Manual §163).

In their study of the Chinese economy Jin and Zahng (2014) evidence the role of TI in reducing fossil fuel consumption and environmental quality improvement. Investigating the nexus between fossil fuel-powered electricity usage and innovation Fei and Rasiah (2014) revealed that the TI is found insignificant in influencing the level of electricity consumption. Investigating the manufacturing industry of India Dasgupta and Roy (2015) concluded that technological progress will lead to reducing energy usage by inducing the efficiency of energy input. Murshed et al., 2022 found that in case of Argentina economy, technological innovation is accounted as indispensable to curb CO_2 emission. According to a study by Karali et al. (2017) technological learning is expected to reduce the EC of the US iron and steel sector by 13% in 2050. In the study by Tang and Tan (2013) the nexus between electricity consumption, TI, energy prices, and economic growth is studied for Malaysia. The results revealed that TI Granger causes the consumption of electricity in Malaysia and has negatively related to electricity consumption. Irandoust (2016) studied the relationship between renewable EC, economic growth, TI, and CO2 emission and found that TI Granger causes renewable EC and leads to reduce the CO2 emission. Aflaki et al. (2014) found that TI positively relates to renewable energy diffusion. Sohag et al. (2015) used time series data from 1980 to 2012 for the Malaysian economy to empirically investigate the impact of TI on energy usage along with control variables, i.e., Trade openness, GDP *per capita*, and energy prices. The results revealed that TI can reduce the EC. Du and Yan (2009) studied the relationship between TI capacity and EC and found that TI capacity is inversely related to EC. Improvement in the TI can lead to reducing EC intensity. Table 1 report different studies done in this area with author names, year of publication, date range for the study, the methodology adopted and the major outcomes of each study.

Most of the work done in energy demand analysis focused on the different determinants of EC. However, to the best of the researcher's knowledge, it can be considered that this study is the first in its contribution to the literature for assessing the impact of product and process innovation on fossil fuels consumption in 43 low and middle-income countries.

3 Methodology

The intention of the researcher in this study is to find out what role did the product and process innovation played so far in the demand for fossil fuel throughout the LMICs. For the analysis, this study used balanced panel data for 43 LMICs for the time span of 14 years, i.e., from 2005 to 2018 from 6 regions.

3.1 Data and variables of the study

This study conducts the macroeconomic analysis of the fossil fuel market using balanced panel data for 43 LMICs. The categorization of LMICs is purely based on World Bank (2021) classification. The selection of 43 countries is based on the availability of data. Table 2 provides the detail for the selected countries from 6 different regions for analysis. The regional classification of the countries is purely based on World Bank regional (2021) classification.

The study used fossil fuel consumption as the dependent variable to be studied. The data is obtained from (IRP)

TABLE 1 **Overview of Literature.**

Author(s) and year of publication	Data range	Methodology	Outcomes
Chaudry, (2010)	1998–2008	Fixed effects estimation	Positive significant relation between income and electricity demand while a negative relationship between price and electricity demand
Asafu-Adjaye, (2000)	1971–1995	Co-integration and error-correction modeling techniques	Significant relationship between income variation and EC
Aqeel and Butt, (2001)	1955–1956 to 1995–1996	Co-integration and Hsiao's version of Granger causality	Significant positive impact of economic growth on the level of petroleum consumption
Ahmad, et al. (2021)	2000–2018	A dynamic common correlated effects mean group approach	Significantly positive relationship between economic progress and intensity of energy use
Rehman et al. (2021)	1980–2020	ARDL	Constructive linkage between ecological footprint and trade, globalization and GDP growth
Dagar et al. (2022)	1995–2019	Dynamic panel data models	Industrial production, total reserve and financial development adversely affect environment in case of OECD countries
Cao et al. (2022)	1985–2018	pooled mean group (PMG)	Stock market, financial development, economic growth and electricity consumption all contribute to the emission of carbon dioxide in OECD
Çoban and Topcu, (2013)	1990–2011	system-GMM model	Significant and positive relation between EC and financial development
Rehman et al. (2022)	1975–2019	Linear autoregressive distributed lag technique	Significant and positive relation of economic growth with fossil fuel energy, GDP *per capita*, renewable energy usage and CO2 emission
Wang et al. (2019)	1980–2015	Granger causality test approach and the impulse response function analysis	An inverse relationship between energy prices and EC
Zaharia et al. (2019)	1995–2014	Panel data techniques	GHG emissions, GDP, oil prices, research and development expenditure, labor growth, and population are positively related to EC while feminine population increase, energy taxes, and expenditure on healthcare have a negative relation with EC.
Fei and Rasiah (2014)	1974–2011	ARDL and VECM	the TI is found insignificant in influencing the level of electricity consumption
Murshed et al. (2022)	1971–2014	ARDL	Technological innovation is accounted as indispensable to curb CO2 emission
Tang and Tan (2013)	1970–2009	Bounds testing approach and The Granger causality test	Negative relation between TI and energy consumption

International resource panel by the UN Environment Program database. The data on Domestic material consumption of fossil fuel is estimated as (DMC = domestic extraction + imports–exports). To analyze the global fossil fuel market the Economic, social, Energy, and innovation variables are included in the study as influencing factors of fossil fuel consumption. The selection of variables is based on literature support. Data on the Fossil fuel price is obtained from the World Economic Outlook database in October 2021. This includes Curd oil, Natural gas, and coal price indices for the entire world. Data on GDP at constant 2015 US $ and population are obtained from World Bank and OECD National Accounts database (2021). A detailed description of the variables is given in Table 3.

3.2 Significance of the Variables and Hypothesis of the study

The instability of the energy prices in international market is another major concern in study of energy demand. Low- and middle-income countries are expected to suffer more as compared to high income countries from energy price volatility, because a large share of their national product depends on energy intensive manufacturing and the use of energy in low- and middle-income countries is less efficient (Aziz et al., 2013). Thus, price is important variable in predicting, explaining and modeling demand for energy. The first hypothesis of the study is that Fossil fuel price is significantly related with fossil fuel energy consumption. The excessive use of traditional energy resource (oil, gas, and coal) results in serious health, social and environmental issues. The use of product and process innovation helps in reducing the dependence on fossil fuels and puts positive impact on sustainable development of the economy. The second hypothesis of the study is that product and process innovation is expected to have a negative relation with fossil fuel energy consumption thus contributing positively to abandoning the fossil fuel energy demand and mitigating the climate change effect. Research and development expenditure has been extensively used as a proxy for innovation in previous literature (Mancusi & Vezzulli, 2010; Lööf & Nabavi, 2016). Recent literature, however, has questioned the suitability of research and development

TABLE 2 List of countries by region.

East Asia and Pacific		Latin America & Caribbean		Europe & Central Asia		South Asia		Middle East & North Africa		Sub-Saharan Africa	
#	Countries	#	Countries	#	Countries	#	Countries	#	Countries	#	Countries
1	China	1	Argentina	1	Armenia	1	India	1	Algeria	1	Zimbabwe
2	Indonesia	2	Brazil	2	Kazakhstan	2	Pakistan	2	Tunisia	2	Nigeria
3	Malaysia	3	Colombia	3	Moldova	3	Sri Lanka	3	Iran	3	South Africa
4	Mongolia	4	Cuba	4	Belarus			4	Lebanon	4	Kenya
5	Philippines	5	Ecuador	5	Georgia			5	Jordan		
6	Thailand	6	El Salvador	6	Bulgaria			6	Morocco		
		7	Guatemala	7	Bosnia and Herzegovina			7	Egypt		
		8	Jamaica	8	North Macedonia						
		9	Mexico	9	Romania						
		10	Peru	10	Russian Federation						
				11	Turkey						
				12	Ukraine						
				13	Uzbekistan						

Note: World Bank.

TABLE 3 Description of variables.

Variable	Description	Source of data	URL
FF	Fossil fuel energy consumption in tones	(IRP) International resource panel by the UN Environment Program database (2022)	https://www.resourcepanel.org/global-material-flows-database
FPI	Fossil Fuel price	World Economic outlook database October 2021	https://www.imf.org/en/Publications/WEO/weo-database/2021/October/download-entire-database
PT	Patent as a proxy for product and process innovation measured in total numbers of EPO application	OECD patent statistics (2022)	https://doi.org/10.1787/data-00508-en
GDP	GDP at constant 2015 US $ in billions	World Bank and OECD National Accounts database (2021)	https://data.worldbank.org/indicator/NY.GDP.MKTP.KD
POP	Population in millions	World Bank and OECD National Accounts database (2021)	https://data.worldbank.org/indicator/SP.POP.TOTL

spending as a proxy for innovation on various grounds when studying small firms and emerging markets. According to Gorodnichenko & Schnitzer, (2013), the use of research and development measures is favorable for large firms moreover research and development do not always result in innovation as it is input rather than output oriented. This study uses patent counts as a proxy for innovation as it provides robust statistical evidence of technical progress. Patents follow an international standardized format (Rübbelke and Weiss, 2011). Approval of a patent application requires the investor to show the public something that is 'novel', 'useful', and 'obscure' which is not possible without an innovative step. A patent application must meet these criteria to get approved (Griliches, 1987; Hall and Ziedonis, 2001). Patent information is the best available source for analyzing innovation. (Grafström, 2017). According to Griliches (1998) "nothing else comes close in the quantity of available data, accessibility and the potential industrial-organizational and technological details". Thus, current study uses patent information as a proxy for product and process innovation. Energy is a vital source that makes the world goes around. The ability of the economy to harness the energy resources for production process results in economic growth and development. According to the economic theory, output results from energy consumption directly or indirectly. The growing economies therefore consume more and more energy resources. Thus, the key factor for increased demand of energy is economic growth and development (Zahg et al., 2012: Lee and Chang, 2008; Apergis and Payne, 2009; Ouedraogo, 2013). So, the third hypothesis of the study is that GDP has a positive relationship with fossil fuel energy consumption. Another important determinant of energy consumption is ever growing population of low- and middle-income countries and the resulting demand for food, products and transportation. All such activities require a huge level of energy sources depletion. (Zaman et al., 2016; Khan et al., 2019; Dokas et al., 2022). The fourth hypothesis of the study is that population is positively related with fossil fuel energy consumption. Thus, GDP and Population are putting an adverse effect on reducing fossil fuel energy consumption.

To achieve the objective of empirically investigating the effect of product and process innovation along with control variables, i.e., Fossil fuel price, GDP and population on the demand for fossil fuel in 43 LMICs around the world is assessed. The following equation is designed for estimation:

$$FF_{it} = f\,(FPI_{it}, PT_{it}, GDP_{it}, POP_{it}) \tag{1}$$

Where FF denotes Fossil fuel consumption, FPI denotes Fossil fuel price, PT denotes patents count, GDP denotes gross domestic product, PP denotes population.

The selection of an appropriate technique for analysis is the key factor in any type of research. The traditional method of estimation such as OLS, GLS, maximum likelihood method, instrumental variable method cannot deal with the endogenous problems caused by the inclusion of lag dependent variable into the explanatory variables and leads to falsifying results. The GMM method is capable of dealing with heteroscedasticity and sequence-related problems and provides more efficient estimates relative to other methods. To estimate the given equation, this study employs the System GMM model as it has several advantages over other alternate techniques of estimation. Arellano and Bover (1995) and Blundell and Bond (1998) proposed this model. System GMM deals with.

- Country specific effect on time invariant variables
- Endogeneity problem when using lagged dependent variable
- Hetroscedasticity and autocorrelation problems

Moreover, this model allows for endogeneity in other regressors up to certain degree it also manages unbalanced panel data. (Harris & Mátyás, 2004), (Nickell, 1981), (Roodman, 2009), (Hsiao, 2022). Previous studies such Rasheed also used this model et al. (2022) and Khan et al. (2023).

The general equation of System GMM model is given as:

$$Y_{it} = \alpha Y_{it(-1)} + \beta X_{it} + \mu_{it} \tag{2}$$

$$\mu_{it} = \varnothing_i + \nu_{it} \tag{3}$$

In above equation X_{it} denotes all the explanatory variables of the model, µit denotes disturbance term. ε_i represents fixed effect and υ_{it} is unusual shocks having an error component structure as given

$$E(\text{øi}) = 0. \tag{4}$$

$$E(\upsilon_{it}) = 0 \tag{5}$$

$$E(\text{ø}_i\ \upsilon_{it}) = 0 \quad \therefore i = 1, \ldots, n \text{ and } t = 2, \ldots, T \tag{6}$$

$$E(\upsilon_{it}, \upsilon_{is}) = 0 \quad \text{for } i = 1 \ldots, n \text{ and } t \neq s \tag{7}$$

From the initial conditions

$$E\,(Y_{i1}\ \upsilon_{it}) = O \quad \text{for every } t \geq 2 \tag{8}$$

And $E\,(\text{ø}_i\ \Delta Y_{i2}) = 0$.

The linear moment conditions under the assumptions are

$$E(Y_{i,t-s,}\Delta\mu_{it}) = 0 \quad \text{for all } t \geq 3, s \geq 2 \tag{9}$$

$$E(\mu_{it}\Delta Y_{i,t-1}) = 0 \quad \text{for all } t \geq 3 \tag{10}$$

To ensure the consistency of the system GMM estimator the problem of over-identification, that is, the restriction that the model instruments are exogenous to the group is evaluated using Hansen J Statistics, (Hansen, 2005), moreover Arellano-Bond test for serial correlation in error term is employed to analyze the AR (1) and AR (2) autocorrelations.

The dynamic panel data model for the study is specified by following equation

$$\begin{aligned} ln\,FF_{it} = \beta_0 + \beta_1\, lnFF_{it-1} + \beta_2\, Ln\,FPI_{it} + \beta_3\, Ln\,PT_{it} + \beta_4\, Ln\,GDP_{it} \\ + \beta_5\, Ln\,POP_{it} + \varepsilon_{it} \end{aligned} \tag{11}$$

Where $\ln FF_{it}$ is the log of fossil fuel consumption, $\ln FF_{i,t-1}$ Shows the lagged value of fossil fuel consumption, βs are the parameters to be estimated, Z_i and ε_{it} represent country specific effect and disturbance term respectively and are independent with identical distributions ($Zi \approx IID\ (0,\ \delta_z^2)$), ($\varepsilon_{it} \approx IID\ (0,\ \delta_\varepsilon^2)$).

Fully Modified OLS (FMOLS) technique is applied for ensuring the robustness of the model.

4 Results and discussions

Table 4 presents the summary statistics of the variables used for the analysis. In total five variables are used including fossil fuel energy consumption, Patents, Fossil fuel price, GDP, and population. For descriptive analysis of Fossil fuel energy consumption is measured in kilotons. GDP is measured in constant 2015 US $ in billions and population is measured as the total number of residents in millions. Patents are estimated as total EPO applications. The data is analyzed for 43 LMICs from East Asia, Latin America, Europe, South Asia, the Middle East, and Sub-Saharan Africa based on World Bank regional classification. According to the results, East Asia and the Pacific have the highest average consumption of fossil fuels (698720.02) followed by South Asia, Europe & Central Asia, Sub-Saharan Africa, and the Middle East respectively. However, Latin America is the lowest average consumer of fossil fuel energy (40277.40).

According to the data on GDP East Asia and the Pacific are categorized as the highest GDP generator economy (1721.170 US$) followed by South Asia, Latin America, Europe, Sub-Saharan Africa, and the Middle East respectively. According to the data in terms of population, South Asia is the most populated region (486.988) followed by East Asia, Sub-Saharan Africa, Latin America, the

TABLE 4 Summary statistics.

Region		Min	Max	Mean	SD
East Asia & Pacific	FF	5427000	4510930136	698720021.05	1420902159.1
	FPI	100.000	234.787	173.244	45.558
	PT	.1000	29958.8926	2545.259421	6413.2338112
	GDP	5.225	13493.418	1721.170	3353.818
	POP	2.526	1402.760	299.079	480.347
Latin America & Caribbean	FF	450000	160544647	40277396.01	52933873.132
	FPI	100.000	234.787	173.244	45.558
	PT	.0769	446.3588	65.657965	115.4728649
	GDP	13.739	1868.463	399.018	537.547
	POP	2.740	209.469	48.201	59.388
Europe & Central Asia	FF	785925	835341258	103198488.18	201061688.76
	FPI	100.000	234.787	173.244	45.558
	PT	.1000	805.9026	71.328987	148.8520529
	GDP	5.507	1430.115	204.179	369.863
	POP	2.036	144.496	27.630	39.246
South Asia	FF	1927100	1,311,543,674	336270628.17	463223274.96
	FPI	100.000	234.787	173.244	45.558
	PT	1.2500	2246.3872	488.762786	755.0574007
	GDP	43.875	2590.898	681.784	804.399
	POP	19.544	1352.642	486.988	555.060
Middle East & North Africa	FF	200000	251206927	50871791.59	69330206.246
	FPI	100.000	234.787	173.244	45.558
	PT	.1667	132.0333	8.586	13.484
	GDP	25.029	525.476	152.335	136.639
	POP	4.698	98.423	36.915	30.628
Sub-Saharan Africa	FF	891830	227199598	56958542.59	88786823.809
	FPI	100.000	234.787	173.244	45.558
	PT	.1000	203.902	42.172	73.0763
	GDP	10.517	492.074	199.827	170.995
	POP	12.076	195.874	68.872	59.192

Sources: World Economic outlook database October 2021, World Bank and OECD, national accounts database; OECD, patent statistics (2022).

Middle East, and Europe, respectively. The analysis revealed that East Asia and the Pacific have on average the highest numbers of patent applications filed at EPO (2545.26) followed by South Asia, Europe, Latin America, Sub-Saharan Africa, and the Middle East, respectively.

The objective of this study is to find out what role product and process innovation play in the demand for fossil fuels in LMICs around the world. To achieve the objective fossil fuels demand in terms of Domestic material consumption of fossil fuel is regressed against 4 Energy and innovation, social and economic variables. The study employed the System GMM model for the estimation of results.

Table 5 presents the results of System GMM estimation. From the Hansen J Statistics, (Hansen, 2005), the null hypothesis of validity of instruments is not rejected so the System GMM estimator is proved to be consistent. The results confirm that AR (1) is present and AR (2) is absent in the data. The results reveal that estimates for lag fossil fuels consumption, fossil fuel price, and GDP are statistically significant and positive with values of (0.602), (0.055) and (0.213) respectively at 1% significance level while estimates for patents and population are

TABLE 5 Estimation results of System GMM model.

Variable	Coefficient	Std. Error	Prob
LFF(-1)	0.602	0.007	<0.01
LFPI	0.055	0.003	<0.01
LPT	−0.005	0.001	<0.01
LGDP	0.213	0.013	<0.01
LPOP	0.025	0.038	0.50
Mean dependent var	−0.037	S.D. dependent var	0.201
S.E. of regression	0.150	Sum squared resid	11.636
J-statistic	39.82	Instrument rank	44
Prob(J-statistic)	0.433	AR (1) (sig-value)	0.0002
		AR (2) (sig-value)	0.7542

Authors own calculation.

negative. According to the results lag fossil fuel domestic consumption has a significantly positive impact on fossil fuels' current consumption. It means the higher the consumption of fossil fuels in the previous period will significantly increase the consumption of fossil fuels in the current period. Contrary to the first research hypothesis a unique relation between fossil fuels price and fossil fuel consumption is evidenced which shows an increase in fossil fuels price will increase fossil fuels consumption. These results are in line with the study by Zaharia et al. (2019) who found a positive relationship between oil price and primary EC for EU countries, and a study by Phoumin & Kimura (2014) who found a positive price elasticity of demand for energy in China. This may be justified by the phenomenon that LMICs have an energy-intensive industrial sector thus for economic growth such industries need more energy and the price of energy continues to increase. Moreover, it is well known that energy is the basic material for growth and development therefore its demand is rigid (Saidi and Hammami, 2015). In the global energy system, fossil fuel still has and continues to play a dominant role. Thus, increase in the prices will not significantly reduce fossil fuel energy consumption.

According to the results, LMICs with high patent rates are found to have low fossil fuel consumption levels. This means that product and process innovation can lead to the abounding fossil fuel demand in the case of LMICs. Thus, the second hypothesis of the study that there is a negative relationship between product and process innovation and fossil fuel energy consumption was accepted. These results are supported by the studies of Jin and Zahng (2014), Karali et al. (2017), and Sohag et al. (2015). Improved technology usage at all stages of production and distribution allows higher efficiency of energy input. With product and process, innovation energy usage reduces at the current level of output or increases the level of production without altering the energy usage level. Improved energy efficiency due to product and process innovation reduces the EC intensity resulting in lower energy imports.

The results also show that countries with high GDPs consume more fossil fuels. The results show a positive relationship between GDP and fossil fuel energy consumption which can be interpreted as putting a negative effect on abandoning fossil fuel energy consumption. Hence the third hypothesis of the study that there is a positive relationship between GDP and fossil fuel energy consumption is accepted. These results are also supported by Zaharia et al. (2019) who found the same relationship for EU countries and with the studies by Ottelin et al.

TABLE 6 Estimation Results of System GMM on regional basis.

Variables	East Asia & Pacific	Latin America & Caribbean	Europe & Central Asia	South Asia	Middle East & North Africa	Sub-Saharan Africa
LFF(-1)	0.246*	0.612*	0.975*	0.608*	0.535*	0.411*
LFPI	0.065**	0.066*	0.041*	0.050	0.052*	0.209**
LPT	−0.022**	−0.004**	−0.002*	−0.043**	−0.0017*	−0.024
LGDP	0.851*	−0.291*	0.023*	0.404***	0.311*	0.418**
LPOP	0.215	1.266*	0.006*	0.220	0.268*	−0.767
Statistical tests						
Mean dependent var	0.041	−0.0043	15.581	−0.193	−0.046	0.035
S.E. of regression	0.153	0.209	0.105	0.076	0.105	0.217
S.D. dependent var	0.158	0.269	1.799	0.134	0.125	0.243
Sum squared resid	1.570	5.051	1.819	0.180	0.871	2.042
Instrument rank	45	44	46	45	46	45
Prob.(J-statistic)	0.34	0.59	0.37	0.62	0.31	0.29
AR(1) (Sig-value)	0.02	0.01	0.01	0.02	0.01	0.03
AR(2) (Sig-Value)	0.45	0.26	0.28	0.38	0.49	0.34

Authors own calculation, * 1%, ** 5% and *** 10% level of significance respectively.

TABLE 7 Estimation results of FMOLS.

Variable	Combine	East Asia & Pacific	Latin America & Caribbean	Europe & Central Asia	South Asia	Middle East & North Africa	Sub-Saharan Africa
LFPI	0.442**	0.723*	0.548**	0.106*	0.640*	2.278**	2.468*
LPT	−0.080**	−1.084*	−2.175*	−0.028**	−0.889**	−0.747*	−1.738*
LGDP	0.305*	0.598**	−1.387**	0.357*	1.167*	1.106*	1.207**
LPOP	0.396	0.874	2.311***	0.580**	0.474847	0.754	1.579
Statistical tests							
R-squared	0.987	0.870	0.818	0.995	0.950	0.879	0.844
Adjusted R-squared	0.986	0.853	0.974	0.994	0.941	0.864	0.831
S.E. of regression	0.245	0.724	0.806	0.140	0.590	0.767	0.624
Long-run variance	0.013	0.010	0.020	0.008	0.004	0.007	0.023
Mean dependent var	16.897	18.488	16.215	16.993	17.725	16.379	16.160
S.D. dependent var	2.130	1.892	1.901	1.954	2.433	2.085	1.956
Sum squared resid	30.801	35.687	37.419	32.986	31.150	47.143	36.134

Authors own calculation, * 1%, ** 5% and *** 10% level of significance respectively.

(2018), Lenzen et al. (2006), and Wiedenhofer et al. (2017). Our findings show a positive relationship between the population of a country and fossil fuel consumption for that country over time. Although the results are according to the theory, however these results are not statistically significant. Thus, based on insignificant results the fourth hypothesis of the study that there is a positive relationship between Population of a country and fossil fuel energy consumption is rejected for low- and middle-income countries under consideration. These results are supported by Dokas et al. (2022) who found insignificant relationship between population growth and electricity consumption.

Table 6 shows the results of System GMM on a regional basis. The GMM estimators are found to be consistent for all the regions. Moreover, the presence of AR (1) is confirmed for all the regions and AR (2) is found absent from the data for all regions. The results show that lag fossil fuel domestic consumption has a significantly positive effect on current fossil fuel domestic consumption for all the regions under consideration with a value of (0.246)for East Asia & Pacific, (0.612) for Latin America & Caribbean, (0.975) for Europe & Central Asia, (0.608) for South Asia, (0.535) for Middle East & North Africa and (0.411) for Sub-Saharan Africa. Fossil fuel price is found to be significantly positive for East Asia & Pacific (0.065), Latin America & Caribbean (0.066), Europe & Central Asia (0.041), Sub-Saharan Africa (0.209), Middle East & North Africa (0.052) (Phoumin, & Kimura, 2014; Zaharia et al., 2019) and insignificant for South Asia (0.050). The variable patent has significantly negative results for all regions (Jin and Zahng, 2014; Karali et al., 2017; Sohag et al., 2015; Murshed et al., 2022) while insignificant for Sub-Saharan Africa with the values of (−0.022), (−0.004), (−0.002), (−0.043), (−0.0017), (−0.024) respectively. According to the results GDP is statistically significant and positive for all regions (Lenzen et al., 2006; Wiedenhofer et al., 2017; Ottelin et al., 2018; Rehman et al., 2021; Rehman et al., 2022) with values of (0.851) for East Asia & Pacific, (0.023) for Europe & Central Asia, (0.404) for South Asia, (0.311) for Middle East & North Africa, (0.418) for Sub-Saharan Africa except for Latin America & Caribbean where it is significantly negative (−0.291). The results of the population are significantly positive for Latin America and the Caribbean (1.266), Europe & Central Asia (0.006), and Middle East & North Africa (0.268) at 1% significance level (Dokas et al., 2022). However, for East Asia & Pacific, South Asia, and Sub-Saharan Africa it is found to be insignificant.

