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EDITED BY
Dan Cudjoe,
Nanjing University of Information Science and Technology, China

REVIEWED BY
Irina Georgescu,
Bucharest Academy of Economic Studies, Romania
Sedat Alatas,
National Research University Higher School of Economics, Russia
Hamid Mattiello,
Fachhochschule des Mittelstands, Germany

*CORRESPONDENCE
Dinkneh Gebre Borojo,
g10dinkneh@yahoo.com

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How do technological innovation and digital infrastructure affect material footprint? the inverted U-shaped effect in resource-rich economies

Shundian Li[1,2] and Dinkneh Gebre Borojo[3]*

[1]Jinfeng Road Primary School, Chengdu, China, [2]School of Economics and Management, Southwest Jiaotong University, Chengdu, China, [3]School of Modern Business, Yiyang Vocational and Technical College, Yiyang, Hunan, China

Introduction: Efficient management of natural resources is a fundamental goal of the SDGs, aimed at supporting responsible production and consumption practices. Technological innovation (TI) and digital infrastructure (DI) serve as crucial tools that influence effective resource management. However, limited focus has been directed toward assessing the non-linear relationships between the material footprint (MFP), TI, and DI. This research seeks to provide fresh perspectives on the influence of TI and DI on MFP, utilising data from resource-rich economies (RE) spanning 1990 to 2021.

Methods: Given the characteristics of the data, we employ the pooled mean group-autoregressive distributed lag (PMG/ARDL) model. Furthermore, for sensitivity analysis, we apply instrumental variables (IV) and methods of moments quantile regression (MMQR) techniques to address distributional heterogeneity and endogeneity issues. The investigation is repeated while accounting for green innovation (GI) to examine the effects of environmentally-associated TI on MFP.

Results and discussion: The findings reveal that the coefficients of the level and squared terms of TI and DI are positive and negative in the long run, respectively. Therefore, TI and DI exhibit a non-linear influence on MFP, suggesting an inverted U-shaped link between TI, DI, and MFP over the long term. Thus, TI and DI contribute to a resource curse up to threshold values of 2.827 and 2.081, after which they enhance resource efficiency in RE, implying that greater investment in TI and DI yields better outcomes for harnessing resource efficiency than lesser investment. Lastly, both small and large changes in GI have a robust negative impact on MFP. These findings carry significant policy implications for enhancing TI and DI, aimed at fostering responsible natural resource management per SDGs 8 and 12, thus ensuring the efficient and sustainable use of natural resources.

KEYWORDS

material footprint (MFP), technological innovation (TI), digital infrastructure (DI), green innovation, resource-abundant economies (RE)

1 Introduction

The sustainable use of natural resources is a crucial goal, balancing economic growth with the protection of our environment (Ali et al., 2023). Nevertheless, this sustainable use confronts challenges from rapid population growth, overexploitation, and various other resource-driven economic expansions (Haider et al., 2021). As a result, resources are being consumed at an alarming rate, leading to increased global efforts to protect them. CO_2 emissions resulting from the use of material resources have doubled over the past 20 years (IRP, 2019). This statement is further supported by the fact that over 30% of global carbon emissions are derived from resource consumption (Dwivedi et al., 2022). Thus, the overuse of natural resources adversely affects nations' environmental performance (Jin and Huang, 2023). Furthermore, the excessive reliance on natural resources is primarily associated with rising global temperatures. It also depletes the supply of material resources, ultimately resulting in shortages for future generations (Chen et al., 2022).

Therefore, it is beneficial to preserve natural resources (NRs) through various methods and strategies. However, sustainable management of natural resources presents a complex challenge, requiring a delicate balance between meeting current societal needs and safeguarding these resources for the future (Liu and Liang, 2024). As a result, the increasing use of material resources within ecosystems has sparked significant discussion in recent times. Consequently, environmental advocates are increasingly focused on reducing the impact of resource use on harmful emissions and promoting sustainability in ecosystems (Yingchao and Xiang, 2024). Thus, the effective utilisation of natural resources has emerged as a crucial objective to encourage responsible usage (Zhou et al., 2024). Therefore, it is essential to utilise NRs sustainably to uncover solutions that enhance the social, environmental, and economic performance of countries (Wu et al., 2021).

The 26th session of the UN Conference of Parties on Climate Variation stresses the goal of decarbonisation by 2050, with resource productivity primarily aligned with SDG-12, in light of pressing environmental challenges. Furthermore, to achieve COP-26 objectives, an extensive decarbonisation procedure for material utilisation is essential. In this environment, enhancing the efficiency of natural resource consumption, as shown by the MFP, is imperative. The MFP considers environmental issues and the pressures from the final demand of economies. It largely emphasises the utilisation of resources and the environmental damage resulting from this utilisation. It thoroughly indicates nations' material consumption by considering local effects and the embodied implications of trade, encompassing both exports and imports (Karakaya et al., 2021; Ulussever et al., 2024). Consequently, it has served as an indicator for SDI-8.4, which focuses on advancing NR efficiency improvements, and SDI-12.2, which seeks to support the sustainable management of NRs (Lenzen et al., 2021).

Thus, understanding the influencing factors of MFP is essential for propelling the shift toward a decarbonised economy via proficient resource management. Among these elements, TI is regarded as a crucial tool shaping the advancement of responsible resource consumption (Hehua et al., 2024; Appiah et al., 2024). In theory, the connection between managing the utilisation of resources and TI can be examined through the lenses of Holdren and Ehrlich (1972) and Commoner et al. (1972). They postulated that environmental sustainability, often illustrated by MFP, is influenced by population, affluence, and technology (Fernández-Herrero and Duro, 2019).

Nonetheless, when viewed through the lens of empirical investigation, the effects of TI on resource efficiency remain uncertain. Some scholars contend that TI is essential for achieving production and optimising resource utilisation, thereby alleviating MFP (Ulussever et al., 2024; Awaworyi Churchill et al., 2019). Furthermore, enhancing TI boosts the efficiency of manufacturing and production processes that utilise fewer resources. It indicates that elevated TI leads to reduced resource consumption by minimising reliance on primary commodities, improving NR efficiency, and fostering environmental stewardship and sustainable development (Hehua et al., 2024; Appiah et al., 2024). Conversely, various empirical studies suggest that TI enhances MFP, which may adversely affect resource efficiency as it drives economic growth that necessitates greater resource consumption (Majeed et al., 2022; Ali et al., 2022). Therefore, exploring the influence of TI on MFP presents significant opportunities for enhancing the sustainability of NRs.

Moreover, certain experts contend that DI could be crucial in enhancing NR efficiency. The DI signifies the digital infrastructure and development within the economy, serving as a fundamental basis for the growth of information technology and innovation (Patro and Raghunath, 2021). Nonetheless, regarding the impacts of DI on MFP, the existing literature is notably lacking, with minimal empirical discourse, despite the growing attention on the significance of DI in resource management (Zhou et al., 2024). Moreover, the evidence concerning the linear connection between DI and resource consumption management remains inconclusive.

On one side, DI makes a beneficial impact on resource efficiency (Mehmood et al., 2023; Ran et al., 2023; Shi et al., 2024), adversely affecting MFP. The widespread embrace of DI stands as a crucial tool for boosting resource productivity, as it can significantly improve a company's environmental performance and the effective use of resources (Rajput and Singh, 2019; Feng et al., 2022). Conversely, while many conventional empirical studies generally endorse the beneficial impact of DI on resource efficiency, some researchers contend that DI requires more energy and resources (Lange and Santarius, 2020) and positively

Abbreviations: AMG, Augmented mean group; CO_2, Carbon dioxide; CD, Cross-sectional dependence; CIPS, Cross-sectionally augmented panel unit root test; CS-DL, Cross-sectionally augmented distributed lag; DFE, Dynamic fixed effect; DI, Digital infrastructure; EKC, Environmental Kuznets curve; FDI, Foreign direct investment; GDP, Gross domestic product; GI, Green innovation; ICT, Information communication technologies; IRP, International Resource Panel; IV, Instrumental variables; MMQR, Method of moments quantile regression; MFP, Material footprint; MG, Mean group; NR, Natural resource; PCA, Principal component analysis; PMG-ARDL, Pooled mean group-autoregressive distributed lag; RE, Resource-rich economies; R&D, Research and development; SDI, Sustainable development goal; STIRPAT, Stochastic impacts by regression on population, affluence, and technology; TI, Technological innovation; UN, United Nations; UNEP, United Nations Environmental Program; WDI, World development indicators.

contributes to MFP. This perspective suggests a detrimental effect on resource efficiency (Lange and Santarius, 2020; Kunkel and Matthess, 2020) and reinforces the notion that DI does not inherently guarantee an enhancement in resource utilisation efficiency (Hu and Zhang, 2023). Consequently, the exact influence of DI on MFP is still predominantly ambiguous and unexamined.

Moreover, while the aforementioned studies explore the linear relationships between TI and efficient use of resources, as well as DI and resource management, there has been limited focus on integrating and assessing the non-linear connections of MFP with TI and DI. While limited research offers insights into the non-linear connection between TI and CO_2 emissions (Twum et al., 2021; Basty and Ghachem, 2023), the non-linear connection between TI and MFP is still underexplored. Likewise, although some current research supports an inverted U-shaped relationship between CO2 and DI, as suggested by the EKC hypothesis (Li et al., 2021; Lange et al., 2020), studies exploring the non-linear connection between MFP and DI are scarce. Thus, by broadening the EKC hypothesis, this research seeks to present fresh perspectives on the non-linear effects of TI and DI on MFP in RE.

The focus of this research is directed toward RE for several compelling rationales. First, the surge in growth and advancements in resource-rich countries often generates a significant demand for the extraction of NR and cutting-edge technologies (Duan and Liu, 2023). NR plays a crucial role in shaping the levels of economic development, especially within large NR economies (Balsalobre-Lorente et al., 2018). Second, throughout the last 30 years, these nations have exhibited a varied growth pattern regarding MFP (see Supplementary Appendix Figure A1). Nonetheless, every sample economy exhibited positive growth in MFP as a result of resource utilisation. Third, the emerging trends confirm that the degradation of the environment remains a continual challenge in these countries (Luo and Mabrouk, 2022). Furthermore, a significant number of REs rank among the highest emitting nations globally. For instance, China, the United States, and Russia rank among the top countries in CO_2 emissions (Hussain et al., 2023).

Therefore, utilising data spanning from 1990 to 2021 and employing the PMG/ARDL approach, this study aimed to investigate the non-linear impacts of TI and DI on MFP and provide a holistic understanding of how technological progress and DI interact with resource sustainability in RE. Thus, it addresses the gaps in existing works in the area by examining the two-fold effects of TI and DI on MFP, encompassing its potential to increase and mitigate MFP in RE.

The investigation is repeated accounting for GI to examine the effects of ecologically associated TI on MFP. Furthermore, we employed the IV method to tackle possible endogeneity concerns. A sensitivity analysis is additionally performed using the MMQR procedure to examine the impact of the MFP's distributional variation resulting from the nonparametric nature of the data.

This research offers several valuable insights into the existing body of work. First, examining the TI-related EKC theory and grasping the non-linear relationships between TI, DI, and MFP carries significant policy ramifications. While earlier empirical research has highlighted a partisan perspective regarding the effects of TI and DI on ecological performance indicators, whether beneficial or detrimental, this study brings together both perspectives by illustrating the non-linear influence of TI and DI on MFP. Consequently, investigating the non-linear effects of TI and DI provides evidence of the life cycle of TI, DI and the material intensity of digital transitions and technological innovations. Hence, it provides detailed evidence on the inverted U-shaped impact of TI and DI on MFP so that it extends the understanding of the EKC-type relationship in the context of material resources productivity, which can enrich the theoretical underpinning of the relationship between technological and digital innovation and responsible resources consumption in RE.

Second, the findings of this work will aid RE in developing policies and practical strategies that enhance the efficiency of resources in RE while taking into account the interconnections between TI, DI, and MFP. It offers a comprehensive understanding of the intricate connections between the TI, DI, and MFP, yielding fresh policy perspectives aimed at fostering the creation of effective and viable solutions that enhance the optimal use of resources to advance SDG. Therefore, the findings of the study specifically support leveraging TI and DI to promote the sustainable use of resources, aligning with SDG-8 and SDG-12.

Third, current studies examining the link between natural resource management and socioeconomic activities have primarily concentrated on domestic material consumption while giving little attention to multifactor productivity. This research utilised the MFP to proxy for NR management due to its superior accuracy in reflecting policies and strategies to improve environmental sustainability, as it takes into consideration the resources engaged in both the consumption of material and production within the economy (Razzaq et al., 2021).

The remainder of this research is articulated as follows: Section 2 delves into the review of the literature; Section 3 discusses the theoretical foundations, data, and method of analysis; Section 4 presents the findings of the study; Section 5 presents robustness analysis, and Section 6 presents discussions and policy suggestions.

2 Review of literature

2.1 TI and NR productivity

Effectively managing NR utilisation is crucial for economic development and environmental quality. Thus, ensuring the effective use of NRs is essential for sustaining environmental quality (OECD, 2008). In this instance, TI can significantly contribute to the management of NR utilisation. TI denotes the creation of novel technologies through innovation, encompassing advancements in materials, methods and processes (Zhao et al., 2023).

The theoretical foundation for linking MFP and TI is based on a range of frameworks. An illustration of this is the curse of resources hypothesis, which underpins the comprehension of the connection between economic expansion and natural resource consumption. In the neoclassical growth model, capital and labour are conventionally regarded as the main drivers of growth. Nonetheless, this perspective has faced growing opposition, as additional elements, like NRs, have come to be acknowledged as vital in influencing the growth path of an economy. The theory of the resource curse posits that an abundance of natural resources can impede growth in nations rich in these resources (Appiah et al., 2024). Moreover, the resource curse hypothesis delves into additional factors beyond NRs that could account for the slower growth performance observed in these nations. Hence, TI is one of the factors supposed to aid in comprehending this phenomenon (Appiah et al., 2024).

Furthermore, the theoretical connection between TI and MFP can be demonstrated through Porter and Linde (1995) hypothesis, which posits that rigorous regulations on the environment motivate companies to enhance their innovative capacities, especially in GIs, thereby improving the efficiency of the environment. Conversely, Goulder and Schneider (1999) contended that although investing in TI may decrease production or emissions reduction costs, it might also result in diminished productivity, potentially harming environmental efficiency. Additionally, the theory of Dutch disease provides an alternative viewpoint on the negative growth impacts stemming from natural resource extraction (Saidi and Omri, 2020). On the other hand, a counternarrative emphasises the significance of TI, foreign investment, and industrialisation in alleviating the resource curse (Appiah et al., 2024).

Furthermore, the conceptual connection between TI and MFP can be grounded in the theoretical frameworks established by Holdren and Ehrlich (1972) and Commoner et al. (1972), along with the subsequent mathematical modelling that has found extensive application in the STIRPAT approach (Fernández-Herrero and Duro, 2019). This study, grounded in theoretical principles, offers an in-depth examination of how TI and DI influence MFP through the lens of the EKC hypothesis.

Building on these theoretical foundations, empirical research was subsequently carried out (see Table 1). Most of the empirical works were concerned with investigating the relationship between environmental performance and TI (Ganda, 2019; Jianguo et al., 2022; Shabir et al., 2023; Shan and Shao, 2024; Han et al., 2025; Sun and Qamruzzaman, 2025). A few studies extended the investigation to examine the non-linear association between environmental indicators and TI (Bai and Nie, 2017; Twum et al., 2021; Basty and Ghachem, 2023). Besides, some studies link TI with natural resource utilisation (Zhang J. et al., 2023; Ulussever et al., 2024; Razzaq et al., 2022; Miao et al., 2017; Sun et al., 2022; Ozturk et al., 2023).

Based on the aforementioned empirical and theoretical works, the following hypothesis is articulated.

Hypothesis 1: (H1): There is an inverted U-shaped relationship between TI and MFP.

2.2 DI and NR productivity

It is claimed that DI has a considerable impact on NR management via multiple channels. In principle, DI influences resources and MFP via the scale effect (the impact of expansion) and the effects of green efficiency. As DI grows and evolves, its scale keeps on expanding. Consequently, the expansion on an industrial scale necessitates a higher input of production inputs (Wang and Lee, 2022), leading to a rise in MFP. Eventually, the progress of DI technology and its features will reshape the production processes of conventional industries. This transition will result in significant improvements in resource productivity through various sectors, such as electricity and energy, industry and manufacturing, and transport.

More importantly, when the level of DI is comparatively low, the scale effect tends to dominate. Conversely, at significantly higher levels of digital intelligence, the green efficiency effect becomes more prominent. As digital intelligence evolves from a lower to a higher state, its role in resource efficiency moves from negative to positive (Li et al., 2023). To put it differently, during the initial phase of digital transformation, the establishment of digital infrastructure and its usage led to a direct rise in the need for resources and energy (Cheng et al., 2023), thereby exerting a major impact on the reduction of MFP. At its advanced phase, DI boosts industrial productivity and promotes international collaboration through digital industrialisation, facilitating growth while lowering marginal costs (Cheng et al., 2023) and reducing NR extraction.

On the aforementioned theoretical basis, several empirical studies have explored the role of DI in enhancing resource productivity and promoting environmental quality. Most of the studies argued that DI promotes environmental sustainability, using indicators such as load capacity factor, ecological footprint (Mehmood et al., 2023; Özpolat, 2022), and carbon productivity (Yu and Liu, 2024). Also, some studies provided evidence of the linear association between resource consumption and DI (Ran et al., 2023; Shi et al., 2024; Abid et al., 2023). A few studies provided a comprehensive analysis of the non-linear association between environmental quality indicators and DI. For example, Li et al. (2021), Li et al. (2023), Ahmadova et al. (2022), and Barış-Tüzemen et al. (2020) found an inverted U-shaped or N-shaped relationship between DI and environmental quality indicators. Existing empirical works on the link between DI and environmental performance, including resource consumption, have been illustrated in Table 2 below.

Based on the outcomes of the empirical studies and theoretical underpinnings of the link between DI and resource efficiency, we develop the following hypothesis.

Hypothesis 2: (H2): DI has an inverted U-shaped impact on MFP.

2.3 Summary and research gaps

First, empirical research on TI mainly focuses on the relationship between TI and environmental performance (CO_2 emissions) (Twum et al., 2021; Ganda, 2019; Jianguo et al., 2022; Shabir et al., 2023; Shan and Shao, 2024; Han et al., 2025; Sun and Qamruzzaman, 2025), leaving a significant research gap on the effects of TI on MFP. Moreover, some existing research works investigated the effects of TI on resource utilisation management and efficiency (Razzaq et al., 2021; Miao et al., 2017; Sun et al., 2022; Ozturk et al., 2023). However, they are mainly concerned with the linear association between TI and resource consumption, indicating an important research gap in the area.

Second, investigating non-linear impacts of TI and DI on the volume of resource flows and consumption, while CO_2-based EKC studies mostly focus on emission reduction without addressing the volume of resource flows. Therefore, investigating the role of TI and DI on MFP extending an EKC-type relationship in the context of material resources productivity is worthwhile. Besides, the CO_2-

TABLE 1 The empirical literature on the MFP-TI nexus.

Authors	Period	Scope/sample	Methodology	Findings
Appiah et al. (2024)	1990–2021	OECD	AMG and CCEMG	The findings indicate that innovation significantly decreases NR extraction
Hehua et al. (2024)	1995–2019	A sample of Asian countries	CS-ARDL	TI positively influences resource management
Zhang et al. (2023b)	2010–2021	25 countries	Fixed effect, Random effect	In higher-income economies, the GI exhibits a more substantial positive effect on sustainability
Basty and Ghachem (2023)	2015–2020	OECD countries	Parametric and Semiparametric regressions	Revealed an inverted U-shaped link between CO_2 and R&D spending
Twum et al. (2021)	1990–2018	A sample of Asian countries	Truncated regression	Inverted U-shaped link between environmental efficiency and TI
Razzaq et al. (2021)	1990–2017	Top 11 highly material-consuming countries	MMQR	Mixed impact of GI on MFP
Ganda (2019)	2000–2014	Selected OECD countries	System GMM	TI improves environmental quality by channelling resources into R&D
Jianguo et al. (2022)	1998–2018	A sample of OECD countries	System GMM	TI significantly decreases environmental quality
Shabir et al. (2023)	2004–2018	APEC countries	AMG and CCMG	Environmentally related TI destructively affects CO_2 emissions
Shan and Shao (2024)	1990–2020	China	Regression	GI has a significant mitigating impact on CO_2 intensity
Miao et al. (2017)	2001–2015	China	Stochastic frontier analysis	The introduction of GI funds and green new product development funds has a notable positive impact on the efficiency of NR utilisation
Sun et al. (2022)	1990–2018	BRICS	CS-ARDL	Changes in technical efficiency increase resource efficiency
Ozturk et al. (2023)	1990–2020	G-20 nations	MMQR	GI substantially decreases the MFP across all distributions, though the extent and significance of its impact vary
Han et al. (2025)	1995–2022	G-20 nations	PMG-ARDL	TI positively influences renewable energy consumption, in turn strongly associated with reductions in CO_2 emissions
Sun and Qamruzzaman (2025)	1990–2022	BRICS + T nations	ARDL	TI reliably mitigates CO_2 emissions and ecological footprints
Ahmad et al. (2023)	40 years	China	Autoregressive distributed lag method	TI promotes sustainable development by supporting economic expansion without harmful effects on the environment
Chen et al. (2025)	2014–2018	China	Fixed effects model	The digital economy exhibits an inverted U-shaped effect on indirect household carbon emissions

focused EKC framework focuses on emission-growth patterns, whereas investigating the non-linear impacts of TI and DI on MFP is vital for sound policy formulation to efficiently utilise resources as MFP focuses on the physical flow of materials, including extraction, consumption, and waste (Ulussever et al., 2024).

Third, in addition to investigating the link between TI and MFP, it is valuable to extend the analysis to the association between environmental-related technology and MFP to further provide a comprehensive understanding of the effects of technological advancement on responsible resource consumption in RE.

Fourth, most of the existing research works except some studies such as Li et al. (2021), Li et al. (2023), Ahmadova et al. (2022) and Barış-Tüzemen et al. (2020) that investigated the non-linear relationship between DI and environmental quality indicators, research works on the comprehensive non-linear association between DI and MFP is limited. Investigating how DI affects MFP helps identify the nature of the relationship and the threshold where additional digital innovations offer marginal efficiency gains on resource management, which will be essential for policy formulation.

Therefore, this study brings new insight by investigating the non-linear impacts of TI and DI on MFP in resource-abundant economies and will contribute to concrete evidence regarding the effects of TI and DI on efficient resource utilisation.

3 Methodology

3.1 Theoretical foundations and model specification

Effectively managing NR utilisation is crucial for promoting sustainable economic growth and environmental performance. Thus, the effective use of NRs is essential for sustaining the health of the environment and promoting environmentally friendly growth (OECD, 2008). The theoretical foundation linking MFP with TI and DI is based on various theoretical frameworks. For instance, the conceptual link between TI and MFP can be supported by the hypothesis put forth by Porter and Linde (1995), which asserts that strict environmental regulations can lead companies to augment their innovative

TABLE 2 The empirical literature on the DI-MFP nexus.

Authors	Period	Scope/sample	Methodology	Findings
Ran et al. (2023)	2006- 2020	China	The input-output method	The digital economy can greatly advance industrial green transformation by enhancing the efficiency of NR consumption
Mehmood et al. (2023)	1990- 2018	G8	CS-ARDL estimator	TI and DI benefit the natural ecological health
Shi et al. (2024)	2010- 2020	China	Slacks-Based Measure	DI advancements improve resource efficiency
Li et al. (2023)	2007-2015	91 countries	OLS	U-shaped relationship between CO_2 and ICT
Özpolat (2022)	1990- 2015	G-8 economies	AMG method	Internet usage is linked to a decreased ecological footprint
Yu and Liu (2024)	2000-2020	136 countries	Fixed-effects and mediation models	Promoting DI significantly boosts carbon productivity, mainly by advancing TI
Abid et al. (2023)	1990- 2019	G10 economies	CS-ARDL	ICTs negatively affect MFP, indicating a vital role in mitigating resource depletion
Ahmadova et al. (2022)	2014–2019	47 countries	The panel smooth transition regression model	U-shaped relationship between DI and environmental performance
Barış-Tüzemen et al. (2020)	1980–2017	Turkey	ARDL	N-shaped non-linear relationship between DI and CO_2
Hou et al. (2024)	1998–2021	BRICS nations	CS-ARDL	Improvement in DI helps control resource depletion
He et al. (2024)		China	Regression and IV	DI lowers energy consumption and fosters sustainable development
Razzaq et al. (2022)	1990- 2018	China	Quantile ARDL approach	infrastructure development significantly increased the MFP
Xu and Li (2022)	2013- 2019	China	A panel threshold model	After a certain development threshold, DI influence on innovation starts to experience diminishing returns
Mu et al. (2025)	2011-2022	China	Tobit model	digital transformation significantly enhances green innovation potential
Tian et el. (2025)	2011- 2022	China	System GMM and OLS	The digital economy positively influences the utilisation efficiency of mineral resources
Gariba et al. (2024)	2018- 2023	EU	Structural equation modeling	Public DI positively affects TI, fostering sustainability progress
Salahuddin et al. (2016)	1985–2012	Australia	ARDL	Internet usage has no long-run effect on CO2 emissions
Bashir et al. (2024)	1996- 2021	Top-ten resource-consuming economies	CS-ARDL	DI promotes environmental sustainability
Yang et al. (2024)	1990 to 2021	South Asian countries		DI contributes to higher green growth.

capacities, mostly in GI, eventually leading to better ecological efficiency.

Furthermore, the theoretical connections between resource utilisation and TI, along with the associations among control variables such as economic growth, population dynamics, industrial development, and FDI and MFP, are grounded in the theoretical frameworks established by Holdren and Ehrlich (1972) and Commoner et al. (1972). These conceptual frameworks have been extensively applied in mathematical modelling, particularly within the STIRPAT structure (Fernández-Herrero and Duro, 2019).

Also, the STIRPAT framework serves as the theoretical foundation for this research, aimed at assessing the effects of DI on the MFP. Yu et al. (2023) extended the STIRPAT specification by incorporating household size and urbanisation. Moreover, various extended STIRPAT frameworks were also produced for the context of NR management in earlier studies (Hussain et al., 2020; Jiang et al., 2022). Furthermore, the theoretical foundation for the relationship between TI and NR utilisation can be determined through a set of guidelines aimed at addressing the appropriate SDGs, which seeks to resolve ecological and economic challenges, particularly enhancements in the resource efficiency of SDI-8 and the sustainable management of the NRs of SDI-12.

Based on this theoretical framework, this research offers an in-depth examination of how TI and DI influence MFP through the lens of the EKC theory. This hypothesis suggests that the MFP exhibits an inverted U-shaped relationship with both the TI and DI. In the initial phases of TI and DI, MFP rises. However, once a certain threshold of TI and DI is surpassed, this trend shifts, resulting in a decline in MFP.

To put it differently, a high (low) TI correlates with a low (high) level of MFP. Also, a large (small) change in DI can be associated with a reduced (increased) MFP level. Thus, the MFP stated in Equation 1 is expected to be positively affected by the TI at the initial stages ($\alpha_1 = \partial \log\mathrm{MFP}/\partial \log\mathrm{TI} > 0$) and adversely affected after the inflection point ($\alpha_3 = \partial \log MFP/\partial \log TI^2 < 0$). Likewise, the MFP in

Equation 1 can be positively impacted by the DI initially ($\alpha_2 = \partial \text{logMFF}/\partial \text{logDI} > 0$) and adversely affected after the threshold value ($\alpha_4 = \partial \log MFP/\partial \text{logDI}^2 < 0$).

$$\text{logMFP}_{i,t} = \alpha_0 + \alpha_1 \text{logTI}_{it} + \alpha_2 \text{logDI}_{it} + \alpha_3 \text{logTI}_{it}^2 + \alpha_4 \text{logDI}_{it}^2 + \alpha_n X_{it} + \eta_{it} \quad (1)$$

MFP represents the material footprint to represent NR utilisation efficiency; *TI* is technological innovation, measured by patent counts. *DI* is represented by a composite index constructed through PCA, *X* controls explanatory variables such as *GDP per capita gross (GDPc)*, *population size (P)* to proxy the demographic dynamics of the countries, *level of industrialisation (Ind)* proxied by value-added of industry sector per GDP, and *FDI* is represented by net FDI inflows. *αs* is a set of coefficients and η indicates the stochastic term. *T* is for the years (1990–2021), and *i* is a sample RE 1. . ..13.

Equation 1 incorporates control variables such as GDP *per capita*, population, and additional variables within the STIRPAT framework, which may influence MFP (Fernández-Herrero and Duro, 2019). The rise in GDP *per capita*, industrialisation, and population growth boost MFP, adversely affecting NR productivity. FDI can influence the MFP both negatively and positively.

3.2 Data

This study utilises data for 18 RE for the period 1990 to 2021 based on data availability.[1]

3.2.1 Dependent variable

MFP was utilised to proxy NR management. MFP signifies trade-adjusted NR management and measures resource usage stemming from domestic activities (Appiah et al., 2024; Ozturk et al., 2023). Moreover, the MFP signifies the overall global material extraction linked to a nation's ultimate domestic demand. It comprises fossil fuels, biomass, metal ores, and nonmetal ores. Employing MFP provides an all-encompassing view of a country's material consumption, extending past just domestic material usage. The MFP considers both the impacts on territory and the inherent effects of trade, encompassing both imports and exports (Karakaya et al., 2021). Data is sourced from the UNEP (IRP) Database.

3.2.2 Target variables

Two key variables have been identified: TI and DI. The total number of patents (with two families) is used as an indicator of TI, as an increase in patent numbers indicates the variety of research and development efforts and technological assets present in an economy (Jianguo et al., 2022; Obobisa et al., 2022; De los Santos-Montero et al., 2020; Ma et al., 2022; Dam et al., 2024). We borrow data from the OECD database, which is the number of patents related to a country's technical advancement (with two families).

DI represents the digitalisation capabilities of nations. Some empirical works used individuals using the internet as % of the population to represent DI (Yang et al., 2024; Zhou and Feng, 2024) and fixed broadband subscriptions (per 100 people) to represent digital infrastructure (Ahmed et al., 2024). However, this study used aggregate indicator of DI calculated using three DI-related factors: mobile cellular subscriptions, fixed telephone subscriptions, and the proportion of individuals who access the internet to capture various aspects of digital applications. The PCA is employed to compute the aggregate DI index, utilising data from the World Bank's WDI database. The findings are reported in Supplementary Appendix Table 6A in Appendix A.

3.2.3 Control variables

To account for the influence of additional control variables on MFP, we incorporate real GDP, population, FDI inflow, and industrialisation, utilising data from the WDI database. The variables considered include *per capita GDP and population*, following the approaches presented by Karakaya et al. (2021). *Industrialisation* denotes the extensive growth of industries, defined by value added per GDP, which is incorporated as a control variable following the research conducted by Appiah et al. (2024). Supplementary Appendix Table A1 presents the definitions and data sources for all variables. Table 3 below presents the essential statistical summaries of variables.

TABLE 3 Statistical summary.

Variable	Obs	Mean	Std. dev.	Min	Max
MFP_{it}	574	2.42E+09	5.22E+09	2.30E+07	3.50E+10
TI_{it}	566	5355.919	16565.500	0.200	88963.300
DI_{it}	566	0.026	1.403	−1.799	3.323
$GDPc_{it}$	569	20075.320	21479.890	531.898	77812.700
FDI_{it}	568	31.418	69.264	−25.000	510.000
P_{it}	576	1.96E+08	3.76E+08	1,800,000	1.40E+09
Ind_{it}	568	36.025	10.830	17.508	68.187
GI_{it}	547	21.393	83.737	0.007	791.661

3.3 Method of analysis

Most empirical investigations primarily rely on short-run panel estimates, including static panel data methods. However, these methods often produce inadequate results due to the data's nonstationarity. Furthermore, these methods primarily concentrate on short-term relationships, and neglecting these drawbacks may result in inaccurate regression outcomes. As a result, there is a growing focus on panel data models in which the number of time series data observations is equal to or greater than the number of the panels (Borojo et al., 2023). In many of these procedures, the central emphasis lies in assessing long-term

1 Sample RE: Algeria, Brazil, Chile, India, Iran, United Arab Emirates, Venezuela, Peru, Oman, Russia, China, Saudi Arabia, Mexico, Viet Nam, Australia, Canada, United States and Norway.

relationships and the speed of long-run adjustments (Pesaran et al., 1999).

We use the PMG/ARDL technique to investigate the short- and long-term roles of the TI and DI on the MFP. This method exhibits a strong ability to manage the dynamic heterogeneity inherent in the adjustment process while also suggesting potential pathways to long-term equilibrium convergence. Additionally, it provides consistent estimates across countries (Pesaran et al., 1999). Also, it effectively controls long-term cointegration between variables, irrespective of their integration sequence and certifies that long-term coefficients are consistent across country sets while accounting for changes in intercepts, short-run dynamics and error terms. Thus, this approach is useful since it yields long- and short-term coefficients, regardless of whether the variables are a mix of the I (1) and I (0) series (Pesaran and Pesaran, 1997).

Thus, having economies, i = 1, 2, 3, . . . , N, and time, t = 1, 2, 3, . . . , T, a long run PMG/ARDL (m, n, n . . . , n) approach is presented in Equation 2:

$$MFP_{i,t} = \sum_{z=1}^{p}\kappa_i MFP_{i,t-z} + \sum_{z=1}^{n}\vartheta_i TI_{i,t-z} + \sum_{z=0}^{n}\alpha_i DI_{i,t-z} + \sum_{z=0}^{n}\delta_i TI^2_{i,t-z} + \sum_{z=0}^{n}\omega_i DI^2_{i,t-z} + \sum_{z=0}^{n}\beta_i X_{i,t-z} + \eta_{it} \tag{2}$$

where $MFP_{i,t}$ is the material footprint and $MFP_{i,t-1}$ is the lag of MFP. $TI_{i,t}$ and $DI_{i,t}$ are target variables. $X_{i,t}$ represents control covariates (GDPc, FDI, P, Ind). κ_{ij} is the estimate of the lag of MFP; ω, δ, ϑ, β, and α are coefficients; m and q are the lag size of the dependent and independent variables, respectively; and η_{it} is the error term.

Equation 2 is rearranged to define the long-run and short-run cointegration connection employing Equation 3:

$$\begin{aligned}\Delta MFP_{i,t} = &\sum_{z=1}^{p}\kappa_i MFP_{i,t-z} + \sum_{z=1}^{n}\vartheta_i TI_{i,t-z} + \sum_{z=0}^{n}\alpha_i DI_{i,t-z} + \sum_{z=0}^{n}\delta_i TI^2_{i,t-z}\\ &+\sum_{z=0}^{n}\omega_i DI^2_{i,t-z} + \sum_{z=0}^{n}\beta_i X_{i,t-z} + \sum_{j=1}^{m-1}\sigma^*_{iz}\Delta MFP_{i,t-z}\\ &+\sum_{z=1}^{n}\vartheta^*_{iz}\Delta TI_{i,t-z} + \sum_{z=0}^{n}\alpha'^*_{iz}\Delta DI_{i,t-z} + \sum_{z=0}^{n}\delta^*_{iz}\Delta TI^2_{i,t-z}\\ &+\sum_{z=0}^{n}\omega'^*_{iz}\Delta DI^2_{i,t-z} + \sum_{z=0}^{n}\beta^*_{iz}\Delta X_{i,t-z} + y_{i,t} + \varepsilon_{it}\end{aligned} \tag{3}$$

Details of the coefficients of both long and short-run estimates in Equation 3 are depicted in Equations 4-11.

$$\kappa_i = -\left(1 - \sum\nolimits_{z=1}^{m}\kappa_{iz}\right) \tag{4}$$

$$\vartheta_i = \sum\nolimits_{z=0}^{n}\vartheta_{iz}, \alpha_i = \sum\nolimits_{z=0}^{n}\alpha_{iz}, \delta_i = \sum\nolimits_{z=0}^{n}\delta_{iz}, \omega_i = \sum\nolimits_{z=0}^{n}\omega_{iz}, \beta_i = \sum\nolimits_{z=0}^{n}\beta_{iz} \tag{5}$$

$$\sigma^*_{iz} = -\sum_{q=z+1}^{m}\sigma_{iq}, z = 1, 2, 3, ..., m-1 \tag{6}$$

$$\vartheta^*_{iz} = -\sum_{q=z+1}^{n}\vartheta_{iz}, z = 1, 2, 3, ..., n-1 \tag{7}$$

TABLE 4 CD and CIPS results.

	CIPS results		CD test results
Variables	Level	1st difference	CD-test
$MFP_{i,t}$	0.356	−6.990***	53.201***
TI_{it}	3.091	−7.520***	44.912***
DI_t	0.410	−4.732***	63.194***
$GDPc_{it}$	−0.837	−2.720***	40.532***
FDI_{it}	−1.167	−9.198***	32.442***
P_{it}	−2.150	−5.529***	53.433***
Ind_{it}	−1.921**	−6.343***	20.301***

Note: ***, ** indicate significance at 1% and 5%.

$$\alpha^*_{iz} = -\sum_{q=z+1}^{n}\alpha_{iq}, z = 1, 2, 3, ..., n-1 \tag{8}$$

$$\delta^*_{iz} = -\sum_{q=z+1}^{n}\delta_{iq}, z = 1, 2, 3, ..., n-1 \tag{9}$$

$$\beta^*_{iz} = -\sum_{q=z+1}^{n}\beta_{iq}, z = 1, 2, 3, ..., n-1 \tag{10}$$

$$\omega^*_{iz} = -\sum_{q=z+1}^{n}\omega_{iq}, z = 1, 2, 3, ..., n-1 \tag{11}$$

Moreover, sensitivity analysis is conducted to investigate the influence of distributional heterogeneity. Therefore, controlling heterogeneity in the resource footprint is essential. After we test for normality assumption using Jarque and Bera's (1987) strategy to obtain reliable information on variable dispersion, we apply the MMQR method (Machado and Santos Silva, 2019).

Moreover, it is essential to tackle the issues related to reverse causality. Concerns of reverse causality might arise when there is a possibility of reverse causality between the dependent variable and the covariates affecting the dependent variable. Therefore, the IV procedure is employed to overcome the endogeneity arising from reverse causation between MFP, TI and DI. Following the approaches used by Li et al. (2021) and Shan and Shao (2024), we employ the first-order lagged value of both the level and quadratic terms of the target variables as IV.

Moreover, to ensure robustness, additional tests are conducted by using R&D expenditures per GDP and its square term as instruments for TI and its square term. Similarly, the number of fixed telephone subscriptions per 100 people in 1982 and its square term are employed as instruments for DI (Lin and Huang, 2023). We used fixed telephone subscriptions in 1982 on the notion that the development of DI builds upon traditional ICT, with fixed telephones being one of the foundational infrastructures. Since the cross-sectional data of this indicator does not directly correspond to the panel data used in this study, the IV variables are constructed by multiplying the number of fixed telephone subscriptions per 100 people in 1982 by a time dummy variable (Lin and Huang, 2023).

TABLE 5 Cointegration outcomes.

	Pedroni			Westerlund
Models	Modified Phillips-P. t	Phillips-P. t	Aug. D.-F. t	
(1)	3.474***	−3.011***	−2.972***	−1.584*
(2)	3.684***	−3.125***	−3.062***	−2.337***
(3)	4.329***	−2.631***	−2.659***	−2.060**

Note: ***, ** and * Show significance at 1%, 5% and 10%.

TABLE 6 Effects of the TI and DI on the MFP.

Variables	(1)	(2)	(3)
Panel (A): Long run outcomes			
$logTI_{it}$	0.094*** (0.022)	0.147*** (0.043)	−0.065*** (0.014)
$logDI_{it}$	0.215*** (0.035)	0.176*** (0.018)	0.154*** (0.025)
$logTI_{it}^2$		−0.026*** (0.004)	
$logDI_{it}^2$			−0.037*** (0.010)
$logGDPc_{it}$	0.028 (0.033)	0.430*** (0.037)	0.411*** (0.026)
$logFDI_{it}$	0.037*** (0.009)	0.049*** (0.011)	0.051*** (0.009)
$logP_{it}$	0.280*** (0.025)	1.384*** (0.013)	1.423*** (0.015)
$logInd_{it}$	0.360*** (0.108)	0.291*** (0.058)	0.373*** (0.086)
Panel (B): Short run results			
ECM	−0.191*** (0.039)	−0.204*** (0.060)	−0.198*** (0.058)
$logTI_{it}$	0.005 (0.078)	0.107 (0.222)	−0.014 (0.016)
$logDI_{it}$	0.004 (0.015)	−0.008 (0.084)	0.031 (0.091)
$logTI_{it}^2$		−0.014 (0.018)	
$logDI_{it}^2$			0.035 (0.030)
$logGDPc_{it}$	0.416*** (0.151)	0.436*** (0.154)	0.415*** (0.152)
$logFDI_{it}$	0.015** (0.006)	0.016** (0.007)	0.020** (0.008)
$logP_{it}$	0.061 (0.373)	0.509 (0.423)	0.778 (1.129)
$logInd_{it}$	−0.047 (0.073)	0.015 (0.086)	−0.017 (0.084)
Cons	2.379*** (0.471)	−2.116*** (0.627)	−2.160*** (0.629)
Observations	467	467	467

Note: ***and ** stand for 1% and 5% level of significance. In parenthesis is the Standard deviation.

4 Findings and discussions

4.1 CD and unit root tests

A CD test was carried out, revealing that the CD is notably significant at the 1% level (Table 4). Also, it has been proposed in prior studies that second-generation unit root tests like the CIPS can be utilised to investigate the stationarity characteristics of variables when confronted with cross-dependence. Consequently, due to the characteristics of the data, we carried out the CIPS (Pesaran, 2007). The results presented in Table 4 indicate that the variables exhibit a combination of orders, I (0) and I (1), which directs the application of the PMG/ARDL method to examine the influence of the TI and DI on the MFP.

4.2 Cointegration analysis

We employed the cointegration assessment strategies proposed by Westerlund (2007) and Pedroni (2004) to find out the cointegration connections. The findings demonstrate the presence of cointegration across all specifications (Table 5). Linear association analysis is represented by Model (1), whereas Model (2) and Model (3) control both the level and quadratic terms of TI and DI, respectively.

4.3 Effects of the TI and DI on the MFP

The Pearson correlation results are reported in Supplementary Appendix Table A3 in Appendix A. Before the application of the PMG/ARDL method, a Hausman test is applied to determine the appropriate Model among the PMG, MG, and DFE methods. The results revealed that the PMG approach provides a more effective estimate compared to the MG and DFE methods (Supplementary Appendix Table A4 in Appendix A). Consequently, we utilise the PMG approach to assess both the linear and non-linear effects of the TI and DI on the MFP. Model 1 illustrates the linear connection between the target variables and MFP. After that, we incorporate the square terms of TI and DI into Models 2 and 3, respectively. The results are reported in Table 6. The Table consists of two sections: Panel A displays the long-term outcomes, while Panel B reports the short-term findings.

The long-run coefficients for all control variables are congruent with both theoretical and empirical shreds of evidence. Furthermore, the findings underscore that the error correction terms hold statistical significance and are negative, confirming the existence of a robust long-term relationship among the variables. Furthermore, the significance of the error correction terms reflects the speed at which short-run deviation converges to the long-term equilibrium (Table 6). The findings indicate that GDP *per capita* significantly boosts the MFP in RE, suggesting that economic growth negatively impacts resource management and encourages resource extraction. The results related to the outcomes of Xu et al. (2024), who contended that *per capita* GDP has a negative impact on the efficiency of resource utilisation.

Furthermore, the findings suggest that industrialisation exerts a significant positive impact on MFP, underscoring its detrimental effect on the management of natural resources. These outcomes align with the research of Fang and Chang (2023). Likewise, population size positively influences MFP, which corroborates the conclusions of Xuan et al. (2023), who observed a direct correlation between population growth and natural resource consumption. As the population grows, resource usage intensifies, thereby contributing to an increase in MFP. Likewise, the results in Model (1) of Table 6 demonstrate that FDI has a positive long-term and short-term effect on MFP.

Focusing on the key variables, the results in Column (1) reveal a positive linear relationship between MFP and TI in both the short and long term. Specifically, a 1% rise in TI leads to a 0.094% increase in MFP in RE over the long term. Similarly, the findings indicate that DI exerts a strong positive linear impact on MFP in the long run, where a 1% increase in the DI index leads to a 0.215% rise in MFP.

On the other hand, the outcomes in Model (2) suggest that while the estimator for the square of TI is significantly negative, the TI itself remains positive, indicating an inverted U-shaped relationship between TI and MFP. Using the estimates from Model (2) in Table 6, we can calculate the inflection point, which in the long run is 2.827 (0.147/2*0.026). This implies that TI does not reduce MFP when it is below the threshold of 2.827 in natural logarithmic terms. However, once TI surpasses 2.827, it starts to lower NR consumption and meaningfully mitigates MFP. These results demonstrate that TI can enhance sustainable resource productivity after crossing the inflection point. This suggests that as the rebound impacts of TI grow, economies begin shifting strategies towards greater investment in green technologies, which helps limit NR consumption and has a negative impact on MFP.

Additionally, the quadratic term of DI is introduced in Model (3) to explore whether DI has a non-linear impact on MFP. The long-term results reveal that while the DI coefficient is positive, the quadratic term is negative and statistically significant at the 1% level. These findings confirm that DI and its square term are strongly positive and negative, revealing a pronounced inverted U-shaped link between DI and MFP. This implies that DI can only reduce MFP once it surpasses a certain threshold. Based on the results, the inflection point is calculated from Model (3) of Table 6, standing at 2.081 [0.154/(2*0.037)]. This means that when the DI index is below 2.081, DI increases MFP, but once the DI exceeds this value, it begins to reduce MFP. Thus, the results confirm the existence of an inverted U-shaped relationship between DI and MFP. Graphical representation of the inverted U-shaped impacts of DI and TI on MFP is depicted in Figures S1,S2 in Supplementary material.

4.4 Effects of GI on MFP

To look further into the effect of the GI, a specific element of the TI, the exercise is conducted further by using the GI in the analysis instead of using the TI. Table 7 presents the obtained results. A linear relationship between the GI and MFP is reported in Column (I). Column (II) includes GI and its squared term.

The findings indicated that innovations related to the environment have an adverse impact on MFP in the long run. Likewise, the long-term estimate of the square of GI is negative and robust, indicating that small and major improvements in GI adversely influence NR utilisation and notably diminish MFP over the long term.

5 Sensitivity analysis

Sensitivity analyses are conducted to account for the distributional heterogeneity of MFP and potential endogeneity issues.

5.1 Distributional heterogeneity concerns

The analysis of robustness begins with an exploration of how the distributional variation of MFP and the nonparametric characteristics of the data affect the outcomes. Thus, handling the heterogeneity in the MFP is crucial. The normality test by Jarque and Bera (1987) is performed to find insights into the distributional nature of the variables. The results revealed that the data did not follow a normal distribution (Supplementary Appendix Table A2 in Appendix A). This demands the use of a nonparametric method, namely, MMQR, incorporating fixed effects (Machado and Santos Silva, 2019). The results are presented in

TABLE 7 Impacts of GI on MFP.

Variables	(I)	(II)
Panel (A): Long run results		
$logGI_{it}$	−0.072*** (0.028)	−0.077*** (0.026)
$LogGI^2_{it}$		−0.033*** (0.010)
$logDI_{it}$	0.261*** (0.024)	0.259*** (0.016)
$logGDPc_{it}$	0.273*** (0.032)	0.279*** (0.030)
$logFDI_{it}$	0.016 (0.013)	0.021* (0.011)
$logP_{it}$	0.730*** (0.011)	0.783*** (0.009)
$logInd_{it}$	0.253*** (0.076)	0.273*** (0.072)
Panel (B): Short-run results		
ECT	−0.224*** (0.052)	−0.244*** (0.054)
$logGI_{it}$	1.281 (2.778)	5.943 (4.033)
$logDI_{it}$		0.004 (0.175)
$logGI^2_{it}$	0.005 (0.084)	0.013 (0.082)
$logGDPc_{it}$	0.433*** (0.166)	0.315* (0.167)
$logFDI_{it}$	0.013*** (0.004)	0.006 (0.007)
$logP_{it}$	0.220 (0.415)	0.496 (0.481)
$logInd_{it}$	−0.006 (0.095)	0.067 (0.088)
Constant	0.807*** (0.183)	0.577*** (0.129)
Observations	458	458

Note: *** and ** stand for 1% and 5% level of significance. In parenthesis is the Standard deviation.

Table 8. It consists of three separate panels. Panel (A) shows the findings of the linear association between MFP, TI and DI, while Panel (B) illustrates the non-linear (an inverted U-shaped) connection between TI and MFP. The final Panel presents the findings regarding the inverted U-shaped relationship between the DI and the MFP.

In alignment with the baseline findings presented in Table 6, the coefficient of TI demonstrates a positive linear influence on MFP throughout all quantiles. Moreover, the DI has a positive role in the MFP in all quantiles. The findings presented in Panel (B) and Panel (C) reveal that the estimates for the level and square of TI and DI are positive and negative. These outcomes suggest that an inverted U-shaped connection occurs between TI and MFP, as well as between DI and MFP.

5.2 Endogeneity concerns

We employed the IV technique to solve the reverse causality between the target variables (TI and DI) and MFP. Following the works of Li et al. (2021) and Shan and Shao (2024), we employed the first-order lags of the level and squared values of the TI and DI as instrumental variables. The Wu–Hausman test for reverse causality shows no evidence of endogeneity, thereby affirming the presence of exogeneity in the linear model specification. However, the second Model presents some endogeneity challenges. The outcomes reported in Table 9 support the evidence found in the baseline results presented in Table 6.

Moreover, we further conducted a robustness test utilising expenditures on R&D per GDP and its square term to instrument TI and its square term. Besides, the number of fixed telephone subscriptions per 100 people in 1982 and its square are used as instruments for DI, and its square term follows the works of Lin and Huang (2023). The results reported in Supplementary Appendix Table A5 support the baseline findings in Table 4, though there are several missing values for R&D data.

6 Discussion and practical implications

Efficient management of NR use is fundamental for promoting both economic growth and environmental sustainability. Ensuring that NRs are utilised effectively plays a vital role in preserving environmental quality and advancing sustainable development (OECD, 2008). With this perspective in mind, examining the influence of TI and DI on MFP, an indicator of trade-adjusted NR management, is valuable (Ozturk et al., 2023). Consequently, this study uses panel data from 13 RE over the period from 1990 to 2021 to investigate the non-linear impacts of TI and DI on MFP.

The findings of this study reveal a long-run inverted U-shaped relationship between TI and (MFP). This relationship is reflected in the positive estimates for TI's level terms and the negative estimates

TABLE 8 The effects of the TI and DI on the MFP (MMQR).

Variables	Location	Scale	$Q_{0\cdot25}$	$Q_{0\cdot50}$	$Q_{0\cdot75}$	$Q_{0\cdot90}$
Panel A: Linear relationship						
$logTI_{it}$	0.048*** (0.014)	0.009 (0.008)	0.040** (0.017)	0.049*** (0.014)	0.056*** (0.015)	0.061*** (0.017)
$logDI_{it}$	0.127*** (0.023)	−0.031*** (0.012)	0.159*** (0.029)	0.125*** (0.023)	0.099*** (0.022)	0.082*** (0.024)
Control variables	Y	Y	Y	Y	Y	Y
Obs	507	507	507	507	507	507
Panel B: Non-linear association between TI and MFP						
$logTI_{it}$	0.084*** (0.026)	−0.038*** (0.011)	0.120*** (0.029)	0.083*** (0.026)	0.050* (0.026)	0.028 (0.027)
$logDI_{it}$	0.053*** (0.013)	−0.001 (0.007)	0.054*** (0.015)	0.053*** (0.013)	0.053*** (0.014)	0.052*** (0.016)
$logTI_{it}^2$	−0.002 (0.002)	0.004*** (0.001)	−0.005** (0.002)	−0.003* (0.002)	−0.002 (0.002)	−0.004 (0.003)
Control variables	Y	Y	Y	Y	Y	Y
Obs	507	507	507	507	507	507
Panel C: Non-linear association relationship between DI and MFP						
$logTI_{it}$	0.058*** (0.015)	0.002 (0.008)	0.056*** (0.018)	0.059*** (0.014)	0.061*** (0.015)	0.062*** (0.016)
$logDI_{it}$	0.071*** (0.014)	−0.012 (0.008)	0.082*** (0.017)	0.070*** (0.013)	0.060*** (0.014)	0.054*** (0.015)
$logDI_{it}^2$	−0.020*** (0.005)	0.001 (0.003)	−0.021*** (0.007)	−0.020*** (0.005)	−0.020*** (0.005)	−0.019*** (0.005)
Control variables	Y	Y	Y	Y	Y	Y
Observations	507	507	507	507	507	507

Note: *** and ** stand for 1% and 5% level of significance. In parenthesis is the Standard deviation.

TABLE 9 Effects of the TI and DI on the MFP (IV).

Variables	(1)	(2)	(3)
$logTI_{it}$	0.391*** (0.048)	0.777*** (0.081)	0.390*** (0.048)
$logDI_{it}$	0.473*** (0.102)	0.254*** (0.090)	0.472*** (0.102)
$logTI_{it}^2$		−0.028*** (0.006)	
$logDI_{it}^2$			−0.086** (0.040)
Control variables	Y	Y	Y
Wald test	20,844.12***	2,781.58***	3,111.44***
R^2	0.903	0.910	0.902
First stage test	291.77***	355.001***	533.87***
Wu-Hausman (p value)	0.188	0.277	0.019

Note: *** and ** stand for 1% and 5% level of significance. In parenthesis is the Standard deviation. Y, Yes.

for its squared terms, suggesting that a higher degree of investment in TI is ultimately more beneficial than a lower degree of investment in RE in the long run. While initial increases in TI drive up resource extraction and expand the resource footprint beyond a certain threshold, TI fosters sustainable resource management, leading to a decline in MFP. Thus, TI acts as a "resource curse" up to a critical point, after which it transforms into a "resource blessing," promoting sustainable resource use.

These findings can be loosely explained that the results suggest a dual-phase effect of TI on the MFP. Initially, TI tends to increase the MFP as it drives greater exploitation of NRs, reflecting economies of scale. However, once TI surpasses a certain threshold, it begins to act as a powerful instrument for improving the efficient utilisation of NRs by reducing MFP. This can be justified as in the early stages of TI adoption, increased mineral extraction enabled by advanced technology may lead to a significant rise in MFP. Eventually, as TI evolves and matures, its resource-saving impacts become more pronounced, leading to a gradual decrease in MFP and reduced NR depletion.

The non-linear association between TI and MFP can also be explained by the fact that long-term advancements in TI yield a higher input-to-output ratio of innovation and scientific resources, which is crucial for enhancing TI, optimising resource productivity, and diminishing resource overutilisation through a more sustainable array of production approaches. This progression not only paves the way for the development of alternative renewable resources but also mitigates the overexploitation and excessive utilisation of finite natural resources. Consequently, TI plays a pivotal role in preserving ecological sustainability and mitigating the ecological footprint (Bai and Nie, 2017). Thus, TI significantly shapes the dynamics of resource consumption in REs, enhancing resource efficiency, lowering overall resource usage, and markedly reducing MFP.

Additionally, from a theoretical perspective, our research presents a number of intriguing implications. This study's findings broaden and enhance the EKC hypothesis, shedding light on the complex relationships between economic growth and environmental indicators. This leads to a non-linear relationship between the TI and MFP. Thus, TI could significantly influence the sustainability of NR usage through a range of mechanisms. It promotes the growth of more resource-savvy methods and aids in establishing a sustainable production framework. Furthermore, the TI harnesses the recycling and repurposing of resources, supporting the mitigation of the depletion of resources. Furthermore, TI can potentially propel the advancement of alternative and renewable resources, thereby diminishing reliance on limited materials and resources (Liu and Liang, 2024).

The positive coefficients of the linear relationship between TI and MFP deviate from the findings of Ulussever et al. (2024), Appiah et al. (2024) and Razzaq et al. (2021), who contend that TI exerts significant mitigating effects on MFP and substantially reduces NR extraction. In contrast, the findings and outcomes of this research align with the research conducted by Dam et al. (2024), which indicates that TI has a significant enhancing impact on ecological sustainability over the long term in E–7 states. Therefore, from the perspective of the empirical works, this research contributes novel insights into the non-linear relationship between TI and MFP.

Therefore, in the resources management context, understanding non-linearity aids policymakers in designing adaptive and flexible strategies that accommodate varying effects over time. For instance, promoting technologies with proven long-term efficiency while mitigating potential short-term resource spikes. Initial phases of innovation might involve resource-intensive R&D, which could increase consumption before achieving efficiency. Understanding these transitional phases helps in evaluating the actual long-term benefits of innovation.

Furthermore, concerning the relationship between GI and MFP, the results of this study reveal that the linear and squared terms of GI exhibit negative coefficients. This indicates that even minor or significant variations in GI substantially decrease MFP in RE. These findings are consistent with the conclusions of Ozturk et al. (2023), who asserted that GI has a considerable mitigating effect on resource footprints. Additionally, the results aligned with the work of Koseoglu et al. (2022), which examined the link between ecological footprint and GI. The findings also conform to theoretical expectations, as GI fosters advancements in technology and equipment within resource-dependent industries, thereby enhancing resource utilisation efficiency. Moreover, it encourages the production of environmentally sustainable products, resulting in notable positive environmental externalities (Hao et al., 2022).

Moreover, this research offers fresh insights into the connection between DI and MFP. The findings show that the DI and its square exhibit strong positive and negative effects, respectively, suggesting an inverted U-shaped relationship between the DI and MFP. Therefore, the initial adoption of DI can promote material consumption due to the demand for digital infrastructure and devices. Once it is at the maturity stage, it can enhance efficiency through several mechanisms such as smart resource management, dematerialisation, and circular economy practices, mitigating resource consumption and adversely affecting MFP. Therefore, DI is capable of diminishing the MFP once it attains a specific threshold. Consequently, during the early phase of digital innovation, a greater allocation of resources is essential to establish a digital framework, leading to heightened natural resource usage and MFP. As DI continues to evolve, its influence on economic activities increasingly becomes more pronounced, fostering growth through the scale effect.

The findings are well-founded, as the widespread adoption of DI emerges as a powerful tool for improving resource efficiency. DI enhances the effective utilisation of resources by enabling robust monitoring and facilitating responsible management practices. Furthermore, it empowers businesses to implement smart equipment control and remote monitoring within their production systems, significantly reducing resource waste (Feng et al., 2022). Additionally, DI aids in optimising resource allocation and minimising waste throughout supply chains and production processes. Consequently, advancements in DI not only bolster resource efficiency but also promote sustainability in the consumption of natural resources.

Theoretically, the results contribute to the existing framework linking DI and MFP, per the EKC hypothesis. The outcomes of this study can be interpreted through two primary channels by which DI affects resources and MFP: scale expansion and enhancements in green efficiency. As DI booms, its scale effect amplifies the demand for production inputs and resources (Wang and Lee, 2022), leading to an initial increase in MFP. Over time, innovations in digital intelligence can revolutionise conventional industries, streamline manufacturing processes, and greatly improve efficiency in operations and resource utilisation across various sectors, including energy, industrial manufacturing, electricity and transportation sectors. Consequently, MFP rises initially but may subsequently decline as the digital economy matures, supporting the theoretical Model and reinforcing the EKC hypothesis (Li et al., 2021). However, some empirical studies, including those by Shi et al. (2024), Özpolat (2022), and Abid et al. (2023), argue that advancements in DI foster more efficient utilisation of natural resources, thereby reducing MFP. This study, however, adds a unique dimension to the literature by identifying an inverted U-shaped impact of DI on MFP.

Finally, regarding short-run findings, both TI and DI have insignificant effects on MFP. These findings can be loosely interpreted that shifting from traditional methods to advanced TI and digital solutions will take time. More specifically, it might take time for businesses and industries to adapt to new DI processes and new technologies. Besides, adapting business models to integrate TI and DI can delay the realisation of resource savings in the short run. The short-run outcome of this study is consistent with the results of Wang et al. (2025), who found the negligible impact of TI and DI on sustainable development indicators in the short run.

The outcomes of this research offer valuable insights for policymakers in RE and underscore practical policies and strategies for progressing sustainable digital innovation and TI in RE to mitigate MFP. Several evidence-based policy suggestions are forwarded to tackle the challenges associated with achieving the SDGs related to sustainable resource production and consumption. Notably, the results reveal an inverted U-shaped influence of TI on MFP, indicating that TI can serve as a pivotal catalyst for enhancing natural resource management. Thus, this study advocates for the promotion and more investment in TI as a means to catalyse progress towards the sustainable consumption and production objectives outlined in the SDGs, particularly in enhancing resource productivity as specified in SDG 12.

Second, the findings of the study significantly support focused policy strategies because understanding the non-linear trajectory assists policymakers in developing strategies for the evolving impact of TI on material resource use. Sustainable monitoring of TI adoption level of economies to predict the inflection point where TI starts to mitigate MFP and to ensure policy support that aligns with both the increasing consumption of resources and mitigating resource usage phases is worthwhile. Thus, RE should develop phase-specific policy interventions addressing the dynamic nature of resource use due to TI.

Third, the results suggest that both minor and major fluctuations in GI negatively impact MFP in RE over the long term. Consequently, it is essential to integrate GI policies and strategies into the technological development and innovation process to limit resource utilisation and enhance efficiency in resource consumption within these economies. Governments in RE should support businesses, industries, and institutions in developing environmental technologies that improve resource efficiency by providing grants and financial and technical support.

Fourth, this study reveals an inverted U-shaped relationship between DI and MFP. As such, REs should allocate more resources towards improving DI and expediting DI projects to alleviate MFP. Additionally, governments and policymakers in RE should keep formulating more dynamic, context-aware, and future-focused policies to promote investment in digital technology by considering the early-stage material resources consumption effect and gradual resource consumption mitigating effect of DI. Additionally, policies should involve integrating resource efficiency into digital transformation strategies from the start to mitigate unsustainable material consumption patterns of early adoption of DI.

Lastly, policymakers should focus on guiding material resource consumption during the early stages of TI and DI in RE. During the mature stages of the TI and DI, policies should encourage promoting TI and DI to optimise resource allocation while promoting responsible production and consumption of resources.

In conclusion, while this research provides significant theoretical, empirical, and practical insights, it also has a few limitations that future research work will address. First, the analysis is confined to data from RE to assess the effects of TI and DI on MFP, offering practical policy implications for countries abundant in natural resources. However, future studies could broaden the scope to encompass a more extensive sample of nations. Second, our DI indicator was constructed using mobile cellular subscriptions, fixed telephone lines, and the number of individuals using the internet. Future research should take into account the rapid advancements in DI, particularly artificial intelligence, the Internet of Things and others, which were ruled out from the DI index derivation because of data limitations. Lastly, future research should control the regional, economic, and demographic heterogeneity of countries as countries vary in economic, demographic, and regional dimensions.

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

SL: Methodology, Formal Analysis, Data curation, Validation, Visualization, Writing – review and editing. DB: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Writing – original draft, Writing – review and editing.

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Conflict of interest

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The author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2025.1522305/full#supplementary-material

References

Abid, N., Ceci, F., and Razzaq, A. (2023). Inclusivity of information and communication technology in ecological governance for sustainable resources management in G10 countries. *Resour. Policy* 81, 103378. doi:10.1016/j.resourpol.2023.103378

Ahmad, N., Youjin, L., Žiković, S., and Belyaeva, Z. (2023). The effects of technological innovation on sustainable development and environmental degradation: evidence from China. *Technol. Soc.* 72, 102184. doi:10.1016/j.techsoc.2022.102184

Ahmadova, G., Delgado-Márquez, B. L., Pedauga, L. E., and Leyva-de la Hiz, D. I. (2022). Too good to be true: the inverted U-shaped relationship between home-country digitalization and environmental performance. *Ecol. Econ.* 196, 107393. doi:10.1016/j.ecolecon.2022.107393

Ahmed, M., Khaskheli, A., Raza, S. A., and Hassan, M. K. (2024). Eco-tech fusion: unraveling the nonparametric causal effects of fintech, natural resources, digital infrastructure, and economic growth on environmental sustainability from a quantile perspective. *Resour. Policy* 98, 105324. doi:10.1016/j.resourpol.2024.105324

Ali, K., Jianguo, D., Kirikkaleli, D., Bács, Z., and Oláh, J. (2023). Technological innovation, natural resources, financial inclusion, and environmental degradation in BRI economies. *Nat. Resour. Model.* 36. doi:10.1111/nrm.12373

Ali, S., Ahmed, W., Solangi, Y. A., Chaudhry, I. S., and Zarei, N. (2022). Strategic analysis of single-use plastic ban policy for environmental sustainability: the case of Pakistan. *Clean. Technol. Environ. Policy* 24, 843–849. doi:10.1007/s10098-020-02011-w

Appiah, M., Li, M., Taden, J., Ashraf, S., Tiwari, A. K., and Laari, P. B. (2024). Enhancing natural resource rents through industrialization, technological innovation, and foreign capital in the OECD countries: does financial development matter? *Resour. Policy* 89, 104520. doi:10.1016/j.resourpol.2023.104520

Awaworyi Churchill, S., Inekwe, J., Smyth, R., and Zhang, X. (2019). R&D intensity and carbon emissions in the G7: 1870–2014. *Energy Econ.* 80, 30–37. doi:10.1016/j.eneco.2018.12.020

Bai, J. H., and Nie, L. (2017). Technological progress and environmental pollution-an inverted U-shaped hypothesis. *R&D Manag.* 29, 132–140.

Balsalobre-Lorente, D., Shahbaz, M., Roubaud, D., and Farhani, S. (2018). How economic growth, renewable electricity and natural resources contribute to CO2 emissions? *Energy Policy* 113, 356–367. doi:10.1016/j.enpol.2017.10.050

Barış-Tüzemen, Ö., Tüzemen, S., and Çelik, A. K. (2020). Does an N-shaped association exist between pollution and ICT in Turkey? ARDL and quantile regression approaches. *Environ. Sci. Pollut. Res. Int.* 27, 20786–20799. doi:10.1007/s11356-020-08513-w

Bashir, M. F., Bashir, M., and Shahzad, L. (2024). Natural resource abundance, digitalization and institutional governance: the critical challenges towards net-zero transformation. *Resour. Policy* 99, 105412. doi:10.1016/j.resourpol.2024.105412

Basty, N., and Ghachem, D. A. (2023). Is relationship between carbon emissions and innovation nonlinear? Evidence from OECD countries. *Borsa istanb. Rev.* 23, 906–918. doi:10.1016/j.bir.2023.03.005

Borojo, D. G., Yushi, J., Miao, M., and Xiao, L. (2023). The impacts of economic policy uncertainty, energy consumption, sustainable innovation, and quality of governance on green growth in emerging economies. *Energy Environ.* 35, 3647–3672. doi:10.1177/0958305x231173997

Chen, J., Hu, X., Razi, U., and Rexhepi, G. (2022). The sustainable potential of efficient air-transportation industry and green innovation in realising environmental sustainability in G7 countries. *Econ. Res.-Ekon. Istraž.* 35, 3814–3835. doi:10.1080/1331677x.2021.2004190

Chen, Y., Chen, D., Gao, C., and Wei, X. (2025). The inverted U-shaped impact of the digital economy on indirect household carbon emissions — an empirical study based on CFPS. *Front. Environ. Sci.* 13. doi:10.3389/fenvs.2025.1519286

Cheng, Y., Zhang, Y., Wang, J., and Jiang, J. (2023). The impact of the urban digital economy on China's carbon intensity: spatial spillover and mediating effect. *Resour. Conserv. Recycl.* 189, 106762. doi:10.1016/j.resconrec.2022.106762

Commoner, B. (1972). For the 1972 discussion between P. *Bull. Atomic Sci.* 28 (5), 42–56.

Dam, M. M., Kaya, F., and Bekun, F. V. (2024). How does technological innovation affect the ecological footprint? Evidence from E-7 countries in the background of the SDGs. *J. Clean. Prod.* 443, 141020. doi:10.1016/j.jclepro.2024.141020

De los Santos-Montero, L. A., Bravo-Ureta, B. E., von Cramon-Taubadel, S., and Hasiner, E. (2020). The performance of natural resource management interventions in agriculture: evidence from alternative meta-regression analyses. *Ecol. Econ.* 171, 106605. doi:10.1016/j.ecolecon.2020.106605

Duan, D., and Liu, K. (2023). Do financial inclusion, natural resources and green innovation affect the Sustainable Environment in Resource Rich Economies? *Resour. Policy* 86, 104190. doi:10.1016/j.resourpol.2023.104190

Dwivedi, Y. K., Hughes, L., Kar, A. K., Baabdullah, A. M., Grover, P., Abbas, R., et al. (2022). Climate change and COP26: are digital technologies and information management part of the problem or the solution? An editorial reflection and call to action. *Int. J. Inf. Manage.* 63, 102456. doi:10.1016/j.ijinfomgt.2021.102456

Fang, M., and Chang, C.-L. (2023). The impact of oil and natural gas trading and globalization on natural resources management in China. *Resour. Policy* 86, 104228. doi:10.1016/j.resourpol.2023.104228

Feng, S., Zhang, R., and Li, G. (2022). Environmental decentralization, digital finance and green technology innovation. *Struct. Chang. Econ. Dyn.* 61, 70–83. doi:10.1016/j.strueco.2022.02.008

Fernández-Herrero, L., and Duro, J. A. (2019). What causes inequality in Material Productivity between countries? *Ecol. Econ.* 162, 1–16. doi:10.1016/j.ecolecon.2019.04.007

Ganda, F. (2019). The impact of innovation and technology investments on carbon emissions in selected organisation for economic Co-operation and development countries. *J. Clean. Prod.* 217, 469–483. doi:10.1016/j.jclepro.2019.01.235

Gariba, M. I., Arthur, E. E., and Odei, S. A. (2024). Assessing the impact of public digitalization on sustainability: the mediating role of technological innovation in the context of the EU. *Discov. Sustain* 5, 204. doi:10.1007/s43621-024-00397-x

Goulder, L. H., and Schneider, S. H. (1999). Induced technological change and the attractiveness of CO2 abatement policies. *Res. Energy Econ.* 21, 211–253. doi:10.1016/s0928-7655(99)00004-4

Haider, S., Malik, S. M., Nadeem, B., Sadiq, N., and Ghaffari, A. S. (2021). Impact of population growth on the natural resources of cholistan desert. *Palarch's J. Archaeol. Egypt/Egyptology* 18, 1778–1790.

Han, S., Peng, D., Guo, Y., Aslam, M. U., and Xu, R. (2025). Harnessing technological innovation and renewable energy and their impact on environmental pollution in G-20 countries. *Sci. Rep.* 15, 2236. doi:10.1038/s41598-025-85182-0

Hao, Y., Guo, Y., and Wu, H. (2022). The role of information and communication technology on green total factor energy efficiency: does environmental regulation work? *Bus. Strat. Environ.* 31, 403–424. doi:10.1002/bse.2901

He, W.-W., He, S.-L., and Hou, H.-L. (2024). Digital economy, technological innovation, and sustainable development. *PLoS One* 19, e0305520. doi:10.1371/journal.pone.0305520

Hehua, L., Iqbal, Z., Abidin, S. Z. U., Alharthi, A. M., Albalawi, O., and Tian, T. (2024). The role of digital finance, technological innovation, and human development to utilize natural resources efficiently: analysis from developing Asia. *Nat. Resour. Forum.* doi:10.1111/1477-8947.12533

Holdren, J. P., and Ehrlich, P. R. (1972). One-dimensional ecology revisited A rejoinder. *Bull. At. Sci.* 28, 42–45. doi:10.1080/00963402.1972.11457946

Hou, F., Khan, M. A., and Hayat, M. T. (2024). Empirical linkages among financial development, digital infrastructure, energy transition and natural resources footprints in BRICS region. *Resour. Policy* 90, 104748. doi:10.1016/j.resourpol.2024.104748

Hu, J., and Zhang, H. (2023). Has green finance optimized the industrial structure in China? *Environ. Sci. Pollut. Res. Int.* 30, 32926–32941. doi:10.1007/s11356-022-24514-3

Hussain, J., Khan, A., and Zhou, K. (2020). The impact of natural resource depletion on energy use and CO2 emission in Belt and Road Initiative countries: a cross-country analysis. *Energy* 199, 117409. doi:10.1016/j.energy.2020.117409

Hussain, M., Lu, T., Chengang, Y., and Wang, Y. (2023). Role of economic policies, renewable energy consumption, and natural resources to limit carbon emissions in top five polluted economies. *Resour. Policy* 83, 103605. doi:10.1016/j.resourpol.2023.103605

International Resource Panel (2019). Cross-cutting key terms. Available online at: http://www.resourcepanel.org/glossary.

Jarque, C. M., and Bera, A. K. (1987). A test for normality of observations and regression residuals. *Int. Stat. Rev.* 55, 163. doi:10.2307/1403192

Jiang, Q., Rahman, Z. U., Zhang, X., Guo, Z., and Xie, Q. (2022). An assessment of the impact of natural resources, energy, institutional quality, and financial development on CO2 emissions: evidence from the B&R nations. *Resour. Policy* 76, 102716. doi:10.1016/j.resourpol.2022.102716

Jianguo, D., Ali, K., Alnori, F., and Ullah, S. (2022). The nexus of financial development, technological innovation, institutional quality, and environmental quality: evidence from OECD economies. *Environ. Sci. Pollut. Res. Int.* 29, 58179–58200. doi:10.1007/s11356-022-19763-1

Jin, G., and Huang, Z. (2023). Asymmetric influence of China's outward FDI and exports on trade-adjusted resources footprint in belt and road node countries: moderating role of governance. *Resour. Policy* 82, 103558. doi:10.1016/j.resourpol.2023.103558

Karakaya, E., Sarı, E., and Alataş, S. (2021). What drives material use in the EU? Evidence from club convergence and decomposition analysis on domestic material consumption and material footprint. *Resour. Policy* 70, 101904. doi:10.1016/j.resourpol.2020.101904

Koseoglu, A., Yucel, A. G., and Ulucak, R. (2022). Green innovation and ecological footprint relationship for a sustainable development: evidence from top 20 green innovator countries. *Sustain. Dev.* 30, 976–988. doi:10.1002/sd.2294

Kunkel, S., and Matthess, M. (2020). Digital transformation and environmental sustainability in industry: putting expectations in Asian and African policies into perspective. *Environ. Sci. Policy* 112, 318–329. doi:10.1016/j.envsci.2020.06.022

Lange, S., Pohl, J., and Santarius, T. (2020). Digitalization and energy consumption. Does ICT reduce energy demand? *Ecol. Econ.* 176, 106760. doi:10.1016/j.ecolecon.2020.106760

Lange, S., and Santarius, T. (2020). *Smart green world? making digitalization work for sustainability*. London, England: Routledge.

Lenzen, M., Geschke, A., West, J., Fry, J., Malik, A., Giljum, S., et al. (2021). Implementing the material footprint to measure progress towards Sustainable Development Goals 8 and 12. *Nat. Sustain.* 5, 157–166. doi:10.1038/s41893-021-00811-6

Li, X., Liu, J., and Ni, P. (2021). The impact of the digital economy on CO2 emissions: a theoretical and empirical analysis. *Sustainability* 13, 7267. doi:10.3390/su13137267

Li, X., Zhang, C., and Zhu, H. (2023). Effect of information and communication technology on CO2 emissions: an analysis based on country heterogeneity perspective. *Technol. Forecast. Soc. Change* 192, 122599. doi:10.1016/j.techfore.2023.122599

Lin, B., and Huang, C. (2023). Nonlinear relationship between digitization and energy efficiency: Evidence from transnational panel data. *Energy* 276, 127601. doi:10.1016/j.energy.2023.127601

Liu, G., and Liang, K. (2024). The role of technological innovation in enhancing resource sustainability to achieve green recovery. *Resour. Policy* 89, 104659. doi:10.1016/j.resourpol.2024.104659

Liu, H., Anwar, A., Razzaq, A., and Yang, L. (2022). The key role of renewable energy consumption, technological innovation and institutional quality in formulating the SDG policies for emerging economies: evidence from quantile regression. *Energy Rep.* 8, 11810–11824. doi:10.1016/j.egyr.2022.08.231

Luo, S., and Mabrouk, F. (2022). Nexus between natural resources, globalization and ecological sustainability in resource-rich countries: dynamic role of green technology and environmental regulation. *Resour. Policy* 79, 103027. doi:10.1016/j.resourpol.2022.103027

Ma, X., Arif, A., Kaur, P., Jain, V., Refiana Said, L., and Mughal, N. (2022). Revealing the effectiveness of technological innovation shocks on CO2 emissions in BRICS: emerging challenges and implications. *Environ. Sci. Pollut. Res. Int.* 29, 47373–47381. doi:10.1007/s11356-022-19053-w

Machado, J. A. F., and Santos Silva, J. M. C. (2019). Quantiles via moments. *J. Econom.* 213, 145–173. doi:10.1016/j.jeconom.2019.04.009

Majeed, A., Ye, C., Chenyun, Y., Wei, X., and Muniba, (2022). Roles of natural resources, globalization, and technological innovations in mitigation of environmental degradation in BRI economies. *PLoS One* 17, e0265755. doi:10.1371/journal.pone.0265755

Mehmood, U., Tariq, S., Aslam, M. U., Agyekum, E. B., Uhunamure, S. E., Shale, K., et al. (2023). Evaluating the impact of digitalization, renewable energy use, and technological innovation on load capacity factor in G8 nations. *Sci. Rep.* 13, 9131. doi:10.1038/s41598-023-36373-0

Miao, C., Fang, D., Sun, L., and Luo, Q. (2017). Natural resources utilization efficiency under the influence of green technological innovation. *Resour. Conserv. Recycl.* 126, 153–161. doi:10.1016/j.resconrec.2017.07.019

Mu, X., Chen, D., and Zhang, H. (2025). The impact of digital transformation on the sustainable development of enterprises: an analysis from the perspective of digital finance. *J. Appl. Econ.* 28. doi:10.1080/15140326.2025.2464488

Obobisa, E. S., Chen, H., and Mensah, I. A. (2022). The impact of green technological innovation and institutional quality on CO2 emissions in African countries. *Technol. Forecast. Soc. Change* 180, 121670. doi:10.1016/j.techfore.2022.121670

OECD (2008). *Sustainable resource use and resource productivity*.

Özpolat, A. (2022). How does internet use affect ecological footprint? an empirical analysis for G7 countries. *Environ. Dev. Sustain.* 24, 12833–12849. doi:10.1007/s10668-021-01967-z

Ozturk, I., Razzaq, A., Sharif, A., and Yu, Z. (2023). Investigating the impact of environmental governance, green innovation, and renewable energy on trade-adjusted material footprint in G20 countries. *Resour. Policy* 86, 104212. doi:10.1016/j.resourpol.2023.104212

Patro, C. S., and Raghunath, K. M. K. (2021). “Digital transformation: influence on business performance in competitive milieu,” in *Managerial issues in digital transformation of global modern corporations, (IGI global)*, 16–31.

Pedroni, P. (2004). Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the ppp hypothesis. *Econ. Theory* 20, 597–625. doi:10.1017/s0266466604203073

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *J. Appl. Econ.* 22, 265–312. doi:10.1002/jae.951

Pesaran, M. H., and Pesaran, B. (1997). *Working with microfit 4.0: interactive econometric analysis*. Oxford: Oxford University Press.

Pesaran, M. H., Shin, Y., and Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *J. Am. Stat. Assoc.* 94, 621–634. doi:10.1080/01621459.1999.10474156

Porter, M. E., and Linde, C. van der (1995). Toward a new conception of the environment-competitiveness relationship. *J. Econ. Perspect.* 9, 97–118. doi:10.1257/jep.9.4.97

Rajput, S., and Singh, S. P. (2019). Connecting circular economy and industry 4.0. *Int. J. Inf. Manage.* 49, 98–113. doi:10.1016/j.ijinfomgt.2019.03.002

Ran, Q., Yang, X., Yan, H., Xu, Y., and Cao, J. (2023). Natural resource consumption and industrial green transformation: does the digital economy matter? *Resour. Policy* 81, 103396. doi:10.1016/j.resourpol.2023.103396

Razzaq, A., Ajaz, T., Li, J. C., Irfan, M., and Suksatan, W. (2021). Investigating the asymmetric linkages between infrastructure development, green innovation, and consumption-based material footprint: novel empirical estimations from highly resource-consuming economies. *Resour. Policy* 74, 102302. doi:10.1016/j.resourpol.2021.102302

Razzaq, A., Sharif, A., Ozturk, I., and Skare, M. (2022). Inclusive infrastructure development, green innovation, and sustainable resource management: evidence from China’s trade-adjusted material footprints. *Resour. Policy* 79, 103076. doi:10.1016/j.resourpol.2022.103076

Saidi, K., and Omri, A. (2020). Reducing CO2 emissions in OECD countries: do renewable and nuclear energy matter? *Prog. Nucl. Energy* 126, 103425. doi:10.1016/j.pnucene.2020.103425

Salahuddin, M., Alam, K., and Ozturk, I. (2016). Is rapid growth in Internet usage environmentally sustainable for Australia? An empirical investigation. Environ. *Sci. Pollut. Res. Int.* 23, 4700–4713. doi:10.1007/s11356-015-5689-7

Shabir, M., Hussain, I., Işık, Ö., Razzaq, K., and Mehroush, I. (2023). The role of innovation in environmental-related technologies and institutional quality to drive environmental sustainability. *Front. Environ. Sci.* 11. doi:10.3389/fenvs.2023.1174827

Shan, H., and Shao, S. (2024). Impact of green innovation on carbon reduction in China. *Sci. Rep.* 14, 14032. doi:10.1038/s41598-024-64554-y

Shi, G., Li, Q., Wei, Y., Ali, M., and Lv, X. (2024). Does digital technology advancement promote natural resource utilization efficiency? *Resour. Policy* 94, 105088. doi:10.1016/j.resourpol.2024.105088

Sun, J., and Qamruzzaman, M. (2025). Technological innovation, trade openness, natural resources, clean energy on environmental sustainably: a competitive assessment between CO2 emission, ecological footprint, load capacity factor and inverted load capacity factor in BRICS+T. *Front. Environ. Sci.* 12. doi:10.3389/fenvs.2024.1520562

Sun, Y., Ajaz, T., and Razzaq, A. (2022). How infrastructure development and technical efficiency change caused resources consumption in BRICS countries: analysis based on energy, transport, ICT, and financial infrastructure indices. *Resour. Policy* 79, 102942. doi:10.1016/j.resourpol.2022.102942

Tian, Y., Chen, M., Yang, W., Wu, X., Cheng, M., and Liu, W. (2025). Research on the impact of digital economy development on mineral resource utilization efficiency. *Front. Earth Sci.* 12. doi:10.3389/feart.2024.1496438

Twum, F. A., Long, X., Salman, M., Mensah, C. N., Kankam, W. A., and Tachie, A. K. (2021). The influence of technological innovation and human capital on environmental efficiency among different regions in Asia-Pacific. *Environ. Sci. Pollut. Res. Int.* 28, 17119–17131. doi:10.1007/s11356-020-12130-y

Ulussever, T., Pata, U. K., and Kartal, M. T. (2024). Evaluating the influence of technology, energy consumption, and financial progress on material footprint in GCC countries. *Environ. Sustain. Indic.* 23, 100447. doi:10.1016/j.indic.2024.100447

Wang, E.-Z., and Lee, C.-C. (2022). The impact of information communication technology on energy demand: some international evidence. *Int. Rev. Econ. Finance* 81, 128–146. doi:10.1016/j.iref.2022.05.008

Wang, X., Wang, K., Xu, B., and Jin, W. (2025). Digitalisation and technological innovation: panaceas for sustainability? *Int. J. Prod. Res.*, 1–18. doi:10.1080/00207543.2025.2468883

Westerlund, J. (2007). Testing for error correction in panel data*. *Bull. Econ. Stat.* 69, 709–748. doi:10.1111/j.1468-0084.2007.00477.x

Wu, B., Jin, C., Monfort, A., and Hua, D. (2021). Generous charity to preserve green image? Exploring linkage between strategic donations and environmental misconduct. *J. Bus. Res.* 131, 839–850. doi:10.1016/j.jbusres.2020.10.040

Xu, J., and Li, W. (2022). The impact of the digital economy on innovation: new evidence from panel threshold model. *Sustainability* 14, 15028. doi:10.3390/su142215028

Xu, J., Yang, B., and Yuan, C. (2024). Enhancing natural resource efficiency through digital government: evidence from the utilization of energy, water, and land resources. *Resour. Policy* 94, 105117. doi:10.1016/j.resourpol.2024.105117

Xuan, D., Jiang, X., and Fang, Y. (2023). Can globalization and the green economy hedge natural resources? Functions of population growth and financial development in BRICS countries. *Resour. Policy* 82, 103414. doi:10.1016/j.resourpol.2023.103414

Yang, C., Qi, H., Jia, L., Wang, Y., and Huang, D. (2024). Impact of digital technologies and financial development on green growth: role of mineral resources, institutional quality, and human development in South Asia. *Resour. Policy* 90, 104699. doi:10.1016/j.resourpol.2024.104699

Yingchao, H., and Xiang, Y. (2024). Influence of trade liberalization and digital trade on material footprint in the BRICS region. *Resour. Policy* 88, 104374. doi:10.1016/j.resourpol.2023.104374

Yu, H., and Liu, H. (2024). Impact of digitization on carbon productivity: an empirical analysis of 136 countries. *Sci. Rep.* 14, 5094. doi:10.1038/s41598-024-55848-2

Yu, S., Zhang, Q., Hao, J. L., Ma, W., Sun, Y., Wang, X., et al. (2023). Development of an extended STIRPAT model to assess the driving factors of household carbon dioxide emissions in China. *J. Environ. Manage.* 325, 116502. doi:10.1016/j.jenvman.2022.116502

Zhang, J., Liu, Y., Zhang, W., and Ma, X. (2023a). Role of green technologies in enhancing the efficiency of natural resources. *Resour. Policy* 83, 103624. doi:10.1016/j.resourpol.2023.103624

Zhang, Y., Huang, Y., and Wang, X. (2023b). Impact of economic policy uncertainty, oil prices, and technological innovations on natural resources footprint in BRICS economies. *Resour. Policy* 86, 104082. doi:10.1016/j.resourpol.2023.104082

Zhao, X., Xu, H., Yin, S., and Zhou, Y. (2023). Threshold effect of technological innovation on carbon emission intensity based on multi-source heterogeneous data. *Sci. Rep.* 13, 19054. doi:10.1038/s41598-023-46406-3

Zhou, F., and Feng, Z. (2024). Resources management, digitalization and government efficiency for economic output: exploring the case for the United States. *Resour. Policy* 95, 105111. doi:10.1016/j.resourpol.2024.105111

Zhou, Z., Long, D., and Xin, Y. (2024). Combining the management of natural resources with the management of environmental resources: modeling the impact of high-tech and ICT service export. *Resour. Policy* 95, 105192. doi:10.1016/j.resourpol.2024.105192