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A new public management model for open data collaboration in sustainable digital insurance ecosystems

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Digital transformation is rapidly reshaping insurance markets, creating unprecedented regulatory challenges that require balancing innovation with market protection. This study develops a theoretical model integrating new public management (NPM) principles, technology acceptance factors, and collaborative governance to explain the emergence of sustainable digital insurance ecosystems powered by open data. Using structural equation modeling with data from 368 professionals (121 regulatory stakeholders, 178 industry professionals, and 69 technology enablers), we investigated how NPM principles and technology adoption factors influence behavioral intention, use behavior, and principled participation in open data initiatives. The results revealed dual pathways to sustainable outcomes: technological adoption ($\beta = 0.27$) and collaborative governance through open data sharing, with principled engagement demonstrating stronger influence ($\beta = 0.45$). Performance expectancy emerged as the strongest predictor of behavioral intention, while accountability and market-driven services significantly enhanced stakeholder engagement in open data platforms. Multigroup analysis showed differential effects across stakeholder categories, with regulatory stakeholders less influenced by efficiency considerations but more likely to translate technology use into collaborative engagement. This study contributes to public administration theory by demonstrating complementarities between NPM and collaborative governance in open data contexts, extends technology adoption frameworks to regulatory technology contexts, and provides evidence-based guidance for developing balanced digital regulatory approaches. The stronger influence of principled engagement on sustainable outcomes suggests that collaborative governance mechanisms are particularly critical for sustainability, challenging technocentric perspectives that prioritize digital tools over relational dimensions of regulatory governance in open data initiatives. By illuminating the complex interplay between managerial principles, technological factors, and collaborative mechanisms in open data ecosystems, this research offers a comprehensive framework to navigate the digital transformation in insurance regulation.

KEYWORDS

new public management, collaborative governance, insurance regulation, digital transformation, public-private partnerships, open data, data governance

1 Introduction

The insurance industry is at a pivotal crossroads where digital transformation forces are reshaping market dynamics, customer expectations, and regulatory approaches simultaneously (Eling and Schaper, 2023). As artificial intelligence, predictive analytics, and platform ecosystems transform insurance operations, the gap between technological innovation and regulatory frameworks continues to widen (Bzhalava et al., 2022; Wilson et al., 2021). This divergence presents significant challenges for both policymakers

and industry participants: inadequate consumer protection in novel digital contexts, regulatory arbitrage opportunities that undermine market stability, and missed innovation opportunities due to regulatory uncertainty. Recent research indicates that 67% of compliance failures in digital insurance initiatives stem from insufficient collaboration between regulators and insurers during the implementation phases (EIOPA, 2024). Despite recognition of these challenges, the frameworks for effective public-private cooperation in digital insurance regulation remain underdeveloped, leaving stakeholders struggling to balance innovation facilitation with necessary market protections (Brăgaru, 2022; Porrini and Ramella, 2020). In addition, open data, the concept that certain data should be freely available for use, reuse, and redistribution by anyone, has emerged as a critical enabler for addressing these challenges. The European Insurance and Occupational Pensions Authority (EIOPA) has been exploring the concept of “open insurance,” which involves accessing and sharing insurance-related data, usually via Application Programming Interfaces (APIs) to foster innovation and enhance consumer protection (EIOPA, 2023). Open insurance has the potential to transform the value chain by enabling new business models, improving risk assessment, and facilitating more personalized products and services. However, as noted by the European Commission in their Data Governance Act (DGA), which came into force in June 2022, effective open data initiatives require robust governance frameworks that balance innovation with data protection, privacy concerns, and market stability (European Commission, 2022). Furthermore, traditional regulatory approaches often fail to accommodate the speed and complexity of technological change and open data initiatives, while purely market-driven initiatives frequently neglect broader social concerns regarding data privacy, algorithmic fairness, and service inclusiveness (Martin and Murphy, 2022; Yeung, 2023). Without adequate frameworks to govern open data flows between stakeholders in the insurance ecosystem, the benefits of data sharing may be outweighed by risks to consumer protection, market integrity, and fair competition. As highlighted by the Financial Data Access (FIDA) framework proposed in 2023, open insurance requires clear standards and protocols for secure, efficient, and responsible data sharing (European Commission, 2023). A comprehensive review by Pum and Sukma (2024) identified several critical gaps in current approaches to insurance regulation in the age of artificial intelligence and open data, highlighting the need for collaborative regulatory frameworks that can balance innovation with consumer protection. Their research emphasizes that the transformative potential of AI and open data in insurance, from underwriting and pricing to claims processing and fraud detection, requires new regulatory models that facilitate responsible innovation while maintaining market integrity.