Table 7 shows the results of fully modified OLS method. The results verified the robustness of the model. The results revealed a positive relationship between fossil fuel price index and fossil fuel energy demand. The variable patent is found to have significantly negative relationship with fossil fuel energy demand for the combine results of 43 low and middle income countries as well as for all the regions separately. GDP is found to be significantly positive for all the regions except Latin America & Caribbean. Similar to the results of SGMM the variable population is according to the theory but found insignificant in most of the cases.

5 Conclusion and recommendations

This study attempts to investigate the role of product and process innovation in abandoning fossil fuel energy consumption in LMICs by utilizing balanced panel data for 43 LMICs for the period of 14 years, i.e., from 2005 to 2018 from 6 regions. For the analysis of the fossil fuel market the Economic, social, Energy, and innovation variables are included in the study as influencing factors of fossil fuel consumption. Fossil fuels demand in terms of Domestic material consumption of fossil fuel is regressed against 4 Energy and innovation, social and economic variables. The study employed the System GMM model for the estimation of results. The selection of the model is based on the belief that traditional methods of estimation such as OLS, GLS, maximum likelihood method, instrumental variable method cannot deal with the endogenous problems caused by the inclusion of lag-dependent variable into the explanatory variables and leads towards falsifying results. The GMM method is capable of dealing with heteroscedasticity and sequence-related problems and provides more efficient estimates relative to other methods. The results of the study provide the following conclusion:

The higher the consumption of fossil fuels in the previous period will significantly increase the consumption of fossil fuels in the current period. The demand for fossil fuel in LMICs is found to be rigid in terms of fossil fuel price. The LMICs with high patent rates are found to have low fossil fuel consumption levels. This means that product and process innovation can lead to the abounding fossil fuel demand in the case of LMICs. It is evidenced from the results that economic progress is the main determinant of fossil fuel energy consumption. GDP is found putting a negative effect on abandoning fossil fuel energy consumption. Based on findings the study suggests the following recommendations:

The LMICs should not use taxation policy to achieve the goal of EC conservation and environmental degradation control. Taxation can be an effective source of revenue generation for LMICs. It is also suggested for LMICs Government to focus on product and process innovation as a critical element while structuring their policy for climate change mitigation. Moreover, the IPC, EPO and USPTO are the main organizations for granting patents and global leaders in understanding pathways to meet climate goals and reducing GHG emissions. Therefore, such organizations should play their role while accepting patent applications by structuring standards to reduce the use of fossil fuel energy consumption and climate change mitigation.

6 Limitations of the study and future research direction

Due to unavailability of data on some variables, this study is limited to 43 low- and middle-income countries for the time span of 14 years, i.e., 2005 to 2018. Such study can be conducted in future for a larger number of countries for a larger time span as well as this study can be extended to higher income countries. This study can be conducted using other econometric techniques like ARDL model, Granger causality test approach, *etc.*

Data availability statement

The original contributions presented in the study are included in the article/supplementary material further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization, HT and AK; methodology, HT, AK, DK, and RM; software, HT and AK; validation, HT, AK, and DK; formal analysis, HT and DK; investigation, HT, DK, and AK; resources, RM; data curation, HT, AK, DK, and RM; writing—original draft preparation, HT, AK, and DK; writing—review and editing, HT, AK, DK, and RM; visualization, DK and RM; supervision, AK and DK; project administration, AK, DK, and RM; funding acquisition, RM All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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How does climate risk matter for corporate green innovation? Empirical evidence from heavy-polluting listed companies in China

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Chinese heavy-polluting companies have been facing enormous challenges in responding to climate risk and energy transformation. This paper uses panel regression model and investigates the impact of climate risk on corporate green innovation in Chinese heavy-polluting listed companies from 2011 to 2020. The empirical results show that climate risk adversely affects green innovation in heavy-polluting companies, and this effect persists throughout a series of robustness and endogeneity tests. Climate risk may affect corporate green innovation through decreasing R&D investment, lowing resource allocation efficiency and increasing company risk. Climate risk has a greater negative impact on mid-western, state-owned and large-size heavy-polluting companies, but can be mitigated by the development of green finance, digital finance and marketization. These findings may help heavy-polluting companies fully utilize existing resources, policies, and channels for green innovation and mitigate climate risks.

KEYWORDS

climate risk, heavy-polluting companies, corporate green innovation, panel regression, fintech

1 Introduction

Climate risk is becoming an unprecedented threat that has a pronounced impact on the sustainability of human lives, natural resources and economic development (Eckstein et al., 2021; Ren et al., 2022; Venturini, 2022; Wagner, 2022; Estrada et al., 2023). According to the China Social Statistical Yearbook 2022 released by the National Bureau of Statistics of China, in 2021, over 107.31 million people are affected by climate events, and direct economic losses totaled around USD 48.28 billion due to extreme weather events in China. The previous researches note that climate risk is becoming an unprecedented threat to Chinese corporate behavior, such as sales and operating revenue (Lin and Sheng, 2022; Chen et al., 2023), investment (Rao et al., 2022a), financing cost (Shih et al., 2021; Huang et al., 2022; Zhou et al., 2022) and environmental strategic decision (Ren et al., 2022).

In Chinese heavy-polluting companies, green innovation is an important component of corporate behavior, especially in the face of severe climate risks and strict climate policies (Rao et al., 2022b; Khalfaoui et al., 2022; Li and Gao, 2022). It is widely known that, in 2020, Chinese President Xi Jinping announced that China would strive to peak its carbon emissions by 2030 and achieve carbon neutrality by 2060. This is the first time that

China has announced a definite timeline for carbon neutrality to the rest of the world, and it is also the largest climate pledge made by all countries to date. As important key sources and stakeholders in the conflict between environmental protection and economic interest, heavy-polluting companies must find a way to assume a high degree of environmental responsibility for their polluting activities (Walter and Chang, 2020). In this context, many heavy-polluting companies are forced to transform and upgrade with the help of green innovation, which is innovative activity to improve resource utilization efficiency and reduce energy consumption and is usually characterized by high risk, high cost and high return (Schiederig et al., 2012; Rao et al., 2022a; Li and Gao, 2022).

Although there are numerous studies about the impact of climate risk on corporate behavior (Shih et al., 2021; Yu et al., 2022a; Rao et al., 2022b; Huang et al., 2022; Lin and Sheng, 2022; Zhou et al., 2022; Ahmad et al., 2023; Lee et al., 2023; Ozkan et al., 2023), research on the impact of climate risk on corporate green innovation is very limited and controversial. On the other hand, climate risk will inevitably bring varying degrees of damage to corporations, thereby directly or indirectly affecting green innovation. For example, climate risk can directly destroy corporate equipment or fixed assets (Rao et al., 2022a; Xu et al., 2022) and block the supply channel (Godde et al., 2021; Pankratz and Schiller, 2021), which hinders corporate green innovation. Climate risk can also prompt the government to tighten environmental laws, forcing heavy-polluting companies to increase production and financing costs (Shih et al., 2021; Dong et al., 2022; Zhou et al., 2022), and indirectly affecting their investment in green innovation. On the other hand, the strategic growth options model indicates uncertainty such as climate risk may breed potential growth opportunities, prompting corporations to increase investment to obtain greater market competition (Kulatilaka and Perotti, 1998). Green innovation, as an important means of gaining greater market competition, will also attract more investment. It appears that climate risk may also have some indirect and potential promoting effects on green innovation, although there is a lack of direct evidence. Therefore, it is necessary to conduct in-depth research on the impact of climate risk on corporate green innovation.

This paper tries to extend the existing research by investigating the impact of climate risk on green innovation in Chinese heavy-polluting listed companies. To examine how climate risk affects green innovation, mediating effect models are proposed. Empirical findings show extreme climate events significantly hinder green innovation in heavy-polluting companies, and this negative effect persists throughout a series of robustness tests. The mechanism analysis reveals that research and development (R&D) investment, resource allocation efficiency and company risk are three potential mediating variables. The heterogeneity analysis demonstrates climate risk has a greater negative impact on midwestern, state-owned, and large companies. However, it is noteworthy that, the development of green finance, digital finance, and marketization can further promote heavy-polluting companies to actively explore green innovation and reduce the negative impact of climate risk.

This paper contributes to the literature in three aspects. First, the existing literature primarily focuses on the impact of a single index like temperature when evaluating the micro-level consequence of climate change. But the manifestations of different types of climate risk are different, not only in the form of temperatures (Lin and Sheng, 2022). This research studies the influencing factors of corporate green innovation in heavy-polluting companies from the perspective of extreme climate events and provides new theoretical and empirical evidence of corporate responses to climate risk. This will aid heavy-polluting companies in emerging markets like China to recognize the impact of climate risk on green innovation and take action. Second, this paper performs heterogeneity analyses on the influence of climate risk on the green innovation of different heavy-polluting companies. It will help the state and local governments provide targeted policy support for heavy-polluting companies in different regions, company ownership and size, to encourage corporate green innovation and resist climate risks. Third, it identifies the potential mechanism behind the negative impact of climate risk on corporate green innovation. Empirical findings may help heavy-polluting companies make full use of available resources, policies and channels to carry out green innovation, thus reducing the premium of green products and the cost of coping with climate risk.

The remainder of this paper is organized as follows. Section 2 develops the hypothesis based on the literature review. Section 3 describes the sample and research methods. Section 4 discusses the empirical results. Section 5 examines the influence mechanism, and Section 6 further analyses the heterogeneity and moderating effects. The final part concludes and provides policy implications.

2 Theoretical foundation and hypotheses development

2.1 Climate risk and corporate green innovation

Numerous studies have shown the significant impact of climate risk on corporate behavior, such as corporate profitability (Hugon and Law, 2019; Addoum et al., 2020; Anton, 2021; Chen et al., 2023), investment (Rao et al., 2022b), financing management (Huang et al., 2022), environmental performance (Ren et al., 2022; Sautner et al., 2023), but research on the impact of climate risk on corporate green innovation is very limited and controversial.

On the other hand, climate risk will inevitably bring varying degrees of damage to corporations, thereby directly or indirectly affecting green innovation. From the perspective of direct effect, climate risk is generally associated with the full or partial destruction of equipment or fixed assets of corporates (Rao et al., 2022a; Xu et al., 2022) and block of the supply channel (Godde et al., 2021; Pankratz and Schiller, 2021), which will abate the efficiency and ability of corporate green innovation. Corporations have to adjust the original resource allocation planning to maintain their operation. From the perspective of indirect effect, climate risk has compelled the government to take further measures to combat environmental pollution, resulting in stronger and improved environmental policies. These policies will prohibit firms from using low-cost but high-polluting energy sources (Dong et al., 2022) and restrict the availability of traditional credit to polluting companies. (Shih et al., 2021; Zhou et al., 2022). This will lead to an increase in financing costs (Shih et al., 2021; Zhou et al., 2022) and a decrease in available funds, thereby affecting corporate investment in green innovation. Besides, climate risk will also urge companies to change their strategies, making them more inclined to hold high liquidity assets such as cash to insist on potential climate risk and reduce available resources for corporate green innovation. Huang et al. (2022) demonstrate that corporates characterized by several climate risks prefer to hold more cash rather than high-risk investment and thereby increase corporate resilience to climate risk.

On the one hand, the strategic growth options model indicates that uncertainty such as climate risk may breed potential growth opportunities, prompting corporations to increase investment to obtain greater market competition (Kulatilaka and Perotti, 1998). Green innovation, as an important means of gaining greater market competition, will also attract more investment. For example, Hugon and Law (2019) show that some corporates will benefit from unusually warm climate because of diversified operation strategy and climate lobby. Sautner et al. (2023) demonstrate that climate risk provides opportunities for renewable energy, electric cars, or energy storage corporates. Rao et al., 2022b find some corporates will stimulate investment after the experience of excess rainfall to regain market competition. Yu et al. (2022b) illustrate that climate risk can significantly improve the investment efficiency of renewable energy firms. It appears that climate risk may also have some indirect and potential promoting effects on green innovation, although there is a lack of direct evidence.

Given the majority of research findings, we propose a hypothesis that needs to be tested for heavily polluting enterprises in China.

H1: Climate risk has a negative impact on corporate green innovation of heavy-polluting companies.

2.2 Impact mechanism of climate risk on corporate green innovation

Previous studies have shown that climate risk can affect corporate green innovation through three channels, including R&D investment, resource allocation efficiency, and company risk.

First, climate risk could reduce corporate profits (Lin and Sheng, 2022; Pankratz et al., 2023), impair the supply chain (Godde et al., 2021; Pankratz and Schiller, 2021), increase operation cost (Hugon and Law, 2019) and harm corporate credit reputation (Capasso et al., 2020), thereby decreasing available funds for high-risk green innovation R&D investments. Second, climate risk will have a direct impact on corporate allocative efficiency of resources. Extreme climate events have a direct impact on corporate tangible assets (Ding et al., 2021) and may damage the equipment and environment required for R&D activities. Unlike traditional economic risks, climate risk will harm human health (McMichael et al., 2006) and attenuate labor supply and production efficiency (Dasgupta et al., 2021; Zhang et al., 2023). The decline in labor supply and productivity will abate the efficiency and ability of corporate green innovation. Third, climate risk also results in a change in corporate strategy (Huang et al., 2022) and forces corporates to postpone high-risk green innovation R&D investment. Previous research has shown that managers are typically risk averse because they are prepared to implement more robust operating strategies to avoid the potential adverse impact of high risks on their careers and salaries (Amihud and Lev, 1981; Gormley and Matsa, 2016). When the potential company risk is very high, its management may take low-risk operating activities rather than high-risk innovations to hedge risk. Climate risk will cause an increase in company risk, which will make a company tend to hold more cash (Huang et al., 2022) and reduce high-risk R&D investments to improve its climate resilience. Based on these previous research findings, this paper proposes the second hypothesis to be tested.

H2: Climate risk negatively impacts corporate green innovation of heavy-polluting companies through decreasing R&D investment, lowing resource allocation efficiency, and increasing company risk.

2.3 Heterogeneity impact of climate risk on corporate green innovation

According to previous research, the impact of climate risk on different companies is heterogeneous and mainly depends on company-specific factors such as location, ownership and size (Ren et al., 2022).

First, the natural environment, economic development and environmental policies in different regions of China vary significantly. The central and western regions are more susceptible to extreme climate events such as droughts, sandstorms and landslides (Ren et al., 2022), which could result in a more severe impact on corporate operating activities and assets. Du et al. (2021) note that when the economic development level is low, environmental regulation inhibits the development of green innovation, while the contrary is true when the level of economic development is high. Meanwhile, the eastern region's financial market, infrastructure and environmental policies are superior to those of the central and western regions (Rao et al., 2022a), which could help companies mitigate the negative effect of climate risk.

Second, company ownership is one of the crucial factors affecting corporate strategy for resisting risk and improving environmental performance. Managers of state-owned companies prefer to avoid risk and select conservative operating activities to preserve their current position (Gao-Zeller et al., 2019; Gao et al., 2022). Meanwhile, state-owned companies need to assume more social and environmental protection responsibility, that is, pay higher costs for their pollution activities, thereby reducing their available resources.

Third, companies of different sizes may adopt different strategies to fend against external hazards. Prior research has shown that mid- and small-size companies are more flexible and adventurous than large-size companies under idiosyncratic risk, and are more willing to pursue high-risk, high-reward activities (Xu et al., 2022). Lin et al. (2019) find that small-size companies are more inclined to seek and access resources for green innovation because the return on green innovation investments for small-size companies is significantly higher than for larger-size companies. Therefore, non-state-owned and small-size companies may be more flexible to deal with climate risk and have a more proactive operating strategy, which decreases the negative impact of climate risk on corporate green innovation. Based on the above analysis, this paper proposes the third hypothesis.

H3: Climate risk has a greater influence on mid-western, state-owned, and large-size heavy-polluting companies.

3 Empirical framework

3.1 Definition and description of main variables

According to the industry classification list of listed companies in environmental verification issued by the former Ministry of Environmental Protection of China in 2008, we select the listed heavy-polluting companies in China[1]. The patent and green patent data are collected from the Chinese Research Data Services Platform (*CNRDS*). The financial data of the sampled companies comes from China Stock Market & Accounting Research Database (*CSMAR*). The sample interval is set between 2011 and 2020, as the fintech index has been available since 2011, while the climate risk index is usually released 2 years later. For example, the Global Climate Risk Index 2021 analyses what extent to countries and regions have been affected by the impacts of weather-related loss events in 2019. And Global Climate Risk Index 2022 is delayed due to a temporary lack of data and is expected to be published in 2023. The data are preprocessed as outlined below: 1) deleting ST and *ST companies; 2) erasing observations with incomplete data for critical variables. Additionally, to reduce the interference of outliers, we apply the Winsorize treatment of 1% and 99% quantiles for continuous financial indicators. Finally, 783 companies and 4,417 firm-year observations are taken as the final sample.

3.1.1 Measurement of the explained variable

The explained variable is corporate green innovation, which is proxied by the number of green patent applications, following Tang et al. (2021), Rao et al., 2022b and Zhong and Peng (2022). Green patent applications that reflect the R&D investment in green innovation and emphasize the application of green innovation can more accurately represent a company's green innovation capacity. Meanwhile, owing to the shorter time between the start of R&D and the filing of a patent application, the number of patent applications is timelier and more sensitive to innovation than the number of patent authorizations, and can better reflect the innovation intention and responses of companies. The number of green patent authorizations is adopted in the robustness analysis instead of green patent applications. We identify corporate green innovation by referring to the research of Wurlod and Noailly (2018). First, we begin by querying the corresponding intellectual property classification number (IPC) of each patent through SIPO based on all patents of the CSMAR and CNRDS databases. Second, the patents belonging to green patents are selected according to the IPC number in the green patent classification database published by the World Intellectual Property Organization (WIPO). Third, green patents are separated into green invention patents and green utility model patents according to the green patent classification database released by WIPO. Finally, we sum up the number of green invention patent applications and green utility model patent applications to present corporate green innovation. It is measured by taking the natural logarithm of the sum of the number of green patent applications.

3.1.2 Measurement of the key explanatory variable

The explanatory variable in this study is climate risk, proxied by the Germanwatch Climate Risk Index (CRI), which measures climate risk in terms of overall mortality from extreme climate events as well as relative and absolute economic damages[2]. It is constructed based on data from *Munich Re NatCatSERVICE*, which is one of the most reliable and complete databases about climate loss (Eckstein et al., 2021). The CRI is a score measured comprehensively by four indicators: fatalities, deaths per 100,000 inhabitants, losses on purchasing power parity, and loss per unit of GDP. A lower CRI score indicates that a region experiences more frequent and abnormal climate catastrophes. The CRI has been employed extensively in previous research, such as by Ding et al. (2021), Huang et al. (2018), Ren et al. (2022), and Xu et al. (2022), which use it to investigate the impact of climate risk on corporate revenue management, financial performance, carbon emissions, and risk-taking, respectively.

3.1.3 Measurement of moderating variables

According to Huang et al. (2022), this paper develops a comprehensive index to measure provincial green finance by composing green credit (interest expense of six high heavy-polluting industries/total industrial interest expense), green investment (investment in environmental pollution control/GDP), green insurance (Agricultural insurance/gross agricultural output value) and government support (financial environmental protection expenditure/financial general budget expenditure). The weight of each index is estimated using the entropy weight approach. All the data are obtained from China Statistical Yearbooks, each province's Statistical Yearbooks, and the China Insurance Yearbooks. Some missing data is substituted by the average value of the data from the previous 5 years.

The digital financial inclusion index released jointly by the Institute of Digital Finance at Peking University and the Ant

1 The paper selects coal mining (B06), gas exploration (B07), ferrous mining (B08), nonferrous mining (B09), nonmetal mining (B10), wine, beverage and refined tea manufacturing (C15), textile (C17,C18,C19), paper (C22), coking and nuclear fuel (C25), chemical raw materials and chemical manufacturing (C26), chemical fiber manufacturing (C28), rubber and plastic products (C29), nonmetallic mineral products (C30), ferrous metal smelting and rolling processing (C31), nonferrous metals smelting and rolling processing (C32), ferrous metals smelting and rolling processing (C33), and electricity, thermal production, and supply (D44) industries as sample.

2 Extreme climate events include climatological events such as droughts, wildfires and freezing; meteorological events such as tornados, storms and extreme weather; hydrological events such as floods and landslide.

Financial Services Group is chosen as a proxy for digital finance in this paper. It assesses the degree of digital finance in different regions of China from three perspectives: breadth of coverage, depth of usage, and level of digitization. The index can be used to quantify corporate capacity to access low-cost financial services and to represent the economic impact of China's digital finance (Guo et al., 2020; Rao et al., 2022a).

We select the marketization index proposed by Fan et al. (2011) to evaluate the degree of marketization in various regions and to analyze the moderating effect of marketization on the association between climate risk and corporate green innovation. This index can reflect the market efficiency of resource allocation and the degree of government intervention to some extent.

3.1.4 Measurement of control variables

Numerous other elements also have an impact on corporate green innovation. Referring to previous studies (Anton, 2021; Ren et al., 2022; Zhong and Peng, 2022), we select the company size (*Size*), returns of assets (*Roa*), current ratio (*Cur*), Tobin Q value (*Q*), total assets turnover (*Tat*) and company age (*Age*) as control variables. They are collected from the *CSMAR* database.

3.1.4.1 Size of assets (*Size*)

Some empirical findings have shown that the efficiency of small-size companies is higher than that of large-size companies (Lin et al., 2019). To control the impact of the company size, this research uses the natural logarithm of the company's total assets at the end of each year as a control variable.

3.1.4.2 Returns of assets (*Roa*)

Since the R&D investment of a company is highly correlated to its profitability, the corporate profit is considered and is calculated as the ratio of the net profit to the total assets.

3.1.4.3 Current ratio (*Cur*)

Prior research has divided corporate slack resources into absorbed and unabsorbed ones. Unabsorbed slack resources have high liquidity and flexibility and can be leveraged to lessen the effect of external risk on corporate operation activities. A higher unabsorbed slack resource has been demonstrated to enhance the development and implementation of corporate green innovation (Wu and Hu, 2020). Following Iyer and Miller (2008), the current ratio calculated as current assets divided by current liabilities is employed to control the impact of slack resources.

3.1.4.4 Tobin Q value (*Q*)

The better the development prospects of a company, the higher its R&D willingness. Tobin Q value is often used to represent corporate development prospects (Anton, 2021). This paper selects the Tobin Q value to control the impact of development prospects.

3.1.4.5 Total assets turnover *(Tat)*

There is a close relationship between a company's operating ability and its R&D decision-making (Anton, 2021). This paper considers the corporate operating ability measured by total assets turnover, which is dividing operating revenue by total assets.

3.1.4.6 Company age (*Age*)

Companies in different life cycles often make different innovation decisions. For example, companies at the mature stage invest less in innovation than those at the start-up and growth stage under specific risk (Shahzad et al., 2022). Therefore, this paper takes company age to control the impact of life cycle.

3.2 Descriptive statistics

Table 1 shows the definition and description of the main variables, and Table 2 reports the descriptive statistics. The average value of $Ginn_{i,t}$ is 0.903, and the min and max values are 0.000 and 5.737, respectively, indicating that the green innovation gap between heavy-polluting companies is quite obvious. The min and max climate risk expressed in the natural logarithm are 3.171 and 3.810, respectively, and the standard deviation is 0.230, suggesting that climate risk has relatively changed from 2011 to 2020. The numerical size difference between key control variables is slight, preventing errors caused by the significant variation among control variables.

3.3 Correlation analysis of main variables

Table 3 displays the Pearson correlation coefficients of the main variables. The results suggest a significant positive relationship between the climate risk index and the number of corporate green patent applications, implying that corporate green innovation may be negatively influenced by climate risk and providing preliminary support for H1. There seems no serious multicollinearity since the correlation coefficient of each pair of explanatory variables is less than 0.50.

3.4 Models setting

This research begins by constructing the panel regression model (1) to test H1 that climate risk will decrease green innovation in heavy-polluting companies.

$$R\left(Ginn_{i,t}\middle|Lncri_{i,t}, et.al.\right) = \alpha_0 + \alpha_1 Lncri_{i,t} + \sum_{j=2}\alpha_n Control_{j-1,t} + YearEffect + IndEffect + \varepsilon_{i,t} \quad (1)$$

where $Ginn_{i,t}$ is the green innovation of company i at time t, and is computed as the natural logarithm of the sum of the number of the green patent applications $P_{i,t}$ and 1. $Lncri_{i,t}$ represents the natural logarithm of the climate risk index. $Control_{i,t}$ represents control variables. $YearEffect$ and $IndEffect$ are a series of dummy variables for the year and industry effects, respectively.

Referring to Baron and Kenny (1986), we use the following models to test the mediating effect:

$$R(M_{i,t}|Lncri_{i,t}, et.al.) = \beta_0 + \beta_1 Lncri_{i,t} + \sum_{j=2}\beta_n Control_{j,t} + YearEffect + IndEffect + \varepsilon_{i,t} \quad (2)$$

TABLE 1 Definition and description of main variables.

Variable type	Variable	Symbol	Variable definitions
Dependent variable	Green technological innovation	*Ginn*	Natural logarithm of green patents application plus 1
Independent variable	Climate risk index	*Lncri*	Natural logarithm of the climate risk index
Mediating variables	R&D investment	*RD*	R&D investment/Operating revenue
	Resource allocation efficiency	*Ineff*	Ln (patent application+1)/Ln (1 + R&D investment)
	Uncertainty risk	*Risk*	$Adj_{ROA_{i,t}} = \frac{EBIT_{i,t}}{ASSET_{i,t}} - \frac{1}{X}\sum_{K=1}^{X}\frac{EBIT_{i,t}}{ASSET_{i,t}}$
			$RISK_{i,t} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(Adj_{ROA_{i,t}} - \frac{1}{T}\sum_{t=1}^{T}Adj_{ROA_{i,t}})}$
Moderating variables	The green finance index	*Gfin*	The green finance index
	Digital economy	*De*	Natural logarithm of the digital economy
	Market development	*Market*	Natural logarithm of the market index
IV	Normalized differential vegetation index	*Ndvi*	$NDVI = \frac{NIR-R}{NIR+R}$
Control variables	Size of assets	*Size*(*Size*1)	Natural logarithm of total company assets (market capitalization)
	Return of assets	*Roa*	Net profit/Total assets
	Current ratio	*Cur*	Current assets/Current liabilities
	Tobin Q value	*Q*	Market capitalization/Total assets
	Total Assets Turnover	*Tat*	Operating revenue/Total assets
	Company age	*Age*	Current year-establishment year

TABLE 2 Descriptive analysis.

Variable	Mean	Median	Max	Min	Std.Dev	Skew	Kurtosis	Jarque-Bera
Ginn	0.903	0.693	5.737	0.000	1.090	1.097	3.427	919.731***
Lncri	3.551	3.638	3.810	3.171	0.230	−0.484	1.691	487.693***
Size	22.275	22.064	25.791	20.269	1.259	0.671	2.872	334.793***
Roa	0.040	0.036	0.188	−0.130	0.050	−0.067	4.833	621.601***
Cur	2.093	1.543	9.742	0.340	1.744	2.149	8.319	8,607.708***
Q	1.744	1.485	4.853	0.887	0.810	1.728	5.997	3,851.741***
Tat	0.709	0.626	2.441	0.146	0.393	1.853	7.850	6,854.895***
Age	16.820	17.000	39.000	3.000	5.238	0.095	3.075	7.640**

Notes: Jarque-Bera denotes the test statistics for normality proposed by Jarque and Bera (1980). ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

$$R\left(Ginn_{i,t}\middle|Lncri_{i,t}, M_{i,t}, et.al.\right) = \gamma + \gamma_1 Lncri_{i,t} + \gamma_2 M_{i,t} + \sum_{j=2}\gamma_n(\tau)Control_{j-1,t} + YearEffect + IndEffect + \varepsilon_{i,t} \quad (3)$$

where $M_{i,t}$ represents the mediating variable. There will be a complete mediating effect if β_1 is significant, but γ_1 is not while γ_2 is significant. While it will have an incomplete mediating effect if γ_1 is also significant. In other cases, no mediating effect exists. If β_1 and γ_2 have the same sign, a positive mediating effect is identified, otherwise, a negative mediating effect is detected.

To test the moderating effect of green finance, digital finance and marketization, we develop the following models:

$$R\left(Ginn_{i,t}\middle|Lncri_{i,t}, et.al.\right) = \theta + \theta_1 Lncri_{i,t} + \theta_2 N_{i,t} + \theta_3 N_{i,t} \times Lncri_{i,t} + \sum_{j=2}\theta_j Control_{j-1,t} + YearEffect + IndEffect + \varepsilon_{i,t} \quad (4)$$

TABLE 3 Main variable correlation analysis.

	Ginn	*Lncri*	*Size*	*Roa*	*Cur*	*Q*	*Tat*	*Age*
Ginn	1.000							
Lncri	0.122***	1.000						
Size	0.495***	0.035***	1.000					
Roa	−0.017	0.097***	−0.081***	1.000				
Cur	−0.204***	0.026*	−0.444***	0.318***	1.000			
Q	−0.161***	−0.109***	−0.409***	0.201***	0.210***	1.000		
Tat	−0.001	0.018	−0.019	0.103***	−0.066***	−0.008	1.000	
Age	0.100***	0.222***	0.153***	−0.056***	−0.128***	0.011	0.010	1.000

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

TABLE 4 Benchmark regression results.

Variable	*Ginn*	*Ginn*
Lncri	2.456***	1.958***
	(0.253)	(0.237)
Size		0.447***
		(0.015)
Roa		−0.524*
		(0.311)
Cur		0.008
		(0.009)
Q		0.100***
		(0.021)
Tat		0.079**
		(0.037)
Age		−0.014***
		(0.003)
Intercept	Yes	Yes
Year	Yes	Yes
Ind	Yes	Yes
N	4,417	4,417
R-squared	0.089	0.285

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

TABLE 5 Robustness tests results.

Variable	*Ginn1*	*Ginn2*	*Ginn*	*Ginn*
	(1)	*(2)*	*(3)*	*(4)*
Lncri	1.042***	1.950***	−2.959**	1.958***
	(0.199)	(0.215)	(1.294)	(0.237)
Size	0.339***	0.389***	0.432***	0.447***
	(0.012)	(0.013)	(0.015)	(0.015)
Roa	−0.215	−0.391	0.080*	−0.524*
	(0.261)	(0.282)	(0.047)	(0.310)
Cur	0.014*	−0.003	0.013	0.008
	(0.008)	(0.009)	(0.009)	(0.009)
Q	0.098***	0.091***	0.023***	0.100***
	(0.018)	(0.019)	(0.006)	(0.021)
Tat	0.060*	0.060*	0.091**	0.079**
	(0.031)	(0.033)	(0.039)	(0.037)
Age	−0.010***	−0.013***	−0.016***	−0.014***
	(0.003)	(0.003)	(0.002)	(0.003)
Intercept	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes
N	4,417	4,417	7,193	4,417
R-squared	0.218	0.281	0.317	0.112

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

where $N_{i,t}$ represents the moderating variable. $N_{i,t}$ will have a moderating effect if θ_2 is significant and not equal to 0. If θ_1 and θ_2 have opposite signs, the moderating effect is negative, otherwise, it is positive.

4 Empirical results and analysis

4.1 Benchmark regression results

The results of the benchmark regression are presented in Table 4. Column (1) shows there is a statistically significant negative impact of climate risk on corporate green innovation at the 1% level when controlling for year and industry-fixed effects. When all control variables are included in column (2), the coefficient of climate risk (*Lncri*) is significantly positive at the 1% significant level, indicating that a rise in extreme climate events and loss may impede corporate green innovation. These results seem to support H1. Some studies (Li and Lu, 2022) also find a correlation between temperature fluctuates and green innovation but this finding extends climate risk from a single index like temperature or precipitation to a complicated climate phenomenon. The reason may be that climate risk can deter corporate green innovation by decreasing R&D investment, lowering resource allocation efficiency, and increasing company risk. These mechanisms will be verified in further detail in the following sections. The benchmark regression results in column (2) reveal that company size, Tobin Q value and total assets turnover are positively correlated with corporate green innovation but company age has a significantly negative impact on corporate green innovation.

4.2 Robustness tests

4.2.1 Alternative measurement of the explained variable

This paper employs the number of green invention patent applications (*Ginn*1) and green patent authorizations with the first-order lag term (*Ginn*2) to replace the previous dependent variable, respectively. *Ginn*1 and *Ginn*2 are calculated by the natural logarithm of the number of green invention patent applications and green patent authorizations plus 1, respectively. According to columns (1) and (2) in Table 5, there are negative correlations between climate risk and corporate green innovation, indicating the robustness of the previous regression results.

4.2.2 Alternative measurement of the explanatory variable

Following Alstadt et al. (2022), Hoeppe (2016) and Neumayer and Barthel. (2011), to further prove the relationship between climate risk and corporate green innovation, we use the proportion of economic losses of climate risk to current GDP as an alternative measure of climate risk to test the robustness of the empirical results. The greater the proportion of direct economic losses to GDP, the worse the climate risk. The sample interval is set between 2011 and 2021 because the green innovation data is available until 2021. The economic losses of climate risk data are from the China Social Statistical Yearbook compiled by the National Bureau of Statistics of China. The results of column (3) in Table 5 confirm that when the direct economic loss of climate disasters/current GDP is used as an alternative variable in the analysis, the correlation between climate risk and corporate green innovation is robust.

4.2.3 An alternative model

It is challenging for OLS estimation to obtain a consistent estimate for regression models where the dependent variable has a partial value of 0 (Davidson and MacKinnon, 2004). In our sample, the number of green patent applications exhibits a pattern of zero and positive values coexisting. Following Rao et al., 2022b and Tang et al. (2021), we employ the Tobit model in place of the original model for further robustness tests in order to more accurately identify the impact of climate risk on corporate green innovation. The results of column (4) in Table 5 demonstrate that the sign, magnitude and significance of the coefficient of climate risk are essentially consistent with those in the benchmark regression, demonstrating that climate risk severely inhibits corporate green innovation in heavy-polluting companies.

TABLE 6 Endogeneity tests results.

Variable	*Ginn*	*Ginn*	*Ndvi*	*Ginn*
	(1)	(2)	(3)	(4)
Lncri	1.922***	1.825***	0.123***	
	(0.237)	(0.234)	(0.032)	
Ndvi				0.365***
				(0.113)
Size1	0.463***			
	(0.015)			
Size		0.437***	0.000	0.447***
		(0.015)	(0.002)	(0.015)
Roa	−0.660**	−0.430	0.035	−0.536*
	(0.311)	(0.313)	(0.041)	(0.311)
Cur	0.010	0.005	−0.000	0.008
	(0.009)	(0.009)	(0.001)	(0.009)
Q	−0.102***	0.080***	−0.003	0.101***
	(0.020)	(0.022)	(0.003)	(0.021)
Tat	0.078**	0.053	0.022***	0.071*
	(0.037)	(0.037)	(0.005)	(0.037)
Age	−0.013***	−0.008***	0.000	−0.014***
	(0.003)	(0.003)	(0.000)	(0.003)
Intercept	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes
Province	No	Yes	No	No
N	4,417	4,417	4,417	4,417
R-squared	0.289	0.315	0.026	0.287

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

4.3 Endogeneity tests

4.3.1 Alternative measurement of the key control variable

Company size has been proven to be a substantial contributor to the heterogeneity in company finance (Dang et al., 2018), that is, the sign, magnitude and significance of the coefficients of explanatory variables may vary when different company size measures are used. Referring to Anton (2021), we conduct the robustness tests by using the natural logarithm of market capitalization as an alternative measure of company size. The empirical results in column (1) of Table 6 indicate that the previous regression results are robust when market capitalization is employed as a substitute proxy for company size.

4.3.2 Controlling for province fixed effect

In benchmark regression, year and industry fixed effects are controlled for, but unobserved regional characteristics could lead to estimation bias. For instance, company location may be accompanied by different resource endowments and regional economic policies, which may result in estimation bias. After controlling for province fixed effect, column (2) of Table 6 shows that the coefficient of climate risk is still significantly positive at the 1% level, suggesting that the impact of climate risk on corporate green innovation seems not to be affected by unobservable regional factors.

4.3.3 IV estimation

This research adopts instrumental variable (IV) estimation as a robustness test to further address the endogeneity issue that may be caused by the two-way causal relationship between climate risk and corporate green innovation. Following Liu et al. (2021), the normalized differential vegetation index ($Ndvi$) is selected as an instrumental variable of the climatic risk index. On the one hand, $Ndvi$ is closely related to climate risk, because it can represent the health and density of vegetation and is often used for climate monitoring (Drisya and Roshni, 2018; Möllmann et al., 2020). On the other hand, as a natural geographic variable, $Ndvi$ is not correlated with the regression residuals based on the sampled companies. Therefore, $Ndvi$ as an instrumental variable satisfies both the relevance and exogeneity conditions. $Ndvi$ data comes from *Moderate Resolution Imaging Spectroradiometer(MODIS)*.

Columns (2) in Table 6 reports that there is a significantly positive correlation between *Lncri* and *Ndvi*, suggesting that an increase in extreme climate events or damage may be related to a deterioration in vegetation health and density. We then substitute *Lncri* with the value of *Ndvi*. Columns (3) illustrates that the coefficient of *Ndvi* is positive and significant at the 1% level, implying that after controlling for endogeneity, the results still support H1 that climate risk harms corporate green innovation in heavy-polluting companies.

4.4 Mechanism analysis

The above results indicate that climate risk has a significantly detrimental effect on corporate green innovation. In this section, we examine the following three potential channels through which climate risk decreases corporate green innovation: R&D investment, resource allocation efficiency and company risk.

4.4.1 Climate risk, R&D investment and corporate green innovation

Corporate innovation, especially corporate green innovation, is a high-risk, high-reward activity requiring large investments. However, climate risk endangers the creditworthiness of loans and bonds issued by heavy-polluting companies, increases financing costs and reduces available funds for corporate green innovation. Due to limited capital, companies that are susceptible to serious climate risks may choose to hold cash rather than invest in green innovation to resist climate risk. Therefore, this research investigates whether the climate risk inhabits corporate green innovation by decreasing R&D investment. A company's R&D investment (RD) is defined by the ratio of R&D investment to operational revenue. As shown in columns (1) and (2) of Table 7, the coefficient of climate risk on R&D investment in Eq. 2 is significantly positive, and the coefficient of R&D investment on corporate green innovation is also significantly positive. It demonstrates that when the risk of extreme climate increases, companies may choose to forego high-risk R&D investment and "save" assets, followed by decreases in corporate green innovation. It also proves the existence of the mediating effect of R&D investment on the impact of climate risk on corporate green innovation.

4.4.2 Climate risk, resource allocation efficiency and corporate green innovation

Extreme climate events can cause direct physical damage to corporate tangible assets, and may even damage the R&D equipment and environment at the crucial moment of core technology innovation, hence decreasing corporate R&D efficiency. Secondly, the existing research has discovered that climate risk might be anticipated to decrease both labor supply and productivity (Dasgupta et al., 2021). Insufficient scientific research supply and ineffective labor productivity will prevent companies from implementing green innovation. Thirdly, climate risk will increase the uncertainty of corporate operation position, making it more difficult for financial institutions to estimate corporate operating status and reducing the efficiency of the available resources provided by financial institutions for corporate green innovation. We measure the resource allocation efficiency ($Ineff$) as $Ln(patent\,application + 1)/\,Ln(1 + R\&D\,investment)$. The lower the value of $Ineff$ is, the more seriously inefficient the resource allocation is. In Columns (3) and (4) of Table 7, resource allocation efficiency is shown to have mediating effects of climate risk on corporate green innovation, indicating that climate risk reduces corporate resource allocation efficiency and then decreases corporate green innovation in heavy-polluting companies. This result is consistent with Lin and Sheng (2022), who found that drought significantly reduces lower investment efficiency.

4.4.3 Climate risk, company risk and corporate green innovation

Green innovation has a larger initial uncertainty risk than other operating activities. Climate risk may affect asset safety and trigger stricter environmental regulation, thus aggravating the operational and regulatory risks of heavy-polluting companies. Heavy-polluting companies may prefer to lower risk via low-risk operational activities rather than high-risk green innovation. Therefore, this paper examines if climate risk can prevent corporate green innovation in heavy-polluting companies by increasing company risk. Following Zhou et al. (2022), company risk can be calculated as

TABLE 7 Mechanism analysis results.

Variable	R&D	Ginn	Ineff	Ginn	Risk	Ginn
	(1)	(2)	(3)	(4)	(5)	(6)
Lncri	0.045***	1.395***	0.137***	1.063***	−0.017**	1.928***
	(0.004)	(0.235)	(0.019)	(0.203)	(0.007)	(0.237)
R&D		12.63***				
		(0.869)				
Ineff				6.548***		
				(0.159)		
Risk						−1.764***
						(0.487)
Size	−0.004***	0.503***	0.020***	0.319***	−0.001**	0.445***
	(0.000)	(0.015)	(0.001)	(0.013)	(0.000)	(0.015)
Roa	0.019***	−0.758**	0.075***	−1.011***	−0.069***	−0.645**
	(0.005)	(0.304)	(0.025)	(0.264)	(0.010)	(0.312)
Cur	0.001***	−0.004	0.000	0.007	0.001***	0.009
	(0.000)	(0.009)	(0.001)	(0.008)	(0.000)	(0.009)
Q	0.000	0.098***	0.002	0.089***	0.006***	0.111***
	(0.000)	(0.021)	(0.002)	(0.018)	(0.001)	(0.022)
Tat	−0.010***	0.207***	0.001	0.072**	0.002	0.082**
	(0.001)	(0.037)	(0.003)	(0.031)	(0.001)	(0.037)
Age	−0.000***	−0.010***	−0.001***	−0.008***	0.000***	−0.013***
	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)	(0.003)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes	Yes
N	4,417	4,417	4,417	4,417	4,417	4,417
R-squared	0.274	0.318	0.119	0.485	0.054	0.288

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

$$Adj_{ROA_{i,t}} = \frac{EBIT_{i,t}}{ASSET_{i,t}} - \frac{1}{X}\sum_{K=1}^{X}\frac{EBIT_{i,t}}{ASSET_{i,t}} \quad (5)$$

$$RISK_{i,t} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(Adj_{ROA_{i,t}} - \frac{1}{T}\sum_{t=1}^{T}Adj_{ROA_{i,t}}\right)} \quad (6)$$

The larger the value of $RISK_{i,t}$, the greater the company's exposure to risk. The rolling period is set as 3-year. In Table 7, columns (5) and (6) show that climate risk can significantly increase company risk and thus hinder corporate green innovation, which demonstrates that company risk plays a mediating role. Our empirical result also concurs with Yan et al. (2021), who points out that company risk-taking negatively affects the green innovation level of Chinese heavy-polluted listed companies.

In summary, the above results support H2, that is, Climate risk negatively impacts corporate green innovation through decreasing R&D investment, lowing resource allocation efficiency, and increasing company risk.

4.5 Heterogeneity analysis

In this section, we further study the heterogeneous impact of climate risk on corporate green innovation in different heavy-polluting companies. According to the analysis in Section 2, the negative impact of climate risk on corporate green innovation may vary with region, company ownership and size.

4.5.1 Heterogeneity analysis on regions

In order to investigate whether the impact of climate risk on corporate green innovation varies significantly across regions, the original sample is split into two sub-samples according to the

TABLE 8 Heterogeneity analysis results.

Variable	Ginn	Ginn	Ginn	Ginn	Ginn	Ginn
	Eastern	Mid-western	State-owned	Non-State-owned	Large-size	Small-size
	(1)	(2)	(3)	(4)	(5)	(6)
Lncri	1.154***	3.501***	3.175***	1.183***	3.080***	1.173***
	(0.287)	(0.408)	(0.437)	(0.282)	(0.427)	(0.254)
Size	0.482***	0.395***	0.431***	0.458***	0.540***	0.405***
	(0.019)	(0.024)	(0.025)	(0.020)	(0.0267)	(0.035)
Roa	−0.401	−0.621	−0.566	−0.180	−0.515	−0.272
	(0.392)	(0.509)	(0.522)	(0.398)	(0.529)	(0.360)
Cur	0.012	0.007	0.041*	−0.005	−0.046*	0.006
	(0.011)	(0.019)	(0.022)	(0.011)	(0.025)	(0.009)
Q	0.118***	0.062*	−0.021	0.171***	0.107**	0.080***
	(0.027)	(0.035)	(0.039)	(0.027)	(0.046)	(0.022)
Tat	−0.006	0.173***	0.221***	−0.046	0.162***	−0.017
	(0.049)	(0.056)	(0.057)	(0.049)	(0.058)	(0.043)
Age	0.001	−0.044***	−0.023***	−0.009***	−0.022***	−0.009***
	(0.004)	(0.005)	(0.006)	(0.003)	(0.005)	(0.003)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes	Yes
N	2,709	1708	1,673	2,744	1898	2,519
R-squared	0.323	0.258	0.308	0.245	0.246	0.103
Empirical p-value	0.000***		0.000***		0.000**	

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The empirical *p*-value is used to test the significance of the difference in coefficient of *Lncri* between two groups, which is obtained by bootstrap 1,000 times.

provinces where the sample companies are registered, namely, the eastern (*Eastern*) and the central and western (*Mid-Western*) provinces[3]. Columns (1) and (2) of Table 8 report the coefficients of *Eastern* and *Mid-Western* are significant at the 1% level, which are 1.154 and 3.501, respectively. The empirical *p*-value is significantly less than 0.01, indicating a statistically significant difference between the two coefficients at the 1% level. These findings show that companies in the central and western regions are more significantly and severely impacted by climate risk. This may be because central and western regions of China are more inclined to mitigate climate risk through mandatory regulations such as emission permits, but eastern regions are more likely to implement market regulations such as R&D subsidies. Mandatory regulations will limit corporate operations, exacerbating the negative effects of climate risk. While market regulations could compensate for the extra costs associated with strict mandatory regulations, thus alleviating the strain of extreme climate events and environmental regulations. Additionally, the eastern region has a higher-quality financial and market environment than the central and western regions, which may make it easier for heavy-polluting companies in the eastern region to access more resources for conducting green innovation.

4.5.2 Heterogeneity analysis on company ownership

Columns (3) and (4) of Table 8 present the estimated results for state-owned companies ($PR = 1$) and non-state-owned companies ($PR = 0$), respectively. The coefficient of climate risk for state-owned is higher than that of non-state-owned companies. Therefore, we could believe that the impact of climate risk on corporate green innovation in state-owned heavy-polluting companies may be stronger than that of non-state-owned heavy-polluting companies. One possible reason is that state-owned heavy-polluting companies are subject to harsher environmental regulations and are expected to assume more social

3 The eastern regions include Beijing, Tianjin, Shanghai, Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong and Hainan, other regions are mid-western regions.

TABLE 9 The moderating effect analysis results.

Variable	*Ginn*	*Ginn*	*Ginn*
	(1)	*(2)*	*(3)*
Lncri	2.004***	5.972**	3.399***
	(0.269)	(3.030)	(0.725)
Gfin	5.153***		
	(1.774)		
Gfin Lncri*	−1.272***		
	(0.493)		
De		3.835**	
		(1.857)	
De Lncri*		−1.023*	
		(0.531)	
Market			2.535**
			(1.078)
Market Lncri*			−0.682**
			(0.306)
Size	0.446***	0.449***	0.450***
	(0.015)	(0.015)	(0.0148)
Roa	−0.585*	−0.590*	−0.584*
	(0.310)	(0.311)	(0.313)
Cur	0.004	0.005	0.006
	(0.009)	(0.010)	(0.010)
Q	0.099***	0.104***	0.102***
	(0.021)	(0.021)	(0.022)
Tat	0.078**	0.074**	0.073**
	(0.037)	(0.037)	(0.037)
Age	−0.012***	−0.014***	−0.014***
	(0.003)	(0.003)	(0.003)
Intercept	Yes	Yes	Yes
Year	Yes	Yes	Yes
Ind	Yes	Yes	Yes
N	4,417	4,417	4,417
R-squared	0.291	0.287	0.287

Notes: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

responsibilities because of the characteristics of China's political system. They are more vulnerable to climate risk and incur higher costs due to climate risk than other types of companies, hence reducing the funds available for green innovation. Secondly, compared with state-owned companies, privately-owned companies are usually more prone to seek diversity and flexibility in resource allocation and corporate strategy than state-owned companies to alleviate the negative impact of climate risk.

4.5.3 Heterogeneity analysis on company size

We define the company whose total assets exceed the average value of the heavily polluting companies' total assets as a large company (large) and assign it a value of 1; otherwise, we assign it a value of 0 in order to compare the impact of climate risk on corporate green innovation across company sizes. The empirical results in columns (5) and (6) of Table 8 indicate that the coefficient of climate risk of large-size companies is greater than that of small-size companies, which shows that climate risk has a greater impact on corporate green innovation of large-size companies. This may be because large-size companies have to consider more aspects of responsibility such as shareholder responsibility and employ more robust operating strategies than those of small-size companies. This result is consistent with Lin et al. (2019), who find that small-size companies which are more maneuverable and variated are more inclined to pursue green innovation than large-size companies.

To sum up, we conclude that climate risk has a greater negative impact on mid-western, state-owned, and large-size heavy-polluting companies, which supports H3.

4.6 Moderating effect analysis

4.6.1 Moderating effect of green finance

Green finance has been proven to play an important and positive role in promoting green innovation through radiation and trickle-down functions (Huang et al., 2022), which motivates us to examine the moderating of green finance. Column (1) in Table 9 reports that the coefficient of *Lncri* is positive but the coefficient of $Lncri^{*}Gfin$ is negative, demonstrating that green finance has a significantly negative moderating effect and could attenuate the negative effect of climate risk. Green finance is a kind of financial innovation that provides financing, investment and other financial services for environment-friendly projects (Huang et al., 2022). On the one hand, green finance can broaden the financing channels for green innovation by promoting the issuance of green credit, green bonds and other financial instruments. On the other hand, it can encourage the government to reform the existing fiscal policies and alleviate the financing-policed pressure of green innovation. Besides, green insurance can decrease the losses of heavy-polluting companies and enhance the risk management ability when conducting corporate green innovation.

4.6.2 Moderating effect of digital finance

The existing research finds that digital finance can improve factor productivity (Chen et al., 2022), and independent innovation (Li and Liu, 2022) and negatively impact companies' default and bankruptcy risk (Ji et al., 2022). The results in column (2) of Table 9 show that the coefficient of *De*Lncri* is opposite to the positive coefficient of *Lncri*, indicating that digital finance has a significantly negative moderating effect on the impact of climate risk on corporate green innovation. That is, digital finance will increasingly mitigate the negative impact of climate risk on green innovation in heavy-polluting companies. Digital finance makes it easier for financial institutions to evaluate company information, identify those who exhibit green behavior and more effectively transfer funds to companies that carry out green innovation. Digital finance also provides diversified financial service modes, which could reduce the cost of corporate green innovation in heavy-polluting companies.

4.6.3 Moderating effect of marketization

According to Feng et al. (2022) and Sha et al. (2022), marketization contributes to corporate green innovation by alleviating financing constraints, reducing information asymmetry, and enhancing environmental consciousness. Column (3) of Table 9 demonstrates that the coefficient of *Lncri* is positive but that of *Market*Lncri* is negative at the 1% and 5% significance level, indicating that the development of marketization alleviates the negative impact of climate risk on heavy-polluting companies' green innovation. On the one hand, marketization can optimize the relationship between the market and the government, and enhance the effectiveness of government decision-making and awareness of environmental protection, hence lowering the pressure on companies in terms of regulation and financing. On the other hand, marketization can strengthen the information transmission between the market and heavy-polluting companies. It could improve the quality of corporate information disclosure, reduce the asymmetry of information obtained by financial institutions, and weaken financing constraints for green innovation in heavy-polluting companies.

5 Conclusion and policy implications

This paper investigates the impact of climate risk on corporate green innovation in Chinese heavy-polluting listed companies from 2011 to 2020. The empirical results show that climate risk adversely affects corporate green innovation of heavy-polluting companies, and this effect persists throughout a series of robustness and endogeneity tests. Climate risk may affect corporate green innovation through decreasing R&D investment, lowing resource allocation efficiency, and increasing company risk. Climate risk has a greater negative impact on mid-western, state-owned, and large-size heavy-polluting companies, but can be mitigated by the development of green finance, digital finance, and marketization.

The findings in this paper are particularly helpful for governments and companies. First, although climate risk has a negative impact on the corporate green innovation of heavy-polluting companies, corporate green innovation is still a favorable means for heavy-polluting companies to cope with climate risk. Compared with defensive and adaptive responses such as industrial restructuring and withdrawal, green innovation is an aggressive response to climate risk, which can better balance the two goals of economic development and energy transformation. The government should provide policy support for heavy-polluting companies to encourage green technology innovation, especially for mid-western, state-owned, and large-size heavy-polluting companies. Second, local governments, particularly those in central and western regions, are suggested to promote the development of green finance such as green credit and green insurance and help heavy-polluting companies mitigate the negative impact of climate risk. Third, the state and local governments need to continue to promote the development of digital finance, especially those in emerging economies, and encourage heavy-polluting companies to use digital financial services to reduce information asymmetry between the market and companies. This can ease the financing constraints and reduce the financing costs, thus promoting corporate green innovation. Forth, in addition to the mandatory provisions on energy conservation and emission reduction, the government should give full play to its "guiding" role, and employ flexible policy tools in combination with the market mechanism to further promote marketization and enhance the green innovation willingness of heavy-polluting companies. Finally, it is suggested that heavy-polluting companies actively strive for national industrial transformation and upgrading funds, green credit and other relevant policy support, and make full use of green finance and digital financial services, so as to actively carry out green technology innovation, reduce the premium of green products and reduce the cost of coping with climate risk.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

HG: Writing—original draft, data curation, software, and writing—review and editing; SL: Conceptualization, writing—original draft, methodology, funding acquisition, supervision, and writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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What can accelerate technological convergence of hydrogen energy: a regional perspective

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Focusing on technological innovation and convergence is crucial for utilizing hydrogen energy, an emerging infrastructure area. This research paper analyzes the extent of technological capabilities in a region that could accelerate the occurrence of technological convergence in the fields related to hydrogen energy through the use of triadic patents, their citation information, and their regional information. The results of the Bayesian spatial model indicate that the active exchange of diverse original technologies could facilitate technological convergence in the region. On the other hand, it is difficult to achieve regional convergence with regard to radical technology. The findings could shed light on the establishment of an R&D strategy for hydrogen technologies. This study could contribute to the dissemination and utilization of hydrogen technologies for sustainable industrial development.

KEYWORDS

open innovation system, technological convergence, triadic patent, Besag–York–Mollie model, hydrogen energy

1 Introduction

Currently, the technological advancement of hydrogen is attracting the interest of researchers and practitioners (Lebrouhi et al., 2022). Hydrogen has been identified as an important candidate for decarbonization of various sectors as hydrogen could contribute to the emergence of renewable energy by reducing the use of fossil fuels (Cheng & Lee, 2022). A focus on technological innovations and convergences might be required to accelerate hydrogen research and enable industrial transitions (Lebrouhi et al., 2022). Therefore, it is important to systematically approach how to facilitate technological innovation in hydrogen-related areas, and one way could be technological convergences in the open innovation era. In recent decades, technologies have been exchanged and interacted globally under the open innovation system (Maskell & Malmberg, 1999; Chesbrough, 2003; Granstrand, 2010). As the interactions of technologies have increased more than ever, it could accelerate the evolution of technologies (Lee & Sohn, 2018). As a result, technological convergence has become a popular phenomenon (Lee et al., 2015), and much effort has been devoted to analyzing and predicting the patterns of technological convergence (Kodama, 1995; Curran & Leker, 2011; Karvonen & Kässi, 2013; Sohn et al., 2013; Kim et al., 2014; Lee et al., 2015; Lee and Sohn, 2018).

Interestingly, patterns of technological innovation and even convergence vary across regions according to the technological capability of a region (Boschma and Martin, 2007). Specifically, the technological capability of a region tends to closely associate with the technological progress in that region (Crescenzi et al., 2012; Fagerberg et al., 2014). The technological capabilities could indicate the knowledge base of a region, which can be an important aspect of the analysis of technological convergence (Binz et al., 2014; Fagerberg et al., 2014; Hajek et al., 2014; Vásquez-Urriago et al., 2016). For instance, infrastructure technologies, such as hydrogen energy, could be influenced by the technological capabilities of a region. Then, how would the convergence pattern of hydrogen-related technologies vary across regions? This study focuses on the relationship between the regional occurrence of technological convergence and the regional knowledge base with respect to hydrogen energy.

This study uses the Organization for Economic Cooperation and Development (OECD) database of triadic patents as of January 2021 (OECD, 2021). Based on OECD triadic patents, the technological convergence and technological exchanges are empirically measured from a regional perspective at the Nomenclature of Territorial Units for Statistics (NUTS) 3 and Territorial Level 3 (TL3) levels compiled by the OECD. NUTS 3 and TL3 are regional-level units that are regarded as small levels intended especially for specific diagnoses. Then, a Bayesian spatial model with integrated nested Laplace approximation (INLA) was applied to investigate how the regional occurrence of technological convergence is associated with regional knowledge base factors.

The results of this study could provide both empirical evidence and a theoretical contribution to deepen our understanding of the technological convergence of hydrogen-related fields from a regional perspective. Findings could indicate which factors, such as diversity or originality, could positively leverage the occurrence of technological convergence at a regional level. The remainder of this paper is organized as follows: Section 2 presents a review of previous studies on technological convergence and related research. Section 3 presents the research framework. Section 4 analyzes the regional occurrence of technological convergence. Based on the analytical results, Section 5 discusses the policy implications for accelerating regional technological convergence. Finally, Section 6 concludes the study.

2 Literature review and research questions

2.1 Hydrogen energy for zero-carbon transition

Hydrogen has been considered an energy source that can trigger the zero-carbon transition (Cheng & Lee, 2022). In particular, it is expected that hydrogen could certainly contribute to the global energy transition with a significant reduction in greenhouse gas emissions (Lebrouhi et al., 2022). As the energy transition could be based on renewable energy, hydrogen and its electrification have attracted the interest of researchers and practitioners in many ways. More efforts are needed to develop technological innovations and their applications in related fields (Cheng & Lee, 2022). Previous research has focused on technical and technological advances for efficient production, stable compression and transportation, and effective utilization of hydrogen (Lebrouhi et al., 2022).

However, although hydrogen seems promising, there is the problem of technological advancement (Hunt et al., 2022). The efficient production and effective use of hydrogen require more technological innovation. Huge efforts from governments, industries, and academia would be required to achieve a satisfactory level of technological innovation in hydrogen-related fields. This could lead to a large-scale, hydrogen-based industrial ecosystem. It is also expected that hydrogen could even enable the grand transition to the decarbonization roadmap (Cheng & Lee, 2022).

Hydrogen is currently considered a promising energy source for the zero-carbon economy. In order to accelerate the technological progress of hydrogen, it is necessary to systematically study the technological development of hydrogen and establish a strategy to generate technological innovations in hydrogen-related fields.

Recently, Ashari et al. (2023) conducted a bibliometric analysis of publications, patents, and standards to specifically understand the evolution of hydrogen technology. They examined the link between the knowledge and technology transfer channels and concluded that the hydrogen technological innovation system is currently experiencing its formative phase. Li et al. (2023) conducted a systematic review of hydrogen technology development and emphasized that it was necessary to have possible and specific pathways to a hydrogen-capable clean energy future. Particularly, they highlighted the economics of hydrogen supply and discussed strategic considerations.

2.2 Open innovation and technological convergence

Technological innovation (henceforth, TI) can be defined as the process of developing a new and unique technology that satisfies the market demand for technology or the need for new technology. Many debates and studies have been devoted to the efficient and effective pursuit of TI. Recently, open innovation systems have attracted considerable attention for their significant contribution to efficient innovation in all industries. An open innovation system allows direct transactions and exchanges of innovative technologies (Chesbrough, 2003; Hemmert, 2004; Tanaka et al., 2007; Granstrand, 2010). In an open innovation system, public entities, whether firms, research institutes, or governments, do not bear the entire risk of R&D, do not keep R&D results in-house, and do not pursue TI on their own but rather release results for broader and more intensive application. Through this technology appropriation, the pursuit of TI has gained momentum, and the leverage effects of such pursuit for society have expanded, as the benefits of innovative technologies are obtained without directly conducting R&D. Previous studies have verified the positive impact of such exploitation of external technology and knowledge on business performance (Huizingh, 2011; Kani & Motohashi, 2012).

This aspect of open innovation leads to the accelerated exchange of technology between different technological domains and contributes to technological convergence. Technological convergence (henceforth, TC) could occur when innovations emerge at the intersection of existing technologies (Lee et al., 2015). A new technological domain could be created through technological change (Karvonen and kässi, 2013). As Dosi and

Nelson (2010) suggested, technological change was widely considered an evolutionary process. The evolutionary theory of technological change (ETTC) explains that technological evolution could be defined as the process of technological change and development through interactions among technologies (Devezas, 2005). As technological evolution is a process of variation, selection, and retention (Geels, 2002), ETTC has been proposed and utilized as a theoretical framework to analyze such technological changes.

TC is currently regarded as the combination of multiple technological elements to create new technological fields (Kodama, 1995; Kim et al., 2014). Under the current circumstances, the mechanisms and patterns of converging technologies need to be systematically analyzed to formulate relevant strategies. More opportunities can be created for the multidisciplinary combination of innovative technologies, thereby promoting TC. From the neo-Schumpeterian perspective, multidisciplinary convergence creates opportunities for new technological innovations and provides competitive advantages for economic entities such as firms and governments (Allarakhia & Walsh, 2012). Then, the convergence of two or more different technologies can lead to innovation in new technological areas (Karvonen & Kässi, 2013; Suh & Sohn, 2015). Consequently, TC accelerates innovation by enabling cross-sectoral knowledge and new ways of combining technologies (Karvonen & Kässi, 2013).

2.3 Regional perspective on technological convergence

TC on hydrogen-related domains in an open innovation system could take different forms in different regions. Because hydrogen-related domains require facilities and regional capabilities (Lebrouhi et al., 2022), taking a regional perspective is important to understand the technological development of hydrogen. Furthermore, TC may eventually occur in many regions that possess technologies with regional knowledge bases. The technological activities of economic actors in each region are critical for innovation (Boschma and Martin, 2007). The emergence and exploitation of TC may vary across regions, as each region has its own strengths in specific technologies. The agglomeration economies of regions contribute to TI through knowledge spillovers (Glaeser et al., 1995). Because the exchange of innovative technologies can be accelerated in the open innovation system, a regional perspective may prove to be an effective means of broadening the understanding of TC. Such an approach could be considered a “spatial spillover” of TI to analyze the mechanism of TC and its diffusion in different regions (Cabrer-Borras & Serrano-Domingo, 2007).

In particular, the technological capabilities of a region that can generate TI are largely influenced by the regional knowledge base (Doloreux & Shearmur, 2012). The regional aspect has been considered important for the study of TI (Todtling & Kaufmann, 2001; Capello & Lenzi, 2015). Many approaches to TI have been proposed in terms of the regional knowledge base. Cabrer-Borras and Serrano-Domingo (2007) analyzed innovation-related regional patterns, exploring the regional dependence and evolution of innovative trends in Spain. They presented regional proximity based on market transactions as an important factor in explaining the spatial spillover effect, highlighting that a certain level of regional development is required to improve the effectiveness of R&D policies. Kwakkel et al. (2014) analyzed spatial data related to TI from different perspectives, with the aim of supporting decision-making. Müller and Ibert (2015) highlighted the importance of the community of practice in the innovation process and applied the aspect of spatial analysis to this concept. These attempts to explain the spatial perspective of TI are based on specific regions or technological fields.

More efforts are being made to understand the technological interaction between regions and within regions. Hajek et al. (2014) systematically analyzed the regional innovation system by visualizing the European case and found that knowledge-intensive regions have a positive effect on spatially close regions. Binz et al. (2014) presented the reasons for the importance of the spatial aspect in TI from the perspective of knowledge dynamics in the biotechnology sector. They provided analytical diagrams of the innovation process based on the spatial concept. Caragliu and Nijkamp (2014) analyzed spatial spillovers in terms of human capital and economic growth. They found that regional labor markets have positive spillovers from local markets and that spillovers are important for cooperation between regions. Sleuwaegen and Boiardi (2014) analyzed regional innovation systems in terms of creative workers in the region. They provided further empirical evidence on regional intelligence.

At the national level, numerous attempts have been made to establish regional approaches to TI and related policies (Crescenzi et al., 2012; Haakonsson et al., 2012). Autant-Bernard et al. (2013) analyzed the impact of regionalized knowledge spillovers on policymaking in Europe. Their results showed the significant function of regions in the pursuit of innovative policies and the importance of regional characteristics. Hammadou et al. (2014) conducted a country-by-country analysis of the determinants of government R&D spending from the perspective of spatial econometrics. They analyzed that despite geographical distance, strong interactions were observed in the R&D spending of countries with similar foreign trade or industrial patterns. Vásquez-Urriago et al. (2016) analyzed science and technology parks (STPs) as an important component of innovation policy. Using a much larger dataset than in previous studies, the authors found that such STPs and their locations can facilitate cooperation for innovation.

2.4 Research issues

In recent decades, the emergence of open innovation system has brought frequent technological interaction among domains and regions. TC may take different forms in different regions, and the technological characteristics might vary from region to region (Comin & Hobijn, 2009). Geography has been found to play an important role in the R&D process (Reuer & Lahiri, 2013; D’Este et al., 2012). As TC could occur with different patterns in different regions (Comin & Hobijn, 2009), R&D collaboration across regions is becoming increasingly important, especially for triggering the innovation of hydrogen technologies (Alnuaimi et al., 2012; Broekel, 2015; Cheng & Lee, 2022).

Hydrogen energy is an infrastructure technology that requires facilities and investments. Diverse domains participating in developing hydrogen energy and regions are closely associated with technological advancement. One could consider the perspective of TC and region when approaching hydrogen technologies. Therefore, this study focuses on three aspects of technological capabilities that could be associated with TC: technological features, degree of technological exchange, and technological adaptability from the regional perspective.

Technological features

Among the different technological aspects, technological features are considered based on the range of hydrogen technology-affiliated domains. Specifically, this study concerns technological features in a region, such as the diversity of technology, their technological boundaries, and the number of countries where these technologies are protected. Then, this study asks whether a region with a broader technological boundary has a higher regional incidence of TC, especially based on the IPC diversity of technologies, the size of the patent family, and the number of patent claims.

First, if there are more diverse technologies, there could be a higher possibility of TC (Lee et al., 2015). That research article suggested that technologies in a region consist of diverse fields, and examined how skewed different fields are in these hydrogen technologies. Diverse technologies provide the potential for convergence, and the degree of skewness of hydrogen technologies indicated how widely technologies could be used. Second, the present study considers the legally protected hydrogen-related technological boundary as the boundary of technological rights. In general, the wider the technological boundary, the higher the market value of the hydrogen technology. Third, the number of countries in which the technologies are legally patented is considered. Hydrogen is an infrastructure issue of national interest. Patenting technology in foreign patent offices is a strategic decision because it involves cost and effort.

Technological exchange

The technological exchange between regions is regarded as an important factor for generating TC, as the advancement of hydrogen-related technologies requires active interaction between different technological domains and different regions. With regard to this, the spillover of such accelerated technological exchange is known to promote further TI and convergence (Cabrer-Borras & Serrano-Domingo, 2007; Ko et al., 2014; Kwakkel et al., 2014). It is known to lead to collaborative R&D in the regional innovation system (Broekel, 2015). This study considers that a high degree of technological exchange can provide opportunities for converging hydrogen technologies and is likely to increase the technological proximity between regions, further contributing to the research collaboration and the pursuit of TI (D'Este et al., 2012).

Such technology exchange can provide a basis for regional technological capabilities and interactions between regions. In particular, the technological exchange between regions can be classified as either a flow into existing technology or a flow out of subsequent technology. The degree of utilization of existing technology can be indicated by the frequency of backward citations of patents in each region (Nemet & Johnson, 2012). Frequent and timely use of existing diverse technologies can increase technological exchange. Utilization of existing diverse technologies can generate new hydrogen-leveraged technologies. The degree of utilization by subsequent technologies indicates the direction of technological exchange and technological value (Harhoff et al., 2003; Gittelman, 2006; Blind et al., 2009; Harhoff & Wagner, 2009; Czarnitzki & Hottenrott, 2011; Fukugawa, 2012; Nemet & Johnson, 2012).

This research paper considers the reliance on existing public science and patented technologies, which may indicate that more complex and fundamental aspects of knowledge are used to accelerate high-quality technology (Narin et al., 1997). Furthermore, technologies and scientific knowledge flow in and out continuously, and such technological interaction needs to be understood systemically. Therefore, it is examined if TC could be associated with the degree of technological interaction between regions as follows: being cited by other patents, citing other patents, and citing non-patent literature.

Technological adaptability

The technological adaptability of a region is important to consider for achieving TI and indicating the possible opportunity for TC (Tuominen et al., 2004). The adaptation of new technologies is likely to occur with many applications (Wood, 2005). Where the technological interaction on hydrogen actively takes place within a range of technologies, the adaptation of diverse technologies to different regions becomes critical for TC. As adaptability means the ability to respond to change (Weigelt & Sarkar, 2012), regional adaptability could be important to consider when managing rapidly evolving technology (Hassink, 2010). Specifically, such technological adaptability could lead to different perspectives for pursuing TC.

As indicated by Hassink (2010), regional adaptability is understood in terms of lock-in and path dependence on technologies. Regarding lock-in, the study considers whether technologies are general to other technologies or not, and this research paper considers the generality and originality of technologies. Technological generality was proposed by Trajtenberg et al. (1997) and has been used to identify general-purpose technologies (Hall and Trajtenberg, 2004). Technological originality represents the breadth of technological fields on which the patent is based. Trajtenberg et al. (1997) proposed technological originality to explain knowledge diversification and stated that inventions that rely on many different sources of knowledge should be original results in terms of path dependence. This study considers the time-variant aspect of regional adaptability. Adaptability can also be understood as the speed of response to change (Weigelt & Sarkar, 2012). The radicality of technology has been proposed by Shane (2001). It can be measured as a time-invariant count of the number of IPC technology classes in which the patents cited by the given patent are classified, but in which the patent itself is not classified.

Overall, this study examines whether a region with higher technological features, degree of technological exchange, and technological adaptability has a higher regional occurrence of TC. The following section examines and analyzes the data and methods used to investigate these research issues.

3 Materials and methods

3.1 Data and variables

Many studies have explained the phenomenon of TC using patents as indicators of technological development and growth (Sen & Sharma, 2006; Dubaric et al., 2011; Han & Sohn, 2014). This study analyzed the Organization for Economic Cooperation and Development (OECD) database of triadic patents as of January 2021. The International Patent Classification (IPC) of triadic patents was used to define TC, and European Patent Office (EPO) citations of triadic patents were used to represent technological exchange. All EPO citations of triadic patents were used to identify the main regions of technological exchange involved in the corresponding TC. In addition, the OECD REGPAT database was used to match patents with applicants' addresses at the Nomenclature of Territorial Units for Statistics (NUTS) 3 and Territorial Level 3 (TL3) levels compiled by the OECD.

An analysis of patents and their IPCs is an effective way to analyze TC (Karvonen & Kässi, 2013). This study analyzed the regional occurrence of TC based on triadic patents, which are considered valuable (Baudery & Dumont, 2006). The study used the triadic patent database provided by the OECD as of January 2021 (OECD, 2021). In this study, TC was defined as patents having multiple IPCs at the seven-digit sub-class level. If there were more than two different IPCs for the same patent, we considered that this exhibited the phenomenon of TC. To define TC, we used the IPC definitions, as of January 2021, of corresponding patents. We assumed that the co-occurrence of the same patent in the IPC defined the occurrence of TC on each patent (Curran & Leker, 2011). Based on this definition of TC, we narrowed all triadic patents to only TC patents for our analysis.

The analysis included 1,594,886 triadic patent families (as of 2021). A patent family was defined as a set of identical patents filed in different countries for the simultaneous protection of the same invention in those countries. Related patents were grouped together as patent families. OECD triadic patents included triadic patent families that had sets of patents filed with the EPO and the Japan Patent Office (JPO) and registered with the United States Patent and Trademark Office (USPTO). Converting the triadic patent families to the number of patents filed with the EPO yielded a total of 1,850,124 patents.

Then, the patents were filtered to 37,058 patents on hydrogen, especially the production and electrification of energy with the following IPCs: H01M004, H01M008, H01M012, C10B053, C10J, E02B009, F03B, F03C, B63H019, F03G007, B60K006, B60W010, H01M010, H01G011, H02J003, and H02J009 based on the WIPO Green Inventory. Then, patents with multiple IPCs at the seven-digit subclass level were considered to represent TC. For example, if there were more than two different IPCs for the same patent, it was considered to represent TC. The IPC definitions, as of January 2021, of the corresponding patents were used to define TC. The co-occurrence of the same patent in the IPC defined the occurrence of TC for each patent (Curran & Leker, 2011). Based on this definition of TC, all triadic patents were narrowed to only those with TC for analysis. As a result, patents on hydrogen and related fields had 832,329 EPO citations, with 140,404 IPC codes analyzed based on EPO assignments.

To understand the regional occurrence of TC, this study used REGPAT, another database provided by the OECD. REGPAT is a regional database of patent applications that can match applicants' addresses with their patents. The addresses provided were matched at the NUTS 3 or TL3 level. Table 1 outlines the variables used in this study to process these data.

EPO patents were used to measure the technological characteristics of a region. As technological characteristics of a region, we used IPC-related variables, such as IP counts and IPC Theil diversity, and those were averaged per region. These variables can indicate how diverse a region's technologies are and how skewed they are (Gao et al., 2013; Leydesdorff et al., 2014; Lee and Sohn, 2018). In addition, the average family size and the average number of claims are considered to represent the technological breadth of a region (Harhoff et al., 2003; Petruzzelli et al., 2015). Patent claims have been widely used to indicate technological boundaries. Previous studies have suggested that a large number of claims can require a higher patent fee, which, in turn, can represent a high market value and broad technological boundary. The family size of a patent can usually indicate how many countries the patent is protected in. The family size is measured by the number of patent offices where a given invention is protected, and it is normalized with respect to the maximum value shown by other patents in the same cohort (OECD, 2021).

The degree of technological exchange can be examined in terms of both citing other technologies and being cited by other technologies. For being cited by other technologies, the current study considered the average number of forward citations at the regional level. The forward citations of triadic patents were measured by the European Patent Office, with a window of 5 years after publication for timeliness. Next, the average number of backward citations and non-patent literature (NPL) citations was considered. Backward citations can be used as a measure of technology flow (Nemet & Johnson, 2012). In this study, technology flow was defined as the degree of dependence on other technologies. According to Lanjouw and Schankerman (2001), backward citation can indicate that the technology refers to relatively well-developed technological areas. Also, NPL citation indicates that the technology has a high quality and makes a public scientific contribution to industrial technology (Narin et al., 1997). Sometimes, technology with NPL citations is considered to have more complex and fundamental knowledge (Cassiman et al., 2008). In this study, backward citations and NPL citations were based on EPO citations. These variables represent how the regional knowledge base depends on the previous technology and knowledge. The degree of technological exchange of each region is measured by calculating the closeness centrality of the citation network regrouped by region (D'Este et al., 2012).

Finally, the adaptability of the region's technologies was studied sequentially. It could be categorized into originality, generality, and radicality. The generality was proposed by Trajtenberg et al. (1997), and this study used the generality as a modification of the Hirchman–Herfinahl index proposed by the OECD (OECD, 2021). The forward citation and citing IPC were measured and normalized from 0 to 1. When the technology was widely cited, the generality was calculated close to 1. On the other hand, originality, proposed by Hall et al. (2001) and calculated by backward citation, works differently. Originality is reduced when the technology cites

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TABLE 1 Research variables.

	Variable	Description	Reference
Dependent variable	Tech_conv	Number of technological convergences per region	Curran and Leker (2011)
Technological feature	IPC diversity	Average IPC Theil diversity of triadic patents by region	Leydesdorff et al. (2014), Suzuki and Kodama (2004)
	Family size	Average family size of triadic patents by region	Harhoff et al. (2003)
	Claim counts	Average claim count of triadic patents by region	Milanez et al. (2017), Petruzzelli et al. (2015)
Technological exchange	Forward Citation	Average count of forward citations by region (as of 2017)	Czarnitzki & Hottenrott (2011), Nemet & Johnson (2012), Fukugawa (2012), Harhoff et al. (2003)
	Backward Citation	Average count of backward citations by region	Nemet & Johnson (2012), Harhoff et al. (2003), Harhoff & Wagner (2009)
	NPL Citation	Average count of NPL citations by region	Narin et al. (1997), Cassiman et al. (2008)
Technological adaptability	Generality	Average generality of triadic patents by region; OECD defined	OECD (2021), Trajtenberg et al. (1997)
	Originality	Average originality of triadic patents by region; OECD defined	OECD (2021), Hall et al. (2001)
	Radicalness	Average radicalness of triadic patents by region; OECD defined	OECD (2021), Shane (2001)

Because triadic patents with multiple IPCs are considered to represent the occurrence of TC, the number of these patents by region is considered the degree of TC per region. With respect to the regional knowledge base, the following aspects are considered: technological specificity, technological exchange, and technological adaptability.

different technologies. Finally, radicality indicates technological capability (Shane, 2001). It can measure the relative weight of each IPC in the cited patents. Its values are then normalized from 0 to 1. A higher degree of radicalness can indicate that the technology relies on more diversified technologies.

3.2 Methodology

To effectively analyze the regional occurrence of TC, important regions were primarily considered in terms of open innovation. Important regions involved in technological exchange were identified by mapping patent-related regions after obtaining a patent network based on all patent citations. The regional level used for mapping regions was NUTS 3 or TL3. Then, a Bayesian spatial model of Poisson response was applied. The Bayesian spatial model required the distance matrix between the regions detected in this study. Because the technological proximity between regions may be more important than the physical distance between regions, the technological distance was used for the analysis. Based on the patent citation in terms of regions, a technological similarity matrix was constructed based on the Jaccard similarity. The elements in this matrix were dichotomized and the diagonal was set to zero. The Jaccard similarity was employed to calculate patent similarity based on patent citations:

$$J\left(Citations\,of\;Patent_A, \text{Citations of}\;Patent_B\right), = \frac{\left|Citations\,of\;Patent_A \cap Citations\,of\;Patent_B\right|}{\left|Citations\,of\;Patent_A \cup Citations\,of\;Patent_B\right|}.$$

As expressed in equation (1), the Jaccard similarity of patent citations presents the degree of citations shared by patents A and B among the total citations of patents A and B. Citation similarities among patents were then mapped as similarities in the inter-regional technological exchange, and regional data related to TC were regrouped around the regions covered under NUTS 3.

Before building the model, all independent variables were scaled with mean and standard deviation.

The model in this study refers to a Bayesian spatial model using INLA, called the Besag–York–Mollie (BYM) model (Besag et al., 1991; Blangiardo et al., 2013). BYM is an intrinsic conditional autoregressive (iCAR) model used to model areal counts of events by region. It models with covariates and provides the linear effect for the covariate (Rue et al., 2009). The following description of BYM was largely based on Blangiardo and Cameletti (2015). For each region i, the number of technological convergences follows a Poisson distribution, and the number of triadic patents for each region acts as an offset for Poisson response. Among various structures, the intrinsic conditional autoregressive (iCAR) structure in the present study was based on Besag et al. (1991). The coefficient could be interpreted as, "What percentage does the independent variable increase the dependent variable?"

A Bayesian spatial model of Poisson response was applied to the regional data with INLA. The Bayesian approach with INLA has been widely adopted, especially in epidemiology and spatial analysis. This approach is particularly effective and easy to use to specify a hierarchical structure of data with spatial and/or temporal characteristics (Blangiardo & Cameletti, 2015). In particular, the data of this study were distributed in the region with diverse technological features. It was also necessary to include the interactions among regions. Thus, this study suggested that the Bayesian spatial model with INLA could fit with the occurrence of TC over regions.

Concerning the proposed model, the estimation of the model could be challenging due to the complicated aspects of the proposed model. Markov chain Monte Carlo (MCMC) is widely used to compute such a Bayesian model. However, due to the complexity of the model and the dimensions of the database, INLA has recently been developed as an alternative to MCMC (Blangiardo & Cameletti, 2015). The INLA approach is computationally efficient; it was developed for latent Gaussian models, with flexible support for models ranging from generalized linear mixed to spatial and spatiotemporal models (Blangiardo & Cameletti, 2015).

The following explanation for BYM is largely based on Blangiardo and Cameletti (2015). For each region i, the number of technological convergences, Y_i, follows a Poisson distribution with λ_i, the average number of technological convergences for each region i. λ_i can be defined in terms of the occurring rate of technological convergences per a triadic patent for each region i ρ_i and the number of triadic patents e_i for each region i. e_i acts as an offset, and the parameters in η_i can be interpreted on the log relative risk scale. Therefore, we assume the following:

$$Y_i \sim Poisson(\lambda_i),\ \lambda_i = e_i\rho_i,\ \log(\rho_i) = \eta_i.$$

Here, ρ_i is modeled through a linear predictor η_i for each region i.

$$\eta_i = log(\lambda_i) = b_0 + u_i + v_i.$$

Here, b_0 represents the intercept, quantifying the average outcome rate in all the regions. v_i indicates the area-specific effect. Another area-specific effect, u_i, represents a spatially structured effect.

Among various structures, the CAR structure considered here is based on Besag et al. (1991). As each area i can be characterized by a set of neighbors, $\mathcal{N}(i)$, among n entire regions, u_i is considered as the following random variable:

$$u_i \Big| \boldsymbol{u}_{-i} \sim Normal\left(\mu_i + \sum_{j=1}^{n} r_{ij}\left(u_i - u_j\right), s_i^2\right).$$

Here, μ_i is the mean for a region i and $s_i^2 = \sigma_u^2/\mathcal{N}_i$ is the variance for the same region ($\mathcal{N}_i = \#\mathcal{N}(i)$). r_{ij} indicates the spatial proximity among regions and can be calculated as $\phi \times W_{ij}$, where $W_{ij} = a_{ij}/\mathcal{N}_i$, a_{ij} is 1 if areas i and j are neighbors and 0 otherwise. Φ controls the properness of the distribution.

Considering W as the matrix of elements W_{ij} and $\boldsymbol{S} = \mathrm{diag}(s_1, \cdots, s_n)$, the proper CAR specification, u is a multivariate normal random variable with the covariance matrix $(\mathrm{I} - \phi \boldsymbol{W})^{-1}\boldsymbol{S}^2$:

$$\boldsymbol{u} \sim \mathrm{MVNormal}\left(\boldsymbol{\mu}, (\mathrm{I} - \phi \boldsymbol{W})^{-1}\boldsymbol{S}^2\right),$$

where $\boldsymbol{\mu} = \{\mu_1, \cdots, \mu_n\}$ is the mean vector and I is the identity matrix. Thus, the conditional distribution of $u_i|\boldsymbol{u}_{-i}$ is

$$u_i \Big| \boldsymbol{u}_{-i} \sim Normal\left(\mu_i + \phi \frac{1}{\mathcal{N}_i}\sum_{j=1}^{n} a_{ij}\left(u_i - u_j\right), s_i^2\right).$$

TABLE 2 Patents per hydrogen-related IPC.

IPC	# of patents	IPC	# of patents
H01M010	14,415	H02J009	816
H01M004	11,555	H01M012	642
H01M008	9,569	F03G007	541
B60W010	4,121	F03C	379
H02J003	2,479	C10B053	342
H01G011	1,542	E02B009	97
F03B	887	B63H019	25
C10J	850	B60K006	0

The aforementioned specification is not widely used due to the difficulty in estimating ϕ. A simplified version of the formulation can be obtained by setting $\phi = 1$, which leads to the following conditional distribution for u_i:

$$u_i \Big| \boldsymbol{u}_{-i} \sim Normal\left(\mu_i + \frac{1}{\mathcal{N}_i}\sum_{j=1}^{n} a_{ij}\left(u_i - u_j\right), s_i^2\right).$$

It is called intrinsic conditional autoregressive (iCAR), and the BYM model originated from the aforementioned specification combined with the exchangeable random effect in the linear formula for η_i. In order to include our predictors, η_i can be modified as

$$\eta_i = log(\lambda_i) = b_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + u_i + v_i,$$

and v_i is the unstructured residual modeled using exchangeability among all regions such that

$$v_i \sim Normal(0, \sigma_v^2).$$

u_i is modeled as a first-order intrinsic Gaussian Markov random field.

$$\pi(\mathrm{u}|\kappa_u) \propto \kappa_u^{\frac{n-1}{2}} exp\left(-\frac{\kappa_u}{2}\sum_{i \sim j}\left(u_i - u_j\right)^2\right) = \kappa_u^{\frac{n-1}{2}} exp\left(-\frac{\kappa_u}{2}\boldsymbol{u}^T\boldsymbol{R}\boldsymbol{u}\right).$$

Both u_i and v_i assume Gamma prior distribution, and inference is conducted using INLA. Further details on INLA can be found in Blangiardo and Cameletti (2015).

4 Results

4.1 Descriptive statistics

The integrated data can be constructed using EPO patent application IDs, which are the key values in all OECD triadic patent applications, EPO patent citations, and the REGPAT of triadic patents. First, the patents derived from the EPO citation data were matched to the corresponding triadic patents. The triadic patents were filtered to 37,058 patents on hydrogen production and electrification of energy based on IPCs, such as H01M004,

TABLE 3 Descriptive statistics (unit: region).

	Mean	SD.	Min	25%	Median	75%	Max
Number of convergences	57.6122	424.4391	0	2.0000	4.0000	13.0000	7330.0000
IPC Theil diversity	0.0261	0.0579	0	0.0000	0.0000	0.0283	0.4112
Family size	7.2158	3.4877	3	5.0000	6.0000	8.2820	29.0000
Claims counts	14.7228	8.4582	3	10.0000	12.6358	16.9286	72.0000
Backward citations	5.7331	2.8510	0	4.0000	5.2500	7.0000	20.0000
NPL citations	0.8171	1.8985	0	0.0000	0.1824	1.0000	27.0000
Forward citations	2.5188	4.8716	0	1.0000	2.0000	3.1139	95.0000
Generality	0.3889	0.2214	0	0.2334	0.4182	0.5645	0.8568
Originality	0.6876	0.1640	0	0.6162	0.7123	0.8009	0.9372
Radicalness	0.2405	0.1775	0	0.1190	0.2059	0.3382	1.0000

In the next subsection, the association is further investigated between the regional occurrence of TC and factors related to the regional knowledge base.

H01M008, H01M012, C10B053, C10J, E02B009, F03B, F03C, B63H019, F03G007, B60K006, B60W010, H01M010, H01G011, H02J003, and H02J009, according to WIPO Green Inventory. Table 2 shows the number of patents for each IPC. As shown in Table 2, more than half of the patents were distributed on H01M, and other IPCs, such as B60W, H02J, H01G, F03B, C10J, F03B, F03C, and F03G, also appeared, indicating hydrogen production and electrification of energy.

The important regions of technological exchange were identified from the patent citation network by matching TCs to corresponding regions. TCs were identified and matched to regions by linking them to the corresponding regional information. The identified regions were matched using NUTS 3 or TL3. This process resulted in 428 regions.

After all the data were mapped by region, the research variables were established based on these main regions of technological exchange. For obtaining the dependent variable, the patents on TC were summarized by the region of applicants at the level of NUTS 3 or TL3. Particularly, if a patent could be filed by two or more applicants, there may be more than one regional code for a patent. In such cases, the number of TCs for each region was adjusted by multiplying the number of convergent patents by the ratio of applicants associated with that region. Then, the number of convergent patents was calculated for each region. In addition, the standard scaling was, respectively, applied to each independent variable. The distribution of the variables is shown in Table 3, and the table does not include the mean and standard deviation due to the standard scaled values with the mean and standard deviation.

4.2 Results of the spatial model

The BYM model was applied to the 428 regional datasets. The dichotomized technological distance matrix was used for the application of BYM. It was also assumed that the Poisson distribution for the dependent variable was used instead of the Poisson distribution because our dependent variable had overdispersion. Based on the results, the resulting matrix was constructed with columns and rows consisting of each region reflected in the BYM model. In addition, the logarithm of the number of triadic patents of each region was considered as the offset. The BYM analysis was performed using the INLA package of open-source R, and Table 4 depicts the estimated parameters of the BYM model.

Table 5 also indicates the estimated coefficients from the BYM model. Findings suggested the important factors of a region that trigger the technological convergences associated with hydrogen.

From the results, it was observed that a diverse exchange of technologies with high originality could exert a positive influence on the convergence of hydrogen technologies. Specifically, IPC diversity, originality, and citation level had a positive influence on TC in hydrogen-related fields. Among these variables, originality, which was expected to be an important variable, was found to increase the regional occurrence of TC by 5.4685 times. Next, IPC diversity gave a 14.68% increase to TC on hydrogen-related domains. Forward citations, NPL citations, and backward citations of technological exchange also increased the regional TC by approximately 5%, 5%, and 2%, respectively.

On the other hand, variables such as family size, generality, and radicalness had a negative influence on regional TC. Generality and radicalness all seemed to have a positive effect on TC, but an unexpected result was obtained. Generality reduced regional TC by 65.1%. In addition, radicality could lead to less occurrence of TC in a region. As the radicality of a region's hydrogen-related technologies increased, the region was 23.89% less likely to be involved in the rate of TC. This finding indicated that radical technology that lacks originality might not contribute to the advancement of hydrogen technology.

5 Discussion

This study examined the regional occurrence of TC to further accelerate TI in hydrogen-related fields. Specifically, triadic patents, EPO triadic patent citations, and REGPAT were used for the analysis. The important regions for an open innovation system

TABLE 4 Parameter estimation.

Model hyperparameter	mean	Sd	0.05quant	0.5quant	0.95quant	Mode
Size of the binomial observations (1/overdispersion)	2441.0010	42700.0000	25.9440	221.5370	7135.5750	38.8370
Precision for id (iid component)	0.1640	0.0140	0.1410	0.1650	0.1860	0.1680
Precision for id (spatial component)	1850.0000	1850.0000	189.7050	1333.7390	5398.1820	347.7560

Deviance information criterion (DIC, saturated): 861.02.
Effective number of parameters: 411.97.
Watanabe–Akaike information criterion (WAIC): 2389.31.

TABLE 5 Fixed effects of BYM for the regional occurrence of technology convergence.

	Variable	Mean	Exponentiated mean	Std. Dev	0.05quant	0.5quant	0.95quant	Mode
Technological Feature	IPC Theil diversity	0.1370	1.1468	2.2480	−3.5700	0.1400	3.8340	0.1460
	Family size	−0.0600	0.9418	0.0370	−0.1210	−0.0600	0.0010	−0.0600
	Claims size	0.0000	1.0000	0.0160	−0.0260	0.0000	0.0260	0.0010
Technological Exchange	Backward citations	0.0240	1.0243	0.0480	−0.0560	0.0240	0.1030	0.0240
	NPL citations	0.0550	1.0565	0.0710	−0.0620	0.0560	0.1710	0.0560
	Forward citations	0.0570	1.0587	0.0260	0.0150	0.0570	0.0990	0.0570
Technological Adaptability	Generality	−1.0500	0.3499	0.5540	−1.9620	−1.0510	−0.1370	−1.0510
	Originality	1.6990	5.4685	0.9100	0.2010	1.6980	3.1990	1.6980
	Radicalness	−0.2720	0.7619	0.8590	−1.6880	−0.2710	1.1410	−0.2700

were selected on the basis of patent citations in order to identify the regions that play a predominant role in technological exchange between regions. Globally, 428 regions contributing to the open innovation system were selected, and a variety of relevant regional data were collected and organized. BYM was then applied to explore the relationships between the factors associated with technological characteristics and TC in hydrogen-related domains.

The results suggest that the convergence of hydrogen technologies can be promoted in a region where there is a high degree of originality, which can be regarded as a region-specific technology. On the other hand, if the technology is associated with a patent family, it is not positively associated with TC in a region. Furthermore, IPC diversity and citations of a region seem to be positively related to the TC of hydrogen. That is, a region with hydrogen technologies plays an important role for TC. It is necessary to design a policy to accelerate the technological exchange among regions to expect more TC. However, if a region is not focused on some technologies, it may be difficult for that region to be positively associated with TC. In addition, if a region has a technology that has a wide technological boundary, it seems to negatively influence TC.

From the perspective of adaptability for technological interaction, generality, radicality, and originality contradict each other for TC. It is expected that generality might negatively influence TC because it might make technologies ordinary. Radicality might hinder TC because it excessively raises the boundary for convergence with other technologies. Radical technology appears to have difficulty in positively influencing interactions with other technologies. However, it is likely to be mixed with other technologies based on its own technological context and boundary. The aforementioned results imply that the policy of promoting TC among regions must take into account the technological adaptability a region currently has.

This study is one of the first to analyze regionally driven TC with all triadic patents, especially for hydrogen-relevant technologies. Based on the results, it is expected that spatial dependence will be reflected in future government or business policies and strategies related to the regional innovation system, especially to promote TC. Furthermore, the results suggest the feasibility of policies to promote TC with a regional focus. By identifying areas of technology with geographical advantages, more detailed research could be conducted to extend the investigation to the analysis of TC and synergistic cooperation on interregional spillover linkages.

This study has several limitations. First, its geographical scope in the analysis of TC was set at the regional level of NUTS 3 or TL3, to the exclusion of more detailed or higher-level analysis. A more detailed geographical level should be addressed in a follow-up study. It is also necessary to examine the phenomenon of non-patented technology, and this is left for future research.

6 Conclusion

Currently, the innovation of hydrogen technology has become increasingly important to ensure continued growth and maintain a competitive advantage in the era of open innovation. It has been recognized that an effective way of achieving TI is embracing TC. In particular, the pursuit of TC is emerging in the field of hydrogen technology. This study attempted to examine how TC occurs differently in various regions within hydrogen technology. The findings present the results of a Bayesian spatial model that incorporates the factors that are associated with the convergence of hydrogen technology with other fields using the valuable triadic patent database and its associated regional data of patent applicants. The findings of this study indicate the need to build R&D regions by generating active interactions and maintaining the diversity of original hydrogen technologies. Furthermore, one could consider the regional aspect in policies and strategies to promote TC. It is expected that this study could contribute to further research on the regional approach to TC and the design of policies for a hydrogen-triggered, zero-carbon industrial ecosystem.

Data availability statement

Publicly available datasets were analyzed in this study. These data can be found in: OECD Patents Database.

Author contributions

WL contributed to the conception and design of the study. WL organized the database and performed the statistical analysis. WL wrote the first draft of the manuscript, contributed to the manuscript revision, and read and approved the submitted version. The author contributed to the article and approved the submitted version.

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Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Renewable energy, GDP and CO_2 emissions in high-globalized countries

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Introduction: Policymakers devote significant efforts to decrease CO_2 emissions, as climate change has Q7 numerous adverse impacts on society. While the global level of CO_2 emissions has been gradually rising since the 1990s, the highest growth was observed in low- and middle-income economies. This study differs from nascent research as it fills the gap by exploring the GDP-energy-CO_2 emissions nexus for the top 50 highly globalized countries under analysis. Our study explores the multidimensional relationship between economic growth, renewable energy, globalization, and climate change, using CO_2 emissions as a proxy for air pollution, and focusing on the most globalized countries.

Methods: In this study, we rely on dynamic panel estimators such as the two-step system GMM estimator. System GMM estimator is recommended to use with the panel data when 1) the correlation between a dependent variable and its lag is above 0.8; and 2) the number of countries (i.e., 50 countries) exceeds the time frame (i.e., 19 years). As our study design fits these conditions, we use extension of a two-step system GMM estimator which restricts the expansion of instruments. Moreover, a two-step system GMM estimator is especially efficient as it controls for heteroskedasticity.

Results: We find that renewable energy and globalization decrease CO_2 emissions. If causal, a 1 percentage point increase in the share of renewable energy in total energy consumption leads to a 0.26% decrease in per capita CO_2 emissions. Similarly, we find that a larger representation of women in national parliament contributes to the reduction in CO_2 emissions. GDP per capita has an inverted U-shaped relationship with CO_2 emissions and the turning point is approximately 67,200 international dollars adjusted for PPP.

Discussion: Our results suggest that renewable energy significantly contributes to the reduction of carbon emissions while GDP per capita has an inverted U-shaped link with CO_2 emissions. Thus, we confirm the presence of the EKC hypothesis for highly-globalized countries. Consequently, our study offers several policy implications. Firstly, it is important for developing countries to increase the share of energy consumed from renewable energy sources. This will have a positive effect not only on air quality, but also on economic growth. Thus, it is essential to increase investment in the renewable energy sector and create conditions and benefits for the rapid adoption of renewable technologies by the private sector and households. Secondly, it is crucial to increase the quality of investment climate. Developing countries can significantly gain from globalization-driven FDI as this can lead to technology transfer, especially in the energy sector. Thirdly, our results suggest that improving female empowerment can significantly reduce the vulnerability to climate change. This can be achieved by increasing women's human capital and investing in women-led organizations and communities.

KEYWORDS

renewable energy, GDP, CO_2 emissions, women in parliament, globalization

Introduction

Policymakers devote significant efforts to decrease CO_2 emissions, as climate change has numerous adverse impacts on society. While the global level of CO_2 emissions has been gradually rising since the 1990s, the highest growth was observed in low- and middle-income economies. Scholarly literature suggests that economic growth and energy consumption are considered as main antecedents of CO_2 emissions at global and regional levels (Acaravci and Ozturk, 2010; Saboori and Sulaiman, 2013). As a result, the transition towards energy efficient and green economic growth has been acknowledged as a new sustainable development agenda. Indeed, the examination of the GDP-energy-CO_2 emissions links has grown considerably in size over the past two decades. Along these lines, with the focus on environmental degradation, the literature can be separated into three streams. The first line of research explores the relationship between economic development and CO_2 emissions through the underpinnings of the Environmental Kuznets curve (EKC) framework stemming from the study by Grossman and Krueger (Grossman and Krueger, 1991). The EKC theory suggests inverted U-shape relationship between economic growth and environmental degradation and posits that "environmental pressure increases faster than income in the early stage of development and slows down relative to GDP growth in higher income levels" (Dinda, 2004). In low-income countries, industrialization and rapid growth of related industries spur pollution due to intensified economic activities and prioritization of economic growth. However, as GDP *per capita* increases the adoption of energy-efficient technologies and the development of industries with lower carbon footprint remove thepressure on the environment, and carbon emissions decrease. The empirical assessment of the existence of the EKC has proliferated with the increased availability of cross-country data [see, e.g., Anwar et al. (2022) for an excellent bibliometric analysis]. For example, the EKC has been confirmed for single countries such as Kenya (Sarkodie and Ozturk, 2020), Malaysia (Suki et al., 2020), Bangladesh (Murshed et al., 2021) and Brazil (Polloni-Silva et al., 2021). In a similar vein, inverted U-shaped link between GDP and CO_2 emissions has been validated for various regions, including PIIGS countries (Balsalobre-Lorente et al., 2022), E7 countries (Bekun et al., 2021), East African countries (Demissew Beyene and Kotosz, 2020), among others. At the same time some studies fail to identify EKC [see, e.g., Dogan and Inglesi-Lotz (2020) for European region, Dogan et al. (2020) for BRICST, Haliru et al. (2020) for West African countries, Ansari et al. (2020) for GCC countries].

The second group of studies explores how renewable energy in the total energy mix influences air quality, and, especially how it can mitigate climate change effects without harming economic growth trajectories. Indeed, a meta-analysis of more than 79,000 studies by (Kılıç Depren et al., 2022) shows that "the number of renewable energy-related studies has exceeded the number of fossil fuel-related studies regarding environmental degradation" (p. 1). Energy is considered an instrumental driver of economic growth (Tang et al., 2016) but it has also been shown to be linked to air pollution (Wang et al., 2018). In contrast, a shift towards the use of renewable energy as a replacement for fossil fuels has been documented to increase air quality and improve energy security (Aized et al., 2018). Moreover, numerous studies confirm the positive contribution of renewable energy to quality of life by showing that investment in renewable energy increases longevity (Rodriguez-Alvarez, 2021) and decreases human mortality (Shah et al., 2022) and income inequality (Topcu and Tugcu, 2020). The International Energy Agency expects that global renewable energy supply can increase by more than 60% compared to the year 2020 (IEA, 2021). Thus, increase deployment of renewables can have numerous positive implications as suggested by extant research. The third strand of studies considers the role of additional macroeconomic factors beyond renewable energy and GDP *per capita*. Within this stream of published evidence global integration is recognized as one of the essential predictors of CO_2 emissions. Under the assumptions of the pollution haven hypothesis (PHH), globalization drives the relocation of carbon-intensive industries to countries with less stringent environmental regulations. Thus, PHH conjectures a positive link between globalization and CO_2 emissions. However, the pollution halo hypothesis postulates that globalization leads to the export of green energy-efficient technologies which expands economic activity without pressure on the environment (Zhang and Zhou, 2016). A number of studies have indeed confirmed that globalization improves environmental quality and increases energy efficiency (Baloch et al., 2021; Liu et al., 2022). The analysis of the effects of renewable energy and GDP *per capita* on CO_2 emissions in the context of high-globalized countries is exceptionally relevant. A significant breakthrough in globalization can affect CO_2 emissions via shifts in energy demand (Doğan et al., 2022), effective distribution of production inputs, technological diffusion, and increased exchange of knowledge (Samimi and Jenatabadi, 2014). To the best of our knowledge, extant studies have explored the joint effects of economic growth, renewable energy, and globalization on CO_2 emissions and reported mixed results. This study differs from nascent research as it fills the gap by exploring the GDP-energy-CO_2 emissions nexus for the top 50 highly globalized countries under analysis. Our study explores the multidimensional relationship between economic growth, renewable energy, globalization, and climate change, using CO_2 emissions as a proxy for air pollution, and focusing on the most globalized countries. As (Leal and Marques, 2020) suggest "globalization is a complex phenomenon made up of many components. Its effect on the environment, when studied as a whole, leaves many questions unanswered" (p. 37). Over the last two decades, two important trends have emerged: a surge in renewable energy deployment and increased globalization in less-developed countries. All these advancements indicate that renewable energy use and economic growth are thus likely to have impacts on greenhouse gas emissions depending. The rest of the study is structured as follows. Section 2 provides a brief overview of the recent empirical literature. Section 3 presents the data and methodology. Section 4 discusses the main results while Section 5 concludes the study.

Literature review

Carbon emissions and GDP *per capita*

Theoretical claims and empirical studies of the link between GDP *per capita* and CO_2 emissions overall suggest the existence of an inverted U-shaped (the so-called EKC) relationship. (Murshed et al., 2020) investigated the EKC hypothesis for OPEC member states using panel spatial regression models. The results for the years 1992–2015 confirm the validity of the EKC hypothesis. At the same time, the sectoral analysis also shows the significance of the non-linear relationship between value added and air pollution varies depending on the sub-sector. (Dogan and Inglesi-Lotz, 2020) examined the relationship between GDP, economic structure, and CO_2 emissions, under the EKC framework for Europe for the years 1980–2014. The study discovered that aggregate economic growth exerts an inverted U-shaped link with CO_2 emissions. However, economic structure has a U-shaped effect on air pollution. (Bibi and Jamil, 2021) tests the existence of the EKC hypothesis for six regions over the period 2000–2018. The study using random effects and fixed effects models documents that EKC is valid for the majority of the regions. Using panel data for EU countries, (Bekun et al., 2021) endorses the existence of an inverted U-shaped relationship between economic development and environmental degradation. The Granger causality test further shows that causality runs from GDP growth to air pollution. (Heidari et al., 2015) found that economic growth is non-monotonically related to CO_2 emissions in ASEAN countries. The panel smooth transition regression (PSTR) validates the EKC hypothesis with the threshold regime at 4,686 USD. (Leal and Marques, 2020) examined the presence of the EKC hypothesis in the top 20 highest CO_2 producing economies over the period 1990–2016. The Driskoll-Kraay estimator showed that EKC is only valid for highly-globalized countries. Noteworthy, a number of studies explored the EKC hypothesis focusing on a single country. (Pata, 2018) analyzed Turkey over the period 1974–2014 using ARDL and FMOLS regressions, documenting the statistically significant inverted U-shaped evidence between GDP and CO_2 emissions. However, the long-run estimates showed that the turning point is 13,523–14,077 US Dollars which is outside the sample data. (Katircioğlu, 2014) document the validity of the tourism-driven EKC hypothesis for Singapore between 1971–2010, using Maki cointegration and other time series regression methods. At the same time, (Işik et al., 2020) explored the presence of the tourism-induced EKC hypothesis for G7 countries from 1995–2015. The authors discovered that the tourism-induced EKC hypothesis holds only for France.

Renewable energy and CO_2 emissions

The relationship between renewable energy and carbon emissions was examined by using regional and single-country cases. The majority of these studies report that renewable energy deployment mitigates CO_2 emissions. Using a number of panel data methods (Haldar and Sethi, 2021) found that renewable energy decreases CO_2 emissions in the long run in the case of 39 developing countries over the period 1995–2017. Moreover, the study highlights that it is instrumental to improve quality of institutions and increase the use of renewable energy to raise air quality. (Zoundi, 2017) tests the hypothesis of whether renewable energy can act as an efficient replacement for fossil fuels for 25 African countries over the period 1980–2012. While the study fails to confirm EKC for selected African countries, renewable energy has a negative and significant effect on CO_2 emissions. By using the cointegration estimator and Granger causality test, (Ben Jebli et al., 2019a) examines the relationship between renewable energy, GDP growth, and CO_2 emissions across 22 Central and South American countries between 1995–2010. The study found that there is unidirectional causality from renewable energy and FDI to CO_2 emissions. The study stresses the need to encourage renewable energy adoption to mitigate climate change. (Dogan and Seker, 2016) assess the drivers of CO_2 emissions in EU member states over the period 1980–2012. Using the dynamic OLS regression method, the authors find that renewable energy mitigates CO_2 emissions and GDP has an EKC type relationship with air pollution. The study also documents bi-directional causality between renewable energy and CO_2 emissions. In turn, using the generalized spatial two-stage least squares (GS2SLS) method, (Radmehr et al., 2021) found a unidirectional causality running from renewable energy to CO_2 emissions. (Leitão and Lorente, 2020) confirms that trade, tourism, and renewable energy reduce climate change in EU member states, using FMOLS, DOLS, and GMM estimators. At the same time, the study showed that economic growth is positively associated with environmental degradation. In turn, (Huang et al., 2021) focus on major energy-consuming economies to assess the relationship between renewable energy and carbon emissions over the period of 2000–2015. Using a two-step GMM estimator, the authors show that the renewable energy sector has substantial potential to mitigate climate change effects in countries with the highest demand for energy use. Mentel et al. (2022b) examine the relationship between industrialization, renewable energy, and CO_2 emissions in 48 countries of Europe and Central Asia (ECA). The study using a two-step GMM estimator finds that 1) renewable energy decrease CO_2 emissions; 2) renewable energy offsets the positive effect of industrialization on CO_2 emissions; 3) the EKC hypothesis is verified for ECA countries. In the case of single-country studies, the importance of renewable energy to decrease CO_2 emissions was verified for Ecuador, Thailand, China, India, and Portugal, among others (Robalino-López et al., 2014; Sinha and Shahbaz, 2018; Chen et al., 2019; Abbasi et al., 2021a; Adebayo et al., 2022).

Globalization and CO_2 emissions

A separate strand of studies has explored the role of globalization in the presence of EKC framework. For example, Farooq et al. (2022)

assessed the relationship between globalization and environmental quality in a sample of 180 nations over the period 1980–2016. Using panel quantile regression methods, the authors find that only economic dimension of globalization has negative effect on CO_2 emissions. Liu et al. (2020), using semi-parametric fixed effects regression estimator for a sample G7 countries over the period 1970–2015, find that globalization exerts non-linear impact on CO_2 emissions. Mehmood (2021) documents that social and economic globalization decrease CO_2 emissions in Singapore using ARDL estimator. Mehmood and Tariq (2020) observed mixed results for South Asian countries over the period 1972–2013. The authors find that inverted U-shaped relationship exists in Nepal, Afghanistan, Bangladesh and Sri Lanka, while U-shaped relationship is observed for Pakistan and Bhutan. Nguyen and Le (2020) use ARDL estimator to assess the relationship between globalization and CO_2 emissions in Vietnam over the period 1990–2016. The results show that globalization increases CO_2 emissions while export oriented policies lead to a reduction in environmental degradation. Overall, the review of studies shows that the effects of globalization are at best mixed for different regions and countries.

Empirical model and data

Empirical model

Although there is no universally adopted empirical model for CO_2 emissions, numerous scholars such as (Mirziyoyeva and Salahodjaev, 2022b; Khoshnevis Yazdi and Shakouri, 2018; Sun et al., 2022; Satrovic and Muslija, 2019; Salahodjaev et al., 2022) included urbanization, tourism, and women's presence in parliament among others to model the relationship between renewable energy, GDP *per capita*, and CO_2 emissions. These studies report that these variables are essential and exhibit significant effects on greenhouse gas emissions. Therefore, our suggested model, which appears to be in line with the general empirical literature on CO_2 emissions discussed above can be expressed as:

$$CO_2 = f(GDP, RE, URB, TR, WP, KOF) \quad (1)$$

This generally implies that CO_2 emissions is a function of GDP *per capita* (GDP), renewable energy consumption (RE), urban population growth (URB), tourism receipts (TR), proportion of women in parliament (WP) and KOF index of Globalization as a proxy for globalization. Considering the panel structure of our data, Eq. **1** can be re-written in the following manner:

$$\begin{aligned} CO_{2i,t} = a_0 + a_1 GDP_{i,t} + a_2 GDP^2_{i,t} + a_3 RE_{i,t} + a_4 URB_{i,t} + a_5 TR_{i,t} \\ + a_6 WP_{i,t} + a_7 KOF_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (2)$$

where i represents country (in this research, we have 50 countries), t stands for time (the time period for this study is between 2000 and 2019) and ε is an error term. We also include GDP squared term to examine the presence of the EKC hypothesis in our sample.

Data and summary statistics

The data applied in this paper come from the World Bank and cover 2000–2019. The variables used are CO_2 emissions (measured in metric tons *per capita*), GDP *per capita* (measured in constant 2017 international $), renewable energy consumption (measured in percentage of total final energy consumption), urbanization (measured in annual urban population growth, %), tourism (as a ratio to GDP), female parliamentarians (proportion of seats held by women in national parliaments) and KOF index as a proxy for globalization.

TABLE 1 Summary statistics.

Variable	Description	Mean	Std. dev.
CO_2	CO_2 per capita emissions, logged	1.9230	0.6431
GDP	GDP per capita, PPP	37.5912	21.3106
URB	Urban population growth, annual	1.1291	1.9385
KOF	KOF Index of globalization	77.5039	8.0932
RE	Renewable energy consumption, %	15.9982	14.0854
WP	Representation of women in national parliaments, %	21.9301	11.0574
TP	Tourism receipts as % of GDP	1.0726	1.4253

The descriptive statistics are reported in Table 1. In this study, following related research on CO_2 emissions, we rely on dynamic panel estimators such as the two-step system GMM estimator. For example, (Asongu et al., 2017), highlights that "(system GMM estimator) considers cross-country variations; accounts for potential endogeneity in all regressions via instrumentation and controls for the unobserved heterogeneity and eliminates potential small sample biases from the difference estimator" (p. 355). System GMM estimator is recommended to use with the panel data when 1) the correlation between a dependent variable and its lag is above 0.8; and 2) the number of countries (i.e., 50 countries) exceeds the time frame (i.e., 19 years). As our study design fits these conditions, we use (Roodman, 2009) extension of a two-step system GMM estimator which restricts the expansion of instruments. Moreover, a two-step system GMM estimator is especially efficient as it controls for heteroskedasticity. The GMM estimator has been intensively used in energy and environmental studies to model the predictors of CO_2 emissions (Bakhsh et al., 2021; Mentel et al., 2022a; Mentel et al., 2022b; Jiang and Khan, 2023). Our suggested model under the condition of a two-step GMM estimator can be presented as follows:

$$CO2_{i,t} = \sigma_0 + \sigma_1 CO2_{i,t-\tau} + \sigma_2 RE_{i,t} + \sum_{h=1}^{k} \gamma_h X_{h,i,t-\tau} + \nu_{i,t} \quad (3)$$

$$\begin{aligned} CO2_{i,t} - CO2_{i,t-\tau} = \sigma_1 (CO2_{i,t-\tau} - lnCO2_{i,t-2\tau}) + \sigma_2 (RE_{i,t} - RE_{i,t-\tau}) \\ + \sum_{h=1}^{k} \delta_h (X_{h,i,t-\tau} - X_{h,i,t-2\tau}) + (\nu_{i,t} - \nu_{i,t-\tau}) \end{aligned} \quad (4)$$

where σ are the coefficients to be estimated, X is the vector of control variables (GDP, WP, URB, TR, KOF), τ is the coefficient of auto-regression and υ is two-way disturbance term.

Results

We present our empirical results in Table 2. We use both fixed and random effects estimators, although the Hausman test suggests

TABLE 2 Fixed effects regression.

Dependent variable: CO_2	Coefficients	Prob. value
CO_2, lagged	0.7035	0.000
GDP	0.0081	0.004
GDP * GDP	−0.0000	0.016
RE	−0.0100	0.000
WP	−0.0015	0.017
KOF	−0.0005	0.769
URB	−0.0062	0.000
TR	−0.0195	0.001
Constant	0.5286	0.000
N	794	
R. sq.	0.95	
Fisher stat	506.55	0.000

TABLE 3 System GMM results.

Dependent variable: CO_2	Coefficients	Prob. value
CO_2, lagged	0.8537	0.000
GDP	0.0118	0.000
GDP * GDP	−0.0001	0.000
RE	−0.0026	0.006
WP	−0.0029	0.008
KOF	−0.0038	0.002
URB	−0.0045	0.015
TR	0.0063	0.281
Constant	0.3583	0.000
N	794	
R. sq.	—	
Fisher stat	89676.01	0.000
AR (1)	−3.84	0.000
AR (2)	0.32	0.748
Hansen *p*-value	30.11	0.460

that a fixed effects estimator is suitable for the baseline analysis (Chi-Sq. stat = 204.77, Chi-sq. Prob. = 0.0000). Therefore, we only interpret the results from a fixed effects regression (Table 2). First, we find that GDP *per capita* has an inverted U-shaped association with CO_2 emissions. The turning point for GDP *per capita* beyond which economic growth decreases CO_2 emissions is 90,000 international dollars. The estimate of the RE is in line with theoretical assumptions. The obtained estimate of −0.0100 documented for renewable energy use is statistically significant at the 1% level. The results suggest that one standard deviation increase in RE is associated with a 14% decrease in CO_2 emissions. In a similar trend, the representation of women in parliament leads to improvement in air quality. These results confirm the importance of female empowerment for environmental sustainability documented by (Lv and Deng, 2019) and (Mirziyoyeva and Salahodjaev, 2022a). We observe that urban population growth decreases CO_2 emissions in high-globalized countries. In accordance with (Ben Jebli et al., 2019b), we find that tourism contributes to the decrease in carbon emissions: one standard deviation increase in *per capita* tourism receipts leads to a 2.7% decrease in CO_2 emissions. The KOF index of globalization is negative, although statistically insignificant. This may imply that globalization does not induce direct reduction in CO_2 emissions, once countries pass certain threshold levels. The impact of globalization may be moderated by other variables such as economic development or tourism sector development.

However, the results in Table 2 only offer correlational evidence for our variables of interest. Thus, to assess the impact of renewable energy and globalization on CO_2 emissions we need to correct for the potential endogeneity. Therefore, Table 3 reports the results for the two-step system GMM estimator. Hansen J-test and second-order autocorrelation [AR (2)] tests confirm the validity of the instruments based on the difference and level equations.

We find that renewable energy and globalization decrease CO_2 emissions. If causal, a 1 percentage point increase in the share of renewable energy in total energy consumption leads to a 0.26% decrease in *per capita* CO_2 emissions. These results can be compared to findings from other regions. For example, Mirziyoyeva and Salahodjaev (2022) find that 1 percentage point increase in renewable energy leads to 0.98% decrease in CO_2 emissions in top carbon intense economies. Radmehr et al. (2021) for the EU member states show that 1% increase in *per capita* renewable energy use leads to 0.05% decrease in CO_2 emissions. In addition, these results are similar to (Abbasi et al., 2021b) for Thailand and (Fu et al., 2021) for BRICS. The enhancing impact of globalization on air quality can be interpreted by the fact that globalization promotes the transfer of technologies that are friendly to air quality (Rahman, 2020). Similarly, we find that a larger representation of women in national parliament contributes to the reduction in CO_2 emissions. Extant research suggests that an increase in the women's share of seats in parliament improves the quality of institutions and the adoption of policies aimed at improvement in quality of life (Ergas and York, 2012; Mavisakalyan and Tarverdi, 2019; Salahodjaev and Jarilkapova, 2019). GDP *per capita* has an inverted U-shaped relationship with CO_2 emissions and the turning point is approximately 67,200 international dollars adjusted for PPP. The AR (2) test and Hansen *p*-value estimates confirm the validity of the use of the econometric approach and the credibility of instruments derived by the system GMM estimator.

We test the robustness of our main results by considering whether the effect of renewable energy on CO_2 emissions in high-globalized countries holds after accounting for the dynamics in the GDP structure. We do so by including the level of industrialization to capture the shift from agriculture to industry driven economic growth. A number of studies how that (Li and Lin, 2015; Liu and Bae, 2018) industrialization increases energy consumption and contributes to CO_2 emissions. At the same time, Mehmood and Tariq (2020) and Mentel et al. (2022c) show that renewable energy consumption can influence the effect of industrialization on CO_2

TABLE 4 Industrialization, renewable energy, and CO_2 emissions.

Dependent variable: CO_2	Coefficients	Prob. value
CO_2, lagged	0.7695	0.000
GDP	0.0135	0.000
GDP * GDP	−0.0001	0.000
RE	−0.0033	0.000
WP	−0.0018	0.004
KOF	−0.0017	0.402
URB	−0.0015	0.010
IND	0.0027	0.000
IND * RE	−0.0001	0.003
Constant		
N	914	
R. sq.	—	
Fisher stat	165738.38	0.000
AR (1)	−4.23	0.000
AR (2)	0.48	0.644
Hansen *p*-value	37.78	0.301

emissions. Therefore, we check whether the effect of renewable energy on CO_2 emissions retains its significance once we account for the level of industrialization in high-globalized countries (Table 4). The results show that industry value added as a share of GDP is positively linked to *per capita* CO_2 emissions. At the same time, the interaction term between renewable energy and CO_2 emissions is negative and significant, at the 1% level. This suggests that increasing renewable energy consumption can help to promote industrial transformation, not at the expense of environmental degradation. The estimates for other variables are not affected and remain robust.

Conclusion

Greenhouse gas emissions have emerged as one of the key topics of discussion within the international agenda. Consequently, policymakers in developed and developing countries attempt to identify the predictors of CO_2 emissions that can help to select and enforce policies which can lead to a reduction in air pollution without harming economic growth. Against this backdrop, environmental research suggests that energy consumption and GDP are among the core predictors of CO_2 emissions in global and single-country studies. Despite that research on renewable energy, economic growth, and CO_2 emissions has grown considerably over the past decade, no study explored the effect of GDP growth and renewable energy consumption on CO_2 emission in highly-globalized countries. Our results are based on panel data between 2000 and 2019. We particularly focused on the top 50 countries by KOF index of Globalization. Our results suggest that renewable energy significantly contributes to the reduction of carbon emissions while GDP *per capita* has an inverted U-shaped link with CO_2 emissions. Thus, we confirm the presence of the EKC hypothesis for highly-globalized countries. Moreover, we found that an increase in the share of female parliamentarians decreases CO_2 emissions. Consequently, our study offers several policy implications. Firstly, it is important for developing countries to increase the share of energy consumed from renewable energy sources. This will have a positive effect not only on air quality, but also on economic growth. Thus, it is essential to increase investment in the renewable energy sector and create conditions and benefits for the rapid adoption of renewable technologies by the private sector and households. Secondly, it is crucial to increase the quality of investment climate. Developing countries can significantly gain from globalization-driven FDI as this can lead to technology transfer, especially in the energy sector. Thirdly, our results suggest that improving female empowerment can significantly reduce the vulnerability to climate change. This can be achieved by increasing women's human capital and investing in women-led organizations and communities. The adoption of these measures can be anticipated to help emerging economies in decreasing CO_2 emissions under the international greenhouse gas emissions targets. Our study has a number of limitations that can serve as avenue for future research. For example, we did not assess the bi-directional causality between globalization, renewable energy and CO_2 emissions. However, scholars can test these relationships for single top-globalization countries to extend our understanding of the interlinks between renewable energy and carbon emissions. In addition, it is essential to assess the impact of other energy-related variables on the CO_2 emissions in high-globalized countries such as energy intensity, fossil fuel consumption or electricity consumption.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: World Bank.

Author contributions

ZM and RS: data collection and methodology. RS: formal analysis. ZM: writing original draft and conceptualization. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Effects of green credit policy on the risk of stock price crash

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Green credit policy (GCP) is a specific instrument for the credit resource allocation dimension in the financial sector, and stock price crashes are an important manifestation of financial market risks that cannot be ignored. However, there are gaps in existing research on how green credit policies affect the stock price crash risk (SPCR). Using the Green Credit Guidelines as a quasi-natural experiment, this paper examines the impact of green credit policies on SPCR of heavily polluting firms. It confirms the crash risk is significantly increased for heavily polluting enterprises, mainly due to facing greater financing pressure; and that corporate governance mechanisms reduce its impact, finding that firms with higher analyst attention, higher levels of independent directors, and higher shares held by institutional investors. The effect between GCP and SPCR is not significant for companies with higher analyst attention, higher levels of independent directors, and higher shareholdings of institutional investors. At the same time, it is less significant in regions with high level of financial development. These results of this paper not only enrich the literature in green credit-related fields, but also provide a reference value for understanding the implementation effect of GCP in China to the stock price crash in the capital market.

KEYWORDS

financing constraint, corporate governance mechanisms, green credit policy (GCP), stock price crash risk (SPCP), DID model

Introduction

For a long time, the dual pressure of environment and economic growth has caused widespread concern from all walks of life. Since 2012, the CBRC has published the Green Credit Guidelines, indicating that the role of financial institutions in improving environmental governance is widely recognized. In order to adher a green and low-carbon economy, Green credit can guide enterprises to implement green production as much as possible through reasonable allocation of credit resources. To date, scholars with an interest in GCP have examined the policy effects of green credit at a different angle. Li et al. (2016) conducted a study how GCP affected the business performance of commercial banks, and the positive and negative effects did not reach a consensus, which was confirmed by Zhang et al. (2021) as well. On the other hand, Sun and Shi (2019) discussed the positive effects of GCP on corporate R&D innovation. Lian (2015) pointed out that GCP can lower a company's financing costs. According to Cai et al. (2019), GCP reduced the pollution emissions of heavy polluters. From the analysis of Li et al. (2020), GCP encourage the modernization of industrial institutions through "incentive" and "push" mechanisms at the macro level. Ma (2016) claimed the effect of green credit on the regional economic quality growth. Shen and Ma (2014) examined the ability of GCP to mitigate the conflict between environmental protection and "maximizing GDP performance". King and Levine (1993) confirmed that green credit can effectly lower credit risk and enhance business performance

TABLE 1 Description of primary variables.

	Variables	Variable description
Explained variables	*Ncskews*	Negative return bias coefficients, as specified in model 3)
	Duvols	Ratio of upward and downward fluctuations in earnings, as specified in model 4)
Explanatory variables	*Treat*	Dummy variable, treatment group assignsthe value of 1; which the control group assigns the value of 0
	After	Dummy variable with a value of 1 for the year after the implementation of the Green Credit Guidelines; otherwise, it takes the value of 0
Control variables	*Size*	Enterprise size, taking the value of the natural logarithm of the total assets of the enterprise
	Lev	Gearing ratio, the ratio of total liabilities to total assets of an enterprise
	Same	Two positions in one, the chairman and general manager by one person to take the value of 1; otherwise, take the value of 0
	Top	Shareholding ratio of top ten shareholders
	Tobinq	Tobin's Q value
	Roa	Return on total assets, corporate net income divided by total assets
	Inst	Shareholding of institutional investors
	Employee	Natural logarithm of the number of employees in the company
	Invest	Investment expenses, (cash paid to construct fixed assets, intangible assets, and other long-term assets plus net cash paid to acquire subsidiaries and other business units minus net cash recovered from disposal of fixed assets, intangible assets, and other long-term assets deduct net cash received from disposal of subsidiaries and other business units)/total assets
	Audit	Natural logarithm of audit fees
	Holding	Management shareholding ratio
	Pay	Employee compensation, cash paid to and for employees/number of employees
	Separate	Separation of powers rate
	Ret	Annual individual stock return considering reinvestment of cash dividends
	Soe	Nature of property rights, state-owned enterprises take the value of 1; private enterprises take the value of 0

from the perspective of banks. In contrast, Biswas (2011) and Luo et al. (2017) hold the opposite view, stating that banks lack incentives to implement green credit and that firms do not invest more in environmental protection.

Inevitably, the possibility of a stock market crash poses a threat to the financial market's stability.In order to support the healthy development of the financial market, it is essential to effectively suppress SPCR. This becomes the top priority for financial market governance. Quan et al. (2016) pointed out that China's capital market is imperfectand that the stock market is more prone to "crash and fall" than other countries. Allen and Faulhaber (1989) explained that managers tends to conceal negative news in order to raise more capital, which increases SPCR in the aspectof information asymmetry, named "Information hiding hypothesis". It proves that investors have difficulty in grasping accurate corporate operating conditions due to the asymmetry of information held inside and outside the company. According to the principal-agent theory, managers has motivation to conceal negative corporate information due to personal reputation, compensation, and promotion considerations. However, once the accumulation of negative news reaches a certain threshold, same as "paper cannot cover fire", then all of negative information instantly floods the market, causing a drastic impact on the stock price, which is more likely to generate a stock price crash (Kothari et al., 2009). Academics have examined the variables impacting SPCR from different perspectives. Ye et al. (2015) examined the ability of internal control toreduce the risk ofstock price crash Robin and Zhang (2015) examined that auditor industry expertise has a significant reducing effect on a company's SPCR. Wang et al. (2014) discussed the effects of investor protection and institutional investors on SPCR. By analyzing the US capital market, Crane et al. (2017) confirmed that institutional investor network connectivity enhances corporate governance effectiveness. Xu et al. (2013) examined how analyst concern how it affects stock price crash. In terms of informal institutions, Zeng and Wei (2017) explored their impact on stock price crashes from a religious standpoint.

From a principal-agent theory perspective, information asymmetry arises when companies possess superior knowledge regarding their operational activities and potential environmental risks. Managers may engage in opportunistic behavior, such as concealing adverse information about their company's environmental performance, to retain access to favorable green credit terms. This information asymmetry exacerbates the risk of stock price crashes, as investors may remain unaware of the true environmental risks and consequently misjudge the company's financial soundness. Moreover, information asymmetry extends beyond the principal-agent relationship to encompass the relationship between companies and investors. Investors rely on publicly available information, financial reports, and disclosures to make well-informed investment decisions. However, if companies manipulate or withhold information concerning their environmental impact or adherence to green credit policies, it can distort perceptions of the company's value and financial stability. The lack of transparency and provision of accurate information significantly heightens the likelihood of stock price crashes as concealed environmental risks eventually come to light.

As the most directly affected heavy polluters, their business decisions are bound to be influenced by the GCP. Heavy polluters would face more severe pressure on debt financing due to the progressively strict and standard requirements of green credit policies. Typically, Implementing green credit inevitably affect the credit environment of heavy polluters, reduce the scope of debt financing, and raise the corporate credit risk. At the same time, in profitability and safety considerations, investors will also be more cautious, increasing the cost of debt for companies. Consequently, a share price crash is a more likely to occur as the rise in corporate risk.Corporate governance is a crucial instrument to mitigate information asymmetry, and is closely related to SPCR. Different internal and external corporate governance factors mitigate SPCR by influencing management mindset, monitoring of executives, information disclosure, performance pressure, and the financing constraint environment, which in turn affects firms' behavior of hiding negative news.

Based on the aforementioned discussion, the study concentrates on answering three questions: first, how GCP effect on SPCR for companies with heavy pollution; second, whether corporate governance mechanisms such as analyst concerns, institutional investors, and independent directors can effectively mitigate the impact of GCP on SPCR; third, it further examines the effect of different regional financial development levels on the relationship between GCP and SPCR.

Using the heavy-polluting firms listed in Shanghai and Shenzhen from 2009 to 2018 as the research objects, we conducted a quasi-natural experiment based on the implementation of the Green Credit Guidelines issued by the CBRC and utilized a difference-in-differences (DID) model to investigate these effects and mechanisms.This study provides empirical evidence that the implementation of green credit significantly increases the SPCR for heavily polluting companies. Furthermore, it emphasizes the role of corporate governance mechanisms in mitigating this impact. Specifically, this influence is statistically insignificant in firms characterized by broader analyst coverage, a higher proportion of independent directors, and increased institutional ownership. Additionally, the study reveals that this effect is more pronounced in regions with lower levels of financial development.

This study has identified several policy implications: firstly, it is recommended that financial institutions rigorously control credit thresholds while concurrently expanding the coverage of green finance. Moreover, emphasis should be placed on fostering innovation and optimizing green financial products and services to ensure the long-term sustainability and stability of green credit policies. Secondly, considering that the effectiveness of green credit is influenced by corporate governance mechanisms and the level of financial development, relevant policies should take into account regional differences in environmental governance pressure. Designing targeted and differentiated assessment indicators can promote voluntary and proactive implementation of green credit policies by local governments. Lastly, financial institutions and local governments need to dynamically adjust the intensity of punishment and incentive mechanisms to avoid phenomena such as financing difficulties and stock price collapses that contradict the long-term objectives of green credit policies. Actively guiding and supporting heavily polluting enterprises in raising their environmental awareness and strengthening green investment and financing is crucial.

The innovations and contributions of this paper are mainly in two areas: on the one hand, quantitative analysis of the policy effect of green credit implementation is conducted from the perspective of SPCR, thereby providing coping strategies and empirical evidence for heavy-polluting companies to deal with the negative effects caused by green finance; on the other hand, the research on the effect of GCP implementation is enriched from different perspective by combining the heterogeneity of corporate governance mechanisms, and it is found that the negative impact between GCP and SPCR varies by different corporate governance mechanisms, and the heterogeneity of financial regional differences is also need tobe considered, which provides suggestions and references for government regulators to improve relevant corporate governance mechanisms.

The research is divided into six parts: Section 2 presents the theoretical analysis and research hypotheses; Section 3 presents the research design; Section 4 presents the empirical results and analysis; Section 5 presents further heterogeneity analysis; and Section 6 contains the research conclusions and policy implications.

Theoretical analysis and research hypothesis

The study of stock price crash has become a temporary phenomenon in the fields of finance and economics since the global financial crisis. Piotroski et al. (2015) show that how badly stock price crashes have impacted on the steady growth of capital market. Therefore, exploring the effect of various policies on stock price crashes and reducing their risk is a crucial research topic that must be addressed by academics. Due to its own position and salary, management has a tendency to conceal the negative behaviors of the company, resulting in the accumulation of negative news. Once the negative news can no longer be concealed or the cost of continued concealment exceeds that of the announcement, it explodes instantly in the stock market, causing a precipitous decline in the company's share price, resulting in a stock crash (Kim et at., 2011). Green credit policies also offer potential benefits. The aim of GCP is to achieve environmental governance by using financial instruments to enable efficient allocation of credit resources and encourage green transformation and technological innovation. Zhou et al. (2021) have highlighted that the implementation of green credit can enhance the future performance of financial institutions. By imposing restrictions, there is a reduced risk for commercial banks when making loan decisions. Yao et al. (2021) have demonstrated that governments can regulate environmental risks associated with bank loans through penalty effects. Green credit

TABLE 2 Descriptive statistics of primary variables.

Variables	N	mean	std	min	p50	max
Ncskews	15199	−0.317	1.088	−3.293	−0.283	2.672
Duvols	15199	−0.175	0.843	−3.145	−0.123	1.909
Treat	15199	0.466	0.499	0	0	1
After	15199	0.812	0.390	0	1	1
Size	15199	21.97	1.245	17.39	21.80	28.25
Lev	15199	0.416	0.207	0.049	0.406	0.900
Same	15199	0.278	0.448	0	0	1
Top	15199	0.590	0.151	0.230	0.601	0.957
Tobinq	15199	2.696	1.871	0.879	2.091	11.00
Roa	15199	4.101	5.497	−18.62	3.808	20.55
Inst	15199	0.06	0.068	0	0.036	0.317
Employee	15199	7.680	1.216	2.197	7.616	12.62
Invest	15199	3.718	5.275	−4.717	1.468	23.55
Audit	15199	13.52	0.639	9.210	13.46	17.52
Holding	15199	0.147	0.210	0	0.005	0.706
Pay	15199	11.35	0.554	0	11.34	17.20
Separate	15199	5.032	7.718	0	0	28.82
Ret	15199	0.140	0.609	−0.593	−0.036	2.641
Soe	15199	0.352	0.478	0	0	1

policies can help mitigate pollution and environmental damage, thereby positively impacting the health and wellbeing of both people and the environment. Additionally, these policies play a crucial role in promoting innovation and driving economic growth within the green economy. However, for the heavily polluting industries, are there any unfavorable effects or ways that can escape the risks brought by the GCP?

Green credit has the potential to affect the stock price crash of heavy-polluting firms several ways. First of all, on the one hand, it improves the green credit standards. Financial institutions will actively corresponding government policy requirements, since the implementation of the GCP will raise the threshold of bank credit. They need to focus on the company's environmental and social risks, the implementation of more stringent standards for corporate environmental governance and environmental information disclosure, which will inevitably directly affect the credit approval of heavy polluters. The difficulty of credit approval is increased for heavy polluters compared to other firms, which exacerbates the difficult financing dilemma. Lian (2015) pointed out that green credit can restrain the financing problem for heavy polluters. On the other hand, due to the normative nature of GCP, heavy polluters will likely fail to meet the credit criteria and obtain debt financing, especially long-term debt financing. Their financing costs will increase. This is primarily because there is the existence of information asymmetry between the company and the external market. Since banks frequently use industry attributes as the benchmark for credit placement when the banks measure and identify th environmental governance and green production of enterprises, it is difficult for companies to meet the green credit lending criteria and obtain sufficient financial support (Wu et al., 2020).

The second function is signaling. According to Wu et al. (2012), green credit can boost the corporate information transparency and conveysignals of enhanced corporate environmental supervision by strengthening the link between financial institutions and environmental protection departments. As for the heavily polluting companies with poor environmental management, there is no doubt that this policy will send negative signals to the capital market. From a reputation risk perspective, the heavily polluting companies would also be subject to greater public pressure and moral condemnation after the credit policy is formally implemented, and they may even at a higher risk of environmental litigation. Given profitability and safety considerations, the higher the creditors' risk perceptions of heavily polluting firms, the less inclined they are to provide debt capital, resulting in creditors' withdrawal or rejection of debt extensions and lower debt financing. Su and Lian (2018) point out that green credit has both a remarkable financing penalty effect as well as an investment disincentive effect.The financing penalty effect refers to the fact green credit significantly increases total debt cost, then sharply decreases the operating performance for heavily polluting firms. The investment disincentive effect refers to the difficulty for companies to maintain the ability to innovate and transform green due to the lack of capital (Cao et al., 2021). This makes the company fall into the dilemma of "poor environmental management - difficult financing - even more difficult green transformation", when the heavy polluters cannot obtain sufficient green credit, the lack of capital will make the company unable to maintain stable green innovation, which in turn worsens the problem of poor financing for heavy polluters. In turn, this exacerbates the financing problem of heavy polluters and increases the incentive for their management to conceal negative information in order to avoid financial pressure.

Last but not least, there is a rise in business risk. As GCP will exacerbate the financing constraints for heavy polluters, the company's operating risks would increased. If the company fails to repay its debts when they are due, this increases the company's risk of credit default. According to modern contract theory, the increase in project risk will result in a rise in principle-agent costs between the company and its creditors. Due to the increased credit default risk of the heavy polluters, from the perspective of risk compensation, banks as creditors may ask the heavy polluters to pay higher credit rates to compensate for the possible default risk. This undoubtedly again increases the financing constraints and the risk of credit default for heavy polluters. As the Guidelines' implementation restricts the credit financing for heavily polluting firms, it reduces the amount of credit available for them, which in turn increases the business risks faced by firms (Yang and Zhang, 2022). The risk of a firm's share price collapsing will unavoidably increase as the firm's risk increases. Increased financing pressure will make heavily polluting firms more likely to manipulate earnings management and the more careful they will be to disclose bad news to obtain more credit resources (Lu and Zhang, 2014). Coupled with internal and external information asymmetries, firms with greater financing constraints will have more incentives to conceal negative

TABLE 3 Green credit policy and SPCR.

VARIABLES	1)	2)	3)	4)
	Ncskews	Ncskews	Duvols	Duvols
*Treat*After*	0.138***	0.086**	0.107***	0.061**
	(3.63)	(2.47)	(3.77)	(2.39)
Treat	−0.076**	−0.764***	−0.049**	−0.405***
	(-2.34)	(-8.26)	(-2.08)	(-6.29)
After	−0.124***	−1.262***	−0.033	−1.048***
	(-4.55)	(-26.16)	(-1.61)	(-27.93)
Size		0.043**		0.006
		(2.44)		(0.45)
Lev		−0.108*		−0.131***
		(-1.88)		(-3.07)
Same		−0.008		−0.017
		(-0.37)		(-1.12)
Top		−0.277***		−0.309***
		(-4.35)		(-6.67)
Tobinq		0.002		−0.034***
		(0.27)		(-5.20)
Roa		−0.012***		−0.010***
		(-6.17)		(-7.12)
Inst		1.768***		1.296***
		(14.07)		(13.28)
Employee		−0.004		0.008
		(-0.28)		(0.74)
Invest		0.001		0.002
		(0.71)		(1.42)
Audit		−0.048**		−0.051***
		(-2.30)		(-3.20)
Holding		−0.184***		−0.182***
		(-3.40)		(-4.43)
Pay		0.029		0.027**
		(1.44)		(1.98)
Separate		−0.001		−0.001
		(-1.28)		(-1.33)
Ret		−1.101***		−0.953***
		(-50.97)		(-54.45)
Soe		−0.047**		−0.051***
		(-2.07)		(-3.03)
Constant	−0.232***	1.306***	−0.165***	1.920***

(Continued on following page)

TABLE 3 (*Continued*) Green credit policy and SPCR.

VARIABLES	1)	2)	3)	4)
	Ncskews	Ncskews	Duvols	Duvols
	(-10.11)	(4.33)	(-9.64)	(8.51)
Province FE	*no*	yes	*no*	yes
Industry FE	*no*	yes	*no*	yes
Year FE	*no*	yes	*no*	yes
Observations	15,199	15,199	15,199	15,199
Adj_R2	0.001	0.219	0.001	0.303

Note: t-values adjusted using robust regression and clustering are in parentheses (same later).

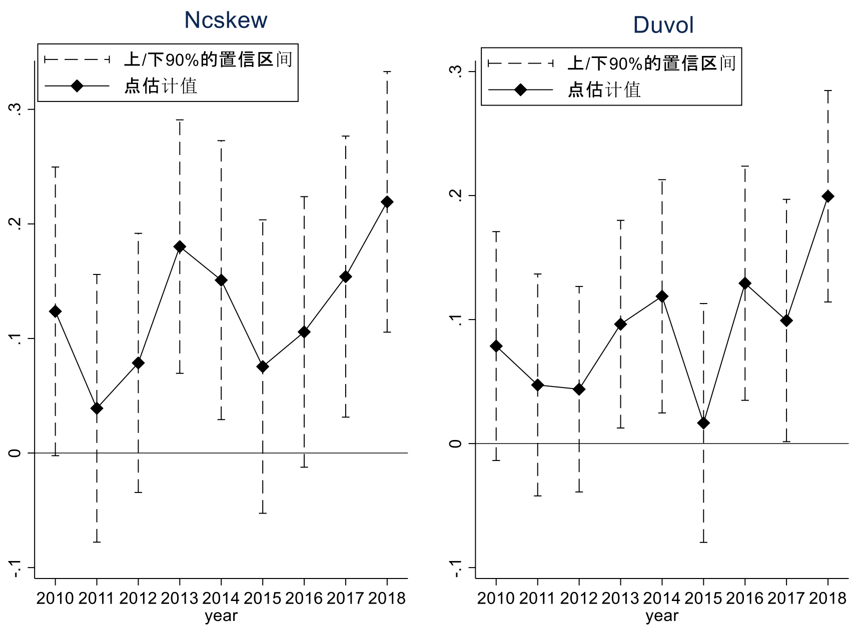

FIGURE 1
Parallel trend test.

information, and these accumulated negative information will undoubtedly raise the likelihood of SPCR, as well as the risk will increase as a result of a deterioration in corporate information disclosure quality and internal controls because of an increase in financing constraints.

The prevention of corporate SPCR has attracted widespread attention in the financial and finance fields. The primary reason for SPCR is information asymmetry within the enterprises. The possibility that management may intentionally or unintentionally conceal negative news beyond the firm's carrying capacity, resulting in an instantaneous outbreak (Bleck and Liu, 2007).According to agency theory, it is known that the severity of the agency problem directly affects the cost and behavior of management in hiding negative news. Lin and Zheng. (2016) confirmed that the higheragency cost of a firm, the higher probability that negative news will be concealed and the higher risk that the firm's share price will crash. Corporate governance, precisely as an effective monitoring mechanism to mitigate agency problems, can increase the of a firm's information transparency, which will inevitably have an impact on the share price crash. Related scholars have also demonstrated how internal and external corporate governance mechanisms affect firms' SPCR. Callen and Fan (2012) explored how religious beliefs reduce a firm's share price crashing by reducing managers' concealment of negative information. An and Zhang (2013) confirmed institutional investors have an impact on SPCR, as well as Callen and Fang (2012). According to Luo and Du. (2014), there is less risk of a stock price crash for a firm with more attention of the media. Similarly, due to the public pressure of analysts' attention, Pan et al. (2011) pointed out that analysts' attention compresses the space for heavy polluters to adopt "avoidance" in environmental information disclosure, which in turn reduces SPCR. Independent directors can supervise companies to avoid the

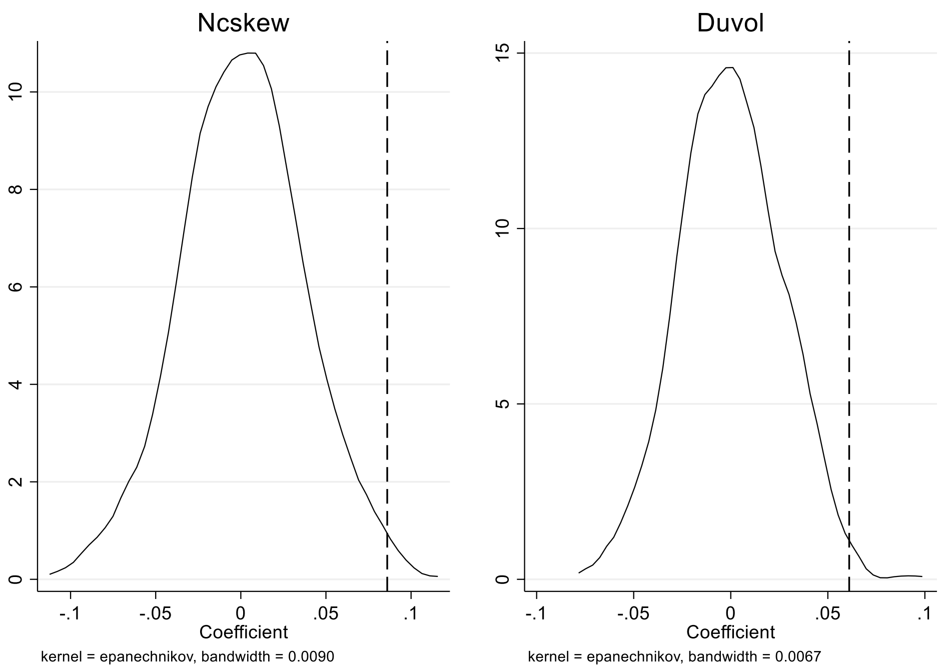

FIGURE 2
Placebo test.

reputational and legal hazards they face as much as possible, thereby decreasing SPCR. The following hypotheses are put forth in this paper in light of the above analysis.

H1. Assuming all other factors remain constant, GCP significantly increase SPCR for heavily polluting firms.

Study design

Sample selection and data sources

This paper analyzes the effect of the GCP implementation on SPCR for heavily polluting firms listed in Shanghai and Shenzhen from 2009 to 2018. In particular, according to the "List of Listed Companies' Environmental Verification Industry Classification Management" issued by the Ministry of Ecology and Environment (formerly the Ministry of Environmental Protection), the "Guidelines on Environmental Information Disclosure of Listed Companies" (draft for public comment) and the "Guidelines on Industry Classification of Listed Companies" of the Securities and Futures Commission, a listed company is defined as a heavy-polluting enterprise if it belongs to the screened heavy-polluting industries. Meanwhile, this paper defines other industries as non-heavily polluting industries, which are served as the control group in order to bulid a difference-in-differences model with reference to Liu and Liu (2015) 's study. After excluding the samples with abnormal financial data and relevant data missing, a total of 15,199 valid samples were obtained. Additionally, we truncate the main continuous variables by 1% at the top and bottom to eliminate the effect of extreme values. The CSMAR and RESSET databases were consulted for the data related to listed companies.

Description of model and variables

In order to mitigate potential endogeneity concerns, it is possible to conceptualize the green credit policy as a quasi-natural experiment. By treating the implementation of the green credit policy as an exogenous shock independent of firm-specific characteristics and other external factors, the identification strategy can provide more robust estimates of the causal impact on the risk of stock price collapse. This approach helps to alleviate potential biases stemming from endogenous factors and enhances the validity of the research findings. To investigatethe effect of GCP on SPCR of heavily polluting firms, the following DID model is constructed:

$$Ncskews\backslash Duvols = \beta_0 + \beta_1 * Treat + \beta_2 * After + \beta_3 * Treat \times After + \delta * Controls + \varepsilon \tag{1}$$

Ncskews and *Duvols* in the model are SPCR variables. According to Xu et al. (2012) and other literature, we use two indicators of negative earnings skew coefficient (*Ncskews*) and earnings up/down volatility ratio (*Duvols*) to evaluate SPCR, respectively. The following is the precise calculation method:

First, the following regressions were run using listed company weekly stock returns by year:

$$R_{i,t} = \alpha_i + \beta_1 * R_{m,t-2} + \beta_2 * R_{m,t-1} + \beta_3 * R_{m,t} + \beta_4 * R_{m,t+1} + \beta_5 * R_{m,t+2} + \varepsilon_{i,t} \tag{2}$$

where $R_{i,t}$ is the weekly individual stock return of listed company i in week t considering cash dividend reinvestment, and $R_{m,t}$ is the weekly market return using the market capitalization-weighted average method of liquidity. Also, the lagged and ahead terms of market returns are included in this model for the two periods before

TABLE 4 Impact of analysts' concerns.

VARIABLES	1)	2)	3)	4)
	High degree of analytical attention	Low degree of analytical attention	High degree of analytical attention	Low degree of analytical attention
	Ncskews	Ncskews	Duvols	Duvols
*Treat*After*	0.006	0.147***	−0.021	0.121***
	(0.11)	(3.03)	(-0.53)	(3.60)
Treat	−0.735***	1.520***	−0.335***	2.063***
	(-6.26)	(8.74)	(-4.08)	(16.29)
After	−1.010***	−0.481***	−0.777***	−0.468***
	(-15.35)	(-6.60)	(-14.63)	(-8.55)
Size	0.078***	−0.013	0.043**	−0.041**
	(3.12)	(-0.51)	(2.24)	(-2.18)
Lev	−0.259***	−0.003	−0.266***	−0.066
	(-2.91)	(-0.04)	(-4.08)	(-1.22)
Same	0.014	−0.028	−0.001	−0.032
	(0.54)	(-0.94)	(-0.05)	(-1.46)
Top	−0.197**	−0.342***	−0.194***	−0.376***
	(-2.20)	(-3.86)	(-2.98)	(-5.87)
Tobinq	−0.012	−0.015	−0.041***	−0.048***
	(-1.14)	(-1.40)	(-4.42)	(-5.16)
Roa	−0.007**	−0.015***	−0.005**	−0.013***
	(-2.19)	(-5.67)	(-2.06)	(-6.68)
Inst	1.258***	2.122***	0.915***	1.626***
	(8.26)	(8.53)	(7.91)	(8.81)
Employee	0.030	−0.033*	0.035**	−0.015
	(1.42)	(-1.67)	(2.23)	(-1.03)
Invest	0.003	−0.001	0.003*	0.001
	(1.12)	(-0.22)	(1.67)	(0.60)
Audit	−0.106***	−0.009	−0.099***	−0.009
	(-3.79)	(-0.27)	(-4.75)	(-0.38)
Holding	−0.059	−0.273***	−0.051	−0.278***
	(-0.85)	(-3.30)	(-0.97)	(-4.38)
Pay	0.003	0.051*	0.016	0.040**
	(0.09)	(1.88)	(0.79)	(2.19)
Separate	−0.001	−0.001	−0.001	−0.001
	(-0.79)	(-0.55)	(-0.69)	(-0.53)
Ret	−1.018***	−1.158***	−0.848***	−1.044***
	(-34.79)	(-34.36)	(-36.60)	(-38.85)
Soe	−0.062**	−0.025	−0.067***	−0.030

(Continued on following page)

TABLE 4 (*Continued*) Impact of analysts' concerns.

VARIABLES	1)	2)	3)	4)
	High degree of analytical attention	Low degree of analytical attention	High degree of analytical attention	Low degree of analytical attention
	Ncskews	Ncskews	Duvols	Duvols
	(-2.02)	(-0.77)	(-2.94)	(-1.27)
Constant	1.243***	−0.209	1.403***	0.137
	(2.94)	(-0.43)	(4.43)	(0.37)
Province FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	7,136	8,063	7,136	8,063
Adj_R2	0.233	0.223	0.302	0.320

and after (Dimson, 1979). Then, based on the residuals $\varepsilon_{i,t}$ of the aforementioned model, weekly specific return of listed company *i is* calculated, which is $W_{i,t} = ln\ (1+\varepsilon_{i,t})$.

Second, the following two variables are created based on the particular weekly returns of listed companies (Wi,t): negative return *skew* coefficient (*Ncskews*) and return up/down volatility ratio (*Duvols*).

$$Ncskews_{i,t} = -\left[n(n-1)^{3/2}\sum W_{i,t}^{3}\right]\Big/\left[(n-1)(n-2)\left(W_{i,t}^{2}\right)^{3/2}\right] \quad (3)$$

$$Duvols_{i,t} = \ln\left\{\left[(n_u-1)\sum\nolimits_{down}W_{i,t}^{2}\right]\Big/\left[(n_d-1)\sum\nolimits_{up}W_{i,t}^{2}\right]\right\} \quad (4)$$

Where n means numbers of trading weeks per year of listed company *i*; *down* and *up are the up* and *down* phases based on whether the weekly characteristic return is higher than annual average return; n_u (n_d) means numbers of weeks when weekly characteristic return of listed company *i is* higher (lower) than the annual average characteristic return. The larger value of *Ncskews*, the more severe the degree of negative skewness coefficient. While, a larger value of *Duvols* indicates that the stock return distribution is more left skewed, as well as the higher SPCR of the firm.

Treat and *After* are dummy variables. If the listed company is part of the treatment group, which includes heavy polluters, *Treat* assigns it a value of 1, but if company belong to control group, *Treat* assigns it a value of 0. *After* assumes a value of 1 in the year following the Green Credit Guidelines' implementation, otherwise it assumes the value of 0 in all other years. The primary explanatory variable for the study is the interaction term *Treat*After*, and if interaction term coefficient is significantly positive, which means GCP implementation leads to higher SPCR for heavy polluters.

The control variables in the paper include: firm size (*Size*), which is the natural logarithm of the firm's total assets; gearing (*Lev*), which is the ratio of the firm's total liabilities to its total assets; two positions in one (*Same*), which takes the value of 1 if the firm's chairman and general manager are both the same person, otherwise, it takes the value of 0; majority shareholder ownership (*Top*), which is measured by the shareholding ratio of the top ten shareholders; return on total assets (Roa), which is the ratio of net profit to total assets; development capability (*Tobing*), measured by the Tobin's Q value; institutional shareholding (*Inst*), the percentage of shares held by institutional investors; number of employees (*Employee*), the natural logarithm of the number of employees; investment expenditure (*Invest*), the ratio of fixed assets, intangible assets and other long-term assets paid by the firm, Investment expenses (*Invest*), measured as cash paid for the construction of fixed assets, intangible assets and other long-term assets plus net cash paid for the acquisition of subsidiaries and other business units minus net cash received from the disposal of fixed assets, intangible assets and other long-term assets deduct net cash received from the disposal of subsidiaries and other business units, and normalized using the total assets of the enterprise; audit quality (*Audit*), measured using the natural logarithm of audit fees; management *Holding*, which is the ratio of management's shareholding, *Pay,* the ratio of cash paid to and for employees to the number of employees, *Separate*, *Ret,* which is the annual return on shares considering reinvestment of cash dividends, and *Soe,* which is 1 for state-owned enterprises (SOE) and 0 for private firms. Additionally, annual fixed effects and the effects of province, industry are controlled. Table 1 provides the description of primary variables.

Descriptive statistics of primary variables

As can be seen, the results of descriptive statistics for the primary variables are shown in Table 2. The negative earnings *skew* coefficient (*Ncskews*) has a mean value of −0.317, a minimum value of −3.293, and a maximum value of 2.672; the up/down earnings volatility ratio (*Duvols*) has a mean value of −0.175, a minimum value of −3.145, and a maximum value of 1.909, illustrating that SPCR varies significantly between firms. The mean value of the *Treat* variable is 0.466, indicating that there is a more balanced sample distribution between treatment and control groups.

TABLE 5 Impact of independent directors.

VARIABLES	1)	2)	3)	4)
	High proportion of independent directors	Low proportion of independent directors	High proportion of independent directors	Low proportion of independent directors
	Ncskews	Ncskews	Duvols	Duvols
*Treat*After*	0.062	0.127***	0.052	0.083**
	(1.14)	(2.69)	(1.33)	(2.39)
Treat	−0.830***	0.416***	−0.504***	0.316***
	(-6.35)	(3.35)	(-5.56)	(3.48)
After	−1.295***	−1.563***	−1.081***	−1.273***
	(-18.07)	(-20.74)	(-19.92)	(-20.93)
Size	0.007	0.077***	−0.016	0.024
	(0.27)	(3.23)	(-0.87)	(1.31)
Lev	−0.116	−0.112	−0.144**	−0.132**
	(-1.36)	(-1.49)	(-2.31)	(-2.34)
Same	−0.011	−0.008	−0.008	−0.026
	(-0.39)	(-0.30)	(-0.39)	(-1.28)
Top	−0.212**	−0.325***	−0.246***	−0.354***
	(-2.13)	(-3.89)	(-3.56)	(-5.71)
Tobinq	0.012	−0.013	−0.025***	−0.048***
	(1.14)	(-1.34)	(-2.76)	(-5.27)
Roa	−0.016***	−0.008***	−0.012***	−0.008***
	(-5.57)	(-3.12)	(-5.94)	(-4.13)
Inst	1.984***	1.580***	1.436***	1.194***
	(10.30)	(9.77)	(9.68)	(9.78)
Employee	0.024	−0.032	0.022	−0.005
	(1.15)	(-1.60)	(1.47)	(-0.36)
Invest	0.005**	−0.002	0.004**	0.000
	(1.98)	(-0.78)	(2.01)	(0.11)
Audit	−0.037	−0.058**	−0.048**	−0.054***
	(-1.25)	(-2.07)	(-2.05)	(-2.68)
Holding	−0.203***	−0.190**	−0.226***	−0.165***
	(-2.61)	(-2.47)	(-3.92)	(-2.83)
Pay	0.071**	−0.018	0.053***	0.001
	(2.32)	(-0.65)	(2.84)	(0.05)
Separate	−0.001	−0.001	−0.002	−0.000
	(-0.71)	(-0.79)	(-1.23)	(-0.32)
Ret	−1.142***	−1.060***	−0.978***	−0.926***
	(-35.69)	(-36.52)	(-37.72)	(-39.09)
Soe	−0.029	−0.066**	−0.032	−0.069***

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TABLE 5 (*Continued*) Impact of independent directors.

VARIABLES	1)	2)	3)	4)
	High proportion of independent directors	Low proportion of independent directors	High proportion of independent directors	Low proportion of independent directors
	Ncskews	Ncskews	Duvols	Duvols
	(-0.82)	(-2.27)	(-1.24)	(-3.09)
Constant	1.207***	0.344	1.922***	1.340***
	(2.74)	(0.86)	(5.96)	(4.37)
Province FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	7,030	8,148	7,030	8,148
Adj_R2	0.228	0.212	0.306	0.301

Empirical results and analysis

Green credit policy and SPCR

The outcomes to determine the impact of GCP on the risk of heavy polluters' stock prices crash are shown in Table 3. These findings reveal that coefficients of the interaction term *Treat*After* in columns 1) and 3) are 0.138 and 0.107, respectively, and both are significant at the 1% level, indicating the negative return bias coefficient and the ratio of upward and downward earnings fluctuations of the heavily polluting firms significantly increase after implementation of GCP, thereby SPCR increases. Even after further controlling for firm-level control variables, the coefficient of the interaction term *Treat*After* remains positive and significant at the 5% level as well as province, industry, and year fixed effects in columns 2) and 4), consistent with previous findings. The above results indicate implementation of GCP has a significant positive impact on SPCR of heavily polluting companies, which leads to higher SPCR for heavy-polluting enterprises and verifies the previous hypothesis.

Parallel trend test

In this study, we also conducted the following model for parallel trend testing, according to Liu and Qiu (2016) 's study:

$$Ncskews\backslash Duvols = \beta_0 + \beta_1 \times Treat + \sum_{j=2010}^{2018} \varphi_j \times year_j + \sum_{j=2010}^{2018} \mu_j \times Treat \times year_j + \delta \times Controls + \varepsilon \tag{5}$$

where $year_j$ is a year dummy variable, and $year_j$ takes the value of 1 if the observation belongs to year j and 0 otherwise. The other variables are defined in line with model 1). Using 2009 as the base period, we examine the trend of SPCR between treatment and control groups from 2010–2018. Figure 1 reports the coefficient estimates and upper and lower 90% confidence intervals for the interaction term $Treat*year_j$. Prior to the implementation of GCP, coefficients of $Treat*year_{2010}$ and $Treat*year_{2011}$ are not significant, indicating that there is relatively consistent and not significantly different between the treatment and control groups for the trend of SPCR, which is passing parallel trend test. Further more, there are mostly significant positive in 2012 and after, indicating that compared to the control group SPCR in the treatment group is significantly higher after implementation of GCP, thereby corroborating the robustness of the previous findings.

Placebo test

Additionally, in order to investigatewhether the treatment effects estimated in the previous section are due to omitted country-industry-time level variables, a placebo test is performed. According to Cai et al. (2016) 's study, a sample of treatment groups are selected randomly for the placebo test. First, we construct the dummy treatment group variable $Treat^{fake}$ by randomly selecting some firms from the sample as dummy heavy polluters and the remaining firms as dummy non-heavy polluters. Then, the placebo test interaction term $Treat^{fake}$ *After*. The effect of the placebo test interaction term on the risk of a firm's stock price crash should not be significant because the treatment group is randomly screened. That is, the placebo coefficient of the placebo test interaction term should not significantly deviate from zero. Conversely, if the coefficients deviate significantly from zero, it implies that there may have been omitted variables in the previous test. Moreover, in order to eliminate the effect of low-probability extreme events, we repeated the preceding technological process 500 times for regression analysis.The computed coefficients for the 500 random sample regression analysis of the placebo interaction term $Treat^{fake}$ *After* are shown in Figure 2, along with their kernel density distribution. The effect on the risk of a corporate stock price crash is not significant because the estimated coefficients of the placebo test interaction term $Treat^{fake}$ *After* are around zero, regardless of the negative earnings *skew* coefficient (*Ncskews*) or

TABLE 6 Impact of institutional investors.

VARIABLES	1)	2)	3)	4)
	High percentage of shares held by institutional investors	Low percentage of shares held by institutional investors	High percentage of shares held by institutional investors	Low percentage of shares held by institutional investors
	Ncskews	Ncskews	Duvols	Duvols
*Treat*After*	0.041	0.105*	0.017	0.088**
	(0.90)	(1.94)	(0.49)	(2.28)
Treat	−0.875***	−0.602***	−0.380***	−0.286***
	(-6.28)	(-5.03)	(-3.83)	(-3.32)
After	−0.490***	−0.525***	−0.324***	−0.480***
	(-7.55)	(-6.77)	(-6.20)	(-8.17)
Size	0.051**	−0.013	0.022	−0.046**
	(2.33)	(-0.46)	(1.40)	(-2.14)
Lev	−0.103	−0.071	−0.139**	−0.098
	(-1.36)	(-0.85)	(-2.55)	(-1.59)
Same	0.022	−0.032	0.004	−0.034
	(0.88)	(-1.05)	(0.22)	(-1.49)
Top	−0.176**	−0.292***	−0.173***	−0.357***
	(-2.08)	(-3.09)	(-2.88)	(-5.20)
Tobinq	0.033***	−0.036***	0.005	−0.074***
	(3.45)	(-3.04)	(0.60)	(-6.81)
Roa	−0.013***	−0.012***	−0.010***	−0.011***
	(-4.71)	(-4.41)	(-5.10)	(-5.30)
Inst	1.177***	7.413***	0.654***	6.190***
	(7.16)	(6.32)	(5.37)	(6.91)
Employee	0.016	−0.022	0.018	−0.004
	(0.85)	(-1.01)	(1.43)	(-0.25)
Invest	0.003	−0.002	0.004**	−0.001
	(1.51)	(-0.63)	(2.41)	(-0.45)
Audit	−0.081***	0.006	−0.075***	−0.006
	(-3.11)	(0.18)	(-3.95)	(-0.23)
Holding	−0.150**	−0.178**	−0.101*	−0.218***
	(-2.06)	(-2.27)	(-1.83)	(-3.70)
Pay	0.024	0.032	0.020	0.030
	(0.85)	(1.06)	(1.22)	(1.34)
Separate	−0.001	−0.001	−0.001	−0.001
	(-0.99)	(-0.74)	(-0.50)	(-1.06)
Ret	−1.108***	−1.086***	−0.928***	−0.974***
	(-39.31)	(-31.05)	(-41.62)	(-34.09)
Soe	−0.082***	0.002	−0.059***	−0.023

(Continued on following page)

TABLE 6 (*Continued*) Impact of institutional investors.

VARIABLES	1)	2)	3)	4)
	High percentage of shares held by institutional investors	Low percentage of shares held by institutional investors	High percentage of shares held by institutional investors	Low percentage of shares held by institutional investors
	Ncskews	Ncskews	Duvols	Duvols
	(-2.78)	(0.06)	(-2.82)	(-0.86)
Constant	1.482***	1.852***	1.645***	2.597***
	(3.59)	(3.94)	(5.57)	(7.08)
Province FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	7,597	7,602	7,597	7,602
Adj_R2	0.249	0.202	0.332	0.299

the up/down earnings volatility ratio (*Duvols*) as explanatory variables. In addition, the dashed line in the figure shows the actual estimates of the true treatment effect interaction term *Treat*After*, which are also larger than majorityof the placebo test estimates. It indicates there is no significant omitted variable bias in the results of the previous tests.

Heterogeneity analysis

The impact of analyst concerns

Relevant literature has confirmed that analysts are able to optimize the information environment in which an investor lives and minimize the level of internal and external information asymmetry to maintain stock price stability (Ayres et al., 2019). Analysts mainly influence company stock price crash for two aspects; on the one hand by virtue of their professional ability to secondarily interpret the information disclosed by companies, analysts can timely and accurately uncover deeper information about companies and provide investors with the true value of securities, thereby reducing the level of internal and external information asymmetry, improving market information transparency, and lowering SPCR (Pan et al., 2011). Conversely, due to analysts' attention to firms, it will increase the cost and difficulty for firms to hide bad news, thereby reducing management earnings manipulation and SPCR. According to Zhu and Zhou (2014), there is a correlation between the accuracy of analysts' earnigns forecasts and SPCR. Based on the median level of analyst concern, the sample is split into two different level of analyst concern groups, named high and low groups, and Table 4 presents the regression results. According to the findings, enterprises with low analyst concern have higher SPCR as a result of the adoptionn of a GCP. Conversely, a high level of analyst attention can reduce this effect.

The role of independent directors

It has long been widely confirmed in academia that independent directors can improve corporate governance and mitigate agency problems between shareholders and management. Du and Yu (2019) confirm that independent directors can rely on their professionalism, independence, and reputation mechanisms to reduce the firms' SPCR. This is mainly since independent directors can participate directly in corporate governance and supervision and have better access to internal information of the company. Huang et al. (2016) point out that independent directors supervise firms mainly through the reputation mechanism. This enhances the quality of information disclosure. Stock crashes are mainly due to the concentration of negative corporate news exposure. Independent directors can improve the firms' earnings quality and reduce SPCR by improving the transparency of company's information disclosure and controlling insiders' interception of personal self-interest. Liang and Zeng (2016) emphasize that independent directors can reduce a enterprise's SPCR by monitoring the quality of enterprise's information disclosure and by influencing management to intercept personal self-interest. Therefore, we predict that SPCR would be lower in companies with a higher percentage of independent directors. The results of the test for the impact of independent directors are shown in Table 5, indicating that regression system of Treat*After in columns 2) and 4) is significantly positive at 1% and 5% confidence level, respectively. It indicates that effect of GCP on SPCR is more significant for companies with a low percentage of independent directors, and conversely, a high percentage of independent directors can effectively reduce this impact.

The impact of institutional investors

There is highly controversial about the relationship between institutional investors and SPCR is. In contrast, institutional investors may act as "market stabilizers". According to Crane et al. (2017), institutional investors can improve corporate governance and effectively monitor management's earnings management behavior. Mainly consists of "voting with their feet" and "exit threat". On the other hand, institutional investors may be a "crash gas pedal". Cao et al. (2015) hold the opposite view, stating that institutional investors act as "accomplices" for managers to conceal bad news. In order to obtain higher profits, institutional

TABLE 7 Regional financial development effect.

VARIABLES	1)	2)	3)	4)
	Higher degree of financial development	Low level of financial development	Higher degree of financial development	Low level of financial development
	Ncskews	Ncskews	Duvols	Duvols
*Treat*After*	0.062	0.105**	0.048	0.066*
	(1.15)	(2.24)	(1.25)	(1.90)
Treat	−0.544**	0.748***	−0.543***	0.446**
	(-2.17)	(2.92)	(-6.14)	(1.97)
After	−1.138***	−0.558***	−0.959***	−0.420***
	(-15.87)	(-7.96)	(-18.25)	(-7.59)
Size	0.067**	0.010	0.026	−0.022
	(2.55)	(0.42)	(1.33)	(-1.16)
Lev	−0.271***	0.038	−0.251***	−0.016
	(-3.41)	(0.47)	(-4.27)	(-0.26)
Same	−0.010	−0.005	−0.021	−0.010
	(-0.33)	(-0.17)	(-0.94)	(-0.50)
Top	−0.311***	−0.264***	−0.340***	−0.289***
	(-3.42)	(-3.01)	(-5.19)	(-4.51)
Tobinq	0.008	−0.007	−0.029***	−0.040***
	(0.74)	(-0.64)	(-3.26)	(-4.27)
Roa	−0.014***	−0.010***	−0.011***	−0.009***
	(-5.05)	(-3.76)	(-5.57)	(-4.56)
Inst	1.913***	1.729***	1.447***	1.230***
	(10.60)	(9.93)	(10.27)	(9.16)
Employee	0.008	−0.006	0.018	0.004
	(0.37)	(-0.33)	(1.09)	(0.30)
Invest	−0.000	0.002	0.001	0.002
	(-0.08)	(0.98)	(0.42)	(1.47)
Audit	−0.076**	−0.018	−0.078***	−0.022
	(-2.46)	(-0.64)	(-3.38)	(-1.01)
Holding	−0.194**	−0.149*	−0.212***	−0.128**
	(-2.52)	(-1.93)	(-3.65)	(-2.20)
Pay	0.051*	0.006	0.045**	0.007
	(1.80)	(0.21)	(2.20)	(0.41)
Separate	−0.003**	−0.000	−0.003**	0.000
	(-2.03)	(-0.02)	(-2.15)	(0.04)
Ret	−1.067***	−1.139***	−0.942***	−0.968***
	(-34.31)	(-37.25)	(-38.38)	(-38.49)
Soe	−0.046	−0.047	−0.068***	−0.036

(Continued on following page)

TABLE 7 (*Continued*) Regional financial development effect.

VARIABLES	1)	2)	3)	4)
	Higher degree of financial development	Low level of financial development	Higher degree of financial development	Low level of financial development
	Ncskews	Ncskews	Duvols	Duvols
	(-1.39)	(-1.55)	(-2.71)	(-1.60)
Constant	0.526	0.595	1.640***	1.606***
	(1.13)	(1.19)	(5.19)	(4.22)
Province FE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Observations	7,208	7,991	7,208	7,991
Adj_R2	0.219	0.224	0.306	0.305

investors may conspire with management to obtain inside information to adjust their positions and profit before the stock price crashs. Table 6 displays regression results of GCP, institutional investors and SPCR. Regardless of *Ncskews* or *Duvols* is used as an indicator of SPCR, the impact is not significant among firms with a high percentage of institutional investors shareholding. This finding demonstrates the role of institutional investors to enhance corporate governance and thus reduce the impact as a monitoring mechanism.

Diverse regional financial development levels

The degree of regional financial growth affects the impact of GCP on SPCR. Under typical conditions, the access threshold for corporate finance loans will increase because of GCP. Enterprises will have more access to fiancning when regional financial development is more advanced. Xie and Huang, (2014) emphasize that a healthy financial market can foster a favorable financial ecological environment, which can significantly alleviate the pressure of corporate financing. Firms rely less on bank loans as a source of funding, and the regulatory role for green financial policies is diminished. On the contrary, enterprises confront a more challenging funding environment with a relatively single financing channel in area with less developed financial market, where business rely more on bank credit, therebythe policy effect of green credit should be stronger. Referring to Wang et al. (2016), Table 7 displays regression results by using marketization index which is commonly used by scholars as an indicator of regional financial development level. It shows impact of GCP on SPCR is not significant at financially developed areas. On the other hand, this effect is more significant in areas with a low degree of financial development, verifying the role of regional financial development level.

Conclusion and insight

GCP is a significant financial instrument for government to stimulate the green development of companies, but also effect operating decisions and financing constraints of enterprises by promoting green transformation and development, especially heavily polluting companies. Green Credit Guidelines used in this essay to demonstrate its impact on SPCR of heavy-polluting companies. The main results of the paper are: 1) The GCP implementation increases SPCR for heavy-polluting enterprises. 2) The above impact is constrained by degree of corporate governance, and the effect is not significant in enterprises with higher analyst attention, higher percentage of institutional investors' shareholding, and higher proportion of independent directors. 3) The aforementioned effectsare also constrained by the degree of regional financial development, where GCP increase SPCR in heavily polluting firms in regions with low regional financial development, while the effects are discernible in regions with low regional financial development.

Green finance aims to guarantee implementation of transformation and upgrading of enterprises, especially heavily-polluting enterprises, in order to improve the rational allocation of green resources. However, GCP may have certain limitations or even adverse effects on the heavily polluting enterprises in the concrete implementation, such as the increased SPCR.

These results of the paper have significant implications for the improvement of the green credit system as well as for the managers of heavy polluters. On the one hand, GCP may aggravate the financing constraints of heavy-polluting firms, resulting in companies falling into a vicious circle of "difficulty in financing–information disclosure quality declined - increased risk of share price crash", which defeats the original purpose of green credit for environmental management. Therefore, financial institutions and local governments must modulate the strength and standards of policy implementation in a timely manner, prevent "one-size-fits-all" GCP, support and guide heavy polluters to actively engage in green transformation and strengthen companies' green awareness. On the other hand, GCP is likely to be a challenge and an opportunity for heavy polluters, as a result, they should focus on their own sustainable development. In order to gain the favor of green financial resources, enterprises should carry out green innovation, eliminate equipment with more serious environmental pollution, enhance the environmental information disclosure standard and carry out green transformation and upgrading. Only when enterprises enforce green transformation and financial institutions collaborate, can we truly promote ecological civilization and high-quality development of economic growth.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www.gov.cn/gzdt/2008-07/07/content_1038083.htm.

Author contributions

Conceptualization, ML and BD; methodology, ML, BD, and YL; formal analysis, YL; investigation, BD; resources, ML; writing—original draft preparation, ML; writing—review and editing, ML and BD; visualization, YL; supervision, BD. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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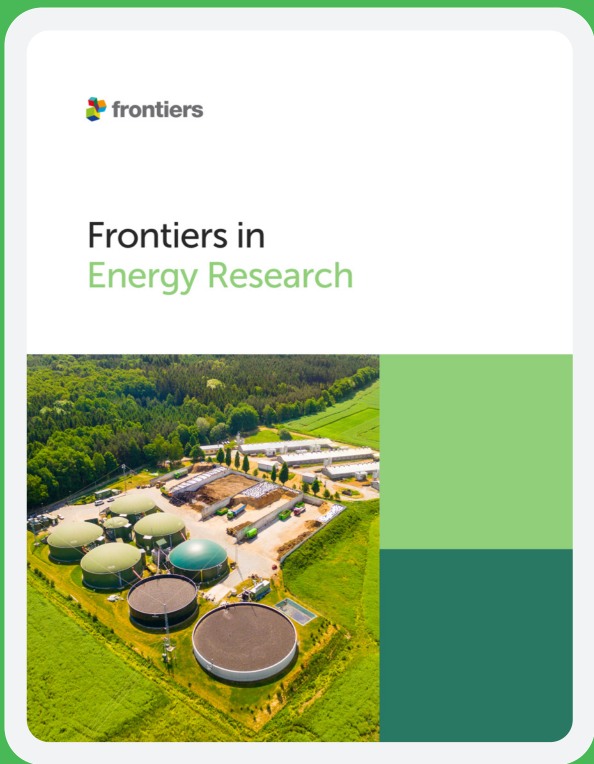

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