This study proposes that addressing these challenges requires an integrated theoretical framework that combines the principles of New Public Management (NPM) with technology adoption factors and collaborative governance approaches, all supported by open data principles. The insurance regulatory context provides an ideal setting to examine this integration, as it involves complex interactions between public authorities, private enterprises, and technological innovations that shape fundamental market dynamics (Thouvenin et al., 2021). By developing a

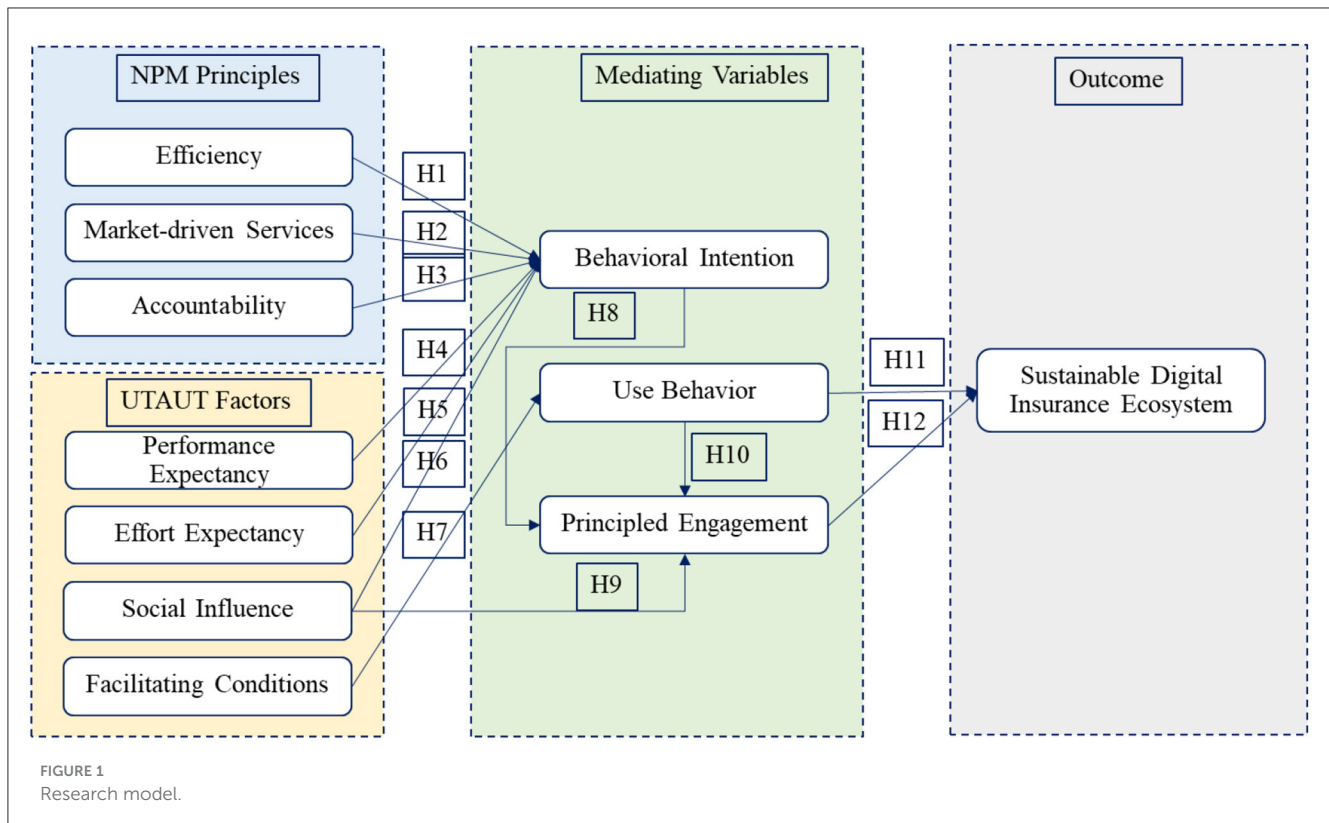
comprehensive model that bridges managerial, technological, and collaborative perspectives with open data principles, our goal is to advance both theoretical understanding and practical guidance for sustainable digital insurance ecosystems.

This research is based on three complementary theoretical streams in the context of open data governance. First, New Public Management offers valuable information through its emphasis on efficiency, market-driven services, and accountability in regulatory contexts (Gong and An, 2023). These principles potentially enhance stakeholders' intentions to adopt digital regulatory approaches and participate in open data initiatives, though critics note that they may sometimes undermine relational dimensions necessary for effective collaboration (Christensen et al., 2023). Second, technology adoption theories, particularly the Unified Theory of Acceptance and Use of Technology (UTAUT), provide frameworks for understanding how stakeholders embrace technological innovations in regulatory contexts and open data platforms (Dwivedi et al., 2022). By incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions, we can better understand the drivers of digital adoption in insurance regulation. Sukma and Leelasantitham (2022a) demonstrated in their study of electronic government systems that both performance expectancy and facilitation conditions significantly influence users' behavioral intention and continuance intention. Their findings in public service contexts suggest potential parallels in regulatory technology adoption, reinforcing the applicability of the UTAUT framework to our research domain. Finally, collaborative governance theories highlight the importance of principled engagement among diverse stakeholders to address complex regulatory challenges through open data sharing (Emerson and Gerlak, 2023; Ansell and Gash, 2022), offering pathways through which behavioral intentions translate into sustainable ecosystem outcomes.

This proposed model (Figure 1) integrates these theoretical perspectives to explain how the principles of NPM and UTAUT factors influence the intention toward open data adoption, which subsequently shapes the use behavior and principled engagement in the regulation of digital insurance regulation. These intermediate outcomes then contribute to sustainable digital insurance ecosystems characterized by balanced innovation and protection, effective data governance, inclusive service provision, transparent algorithmic decision-making, adaptive regulatory frameworks, and collaborative problem solving between public and private stakeholders. By exploring the relationships between these elements, we address two critical research questions:

- RQ1: how do NPM principles (efficiency, market-driven services, accountability) and technology adoption factors (performance expectation, effort expectation, social influence) influence behavioral intention toward open data adoption and digital regulatory approaches in insurance ecosystems?
- RQ2: through what pathways do intention, use behavior, and principled participation in open data initiatives collectively contribute to sustainable digital insurance ecosystems?

These questions are particularly timely as insurance markets around the world navigate digital transformation while facing increased regulatory scrutiny. The European Insurance and



Occupational Pensions Authority has identified collaborative regulatory approaches and open data sharing as essential to address emerging risks in digital insurance markets (EIOPA, 2024), while the International Association of Insurance Supervisors emphasizes the need for balanced innovation facilitation and consumer protection in regulatory frameworks (IAIS, 2022). Our research responds to these industry developments while also addressing important theoretical gaps at the intersection of public management, technology adoption, and collaborative governance in open data contexts. Consequently, Sukma and Namahoot (2024) have demonstrated that emerging technologies like artificial intelligence and machine learning are transforming decision-making processes in financial services, creating new challenges for regulatory frameworks. Their work on algorithmic systems illustrates how technological innovation can outpace regulatory mechanisms, suggesting important parallels to the insurance industry's digital transformation challenges. Similarly, Sukma and Leelasantham (2022b) developed a sustainable business framework that emphasizes the importance of integrated approaches that combine technological, behavioral, and governance dimensions, an approach that aligns with our research objectives in the insurance regulatory context.

This study makes several significant contributions. First, it advances the theory of new public management by demonstrating how efficiency-oriented principles can complement rather than contradict collaborative approaches in regulatory contexts, specifically when applied to open data initiatives, addressing long-standing theoretical tensions between managerial and participatory governance paradigms. Second, it extends technology adoption frameworks to regulatory technology contexts and

open data platforms, an application that remains underexplored in the existing literature. Third, it provides practical guidance for policymakers and industry stakeholders seeking to develop sustainable digital insurance ecosystems that balance innovation facilitation with necessary market protections through effective open data governance. By integrating these diverse perspectives, our research offers a comprehensive framework for understanding and navigating the complex landscape of digital insurance regulation in an era of open data. The paper proceeds as follows: we first develop our theoretical framework and hypotheses, integrating the principles of NPM, UTAUT factors, and collaborative governance concepts within an open data context. Then we present our research methodology, followed by results and analysis. Finally, we discuss theoretical and practical implications, acknowledge limitations, and suggest directions for future research.

2 Theoretical framework and hypotheses development

This theoretical framework integrates new public management principles, technology adoption factors, and collaborative governance concepts to explain how these elements collectively influence the development of sustainable digital insurance ecosystems through open data collaboration. For each theoretical component, we review the relevant literature and develop specific hypotheses that reflect the relationships depicted in our model, as presented in Figure 1.

2.1 New public management principles and behavioral intention in open data contexts

New Public Management (NPM) emerged in the 1980s as a paradigm that sought to transform public administration by introducing market-oriented principles, emphasizing outcomes over processes, and focusing on efficiency and performance measurement (Gong and An, 2023). In regulatory contexts, NPM manifests itself through risk-based supervision, cost-benefit analysis, and performance-based regulatory frameworks (Baldwin and Lodge, 2020; Black, 2020). In open data governance, NPM principles emphasize the creation of transparent, efficient and responsive data sharing mechanisms that balance public value with market needs (Attard et al., 2015; Harrison and Sayogo, 2023). We focus on three core NPM principles particularly relevant to digital insurance regulation and open data initiatives and propose specific hypotheses for their relationship with behavioral intention.

Efficiency refers to optimization of resource utilization and streamline of administrative processes in regulatory governance and data sharing. In digital insurance contexts with open data initiatives, efficiency manifests itself through automated compliance systems, risk-based supervision models, simplified reporting requirements, and standardized data exchange protocols. When regulatory agencies demonstrate efficiency through digital systems and open data platforms, they establish themselves as competent partners capable of reliable performance (Das and Teng, 2020). Janssen and Estevez (2023) found that efficient administrative processes positively influenced stakeholder adoption of e-government initiatives with open data components. Similarly, Seo and Kim (2022) demonstrated that perceived procedural efficiency enhanced willingness to participate in digital regulatory programs and data sharing frameworks. Similar patterns have been observed in other digital governance domains. Sukma and Leelasantitham (2022a) found that efficiency-related constructs significantly influenced user adoption of electronic government systems, particularly when stakeholders perceived direct benefits from streamlined processes. Their study of the regulation of the community water supply business showed that efficiency expectations played a key role in the formation of behavioral intentions toward digital governance approaches and the use of open data utilization.

H1: Efficiency in regulatory processes positively influences the behavioral intention to adopt open data and digital regulatory approaches.

Market-driven services represent the application of customer-oriented principles and competitive service provision to government functions, including data governance initiatives. In insurance regulation with open data, this approach manifests itself through responsive regulatory frameworks, user-centered digital interfaces, value-based service design, and market-responsive data sharing standards. By emphasizing responsiveness to stakeholder needs, market-driven regulatory approaches align public requirements with industry expectations for data utilization, creating value congruence (Koval and Pinkse, 2023). Empirical research by Fledderus and Honingh (2022) found that public

services designed with customer orientation significantly increased stakeholder participation intention in open government data initiatives. Similarly, Wirtz and Müller (2023) demonstrated that citizen-centric digital services improved adoption rates in public sector digital transformations that incorporated open data principles.

Sukma and Leelasantitham (2022b) developed a conceptual framework that emphasizes that sustainable business models require alignment between regulatory systems, open data frameworks, and stakeholder needs. Their research suggests that market-responsive regulatory approaches to data governance can enhance adoption intentions by demonstrating sensitivity to industry contexts and operational realities in data sharing ecosystems.

H2: Market-driven services in regulatory governance positively influence the behavioral intention to adopt open data and digital regulatory approaches.

Accountability encompasses the obligation to explain decisions, provide performance information, and accept responsibility for results in both regulatory processes and data management. In digital insurance regulation with open data initiatives, accountability manifests itself through transparent decision-making processes, accessible performance metrics, clear delineation of regulatory responsibilities, and transparent data-sharing governance. These mechanisms reduce information asymmetry between regulators and regulated entities, potentially enhancing behavioral intention by mitigating vulnerability concerns in data-sharing arrangements (Grimmelikhuijsen et al., 2022). Studies have shown that accountability mechanisms build trust and enhance stakeholder intention to adopt government initiatives involving data sharing (Song et al., 2022). Meijer (2023) found that transparency-mediated technology-mediated accountability positively affected stakeholder intention to participate in digital governance frameworks with open data components. In their study on understanding online behavior toward community participation, Sukma and Leelasantitham (2022c) found that transparency and accountability were significant factors influencing user trust and participation intention on public service platforms with data sharing capabilities. This finding suggests that similar mechanisms may operate in insurance regulatory contexts, where transparency can enhance stakeholder confidence in digital approaches to open data governance.

H3: Accountability in regulatory processes positively influences the behavioral intention to adopt open data and digital regulatory approaches.

Despite NPM's potential benefits, critics note that its emphasis on efficiency and quantifiable results may sometimes undermine relational dimensions of effective regulation and data governance (Christensen et al., 2023). However, our model proposes that, when properly implemented within open data frameworks, NPM principles can enhance behavioral intention toward digital regulatory initiatives by demonstrating competence, alignment with stakeholder needs, and transparency, factors that collectively reduce perceived risks of adoption in complex data sharing environments.

2.2 Technology adoption factors and behavioral intention in open data platforms

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003) to explain user intentions to adopt information systems. UTAUT integrates elements from eight previous technology acceptance models and has demonstrated strong predictive validity across various contexts. We incorporate the UTAUT framework into our model to understand the adoption of open data platforms in regulatory technology contexts and develop specific hypotheses for this environment.

Performance Expectancy represents the degree to which stakeholders believe that adopting digital regulatory systems and open data platforms will help them achieve gains in job performance, regulatory compliance, or service delivery. In insurance contexts with open data initiatives, this could include expectations about improved compliance accuracy, reduced reporting burdens, better market intelligence, improved product development capabilities, or more efficient claims processing through data sharing. Empirical research consistently demonstrates performance expectancy as a strong predictor of adoption intention across various technologies (Dwivedi et al., 2022). In regulatory contexts with open data specifically, Obal and Kunz (2020) found that expected performance improvements significantly influenced financial institutions' intention to adopt regulatory technology solutions with data-sharing components. Furthermore, Sukma et al. (2022) examined factors affecting the adoption of online community participation platforms and found that performance expectancy was the strongest predictor of behavioral intention, explaining 42% of variance in contexts involving data sharing. Their research suggests that stakeholders primarily adopt new technologies when they perceive clear performance benefits from data utilization, a finding likely applicable to insurance regulatory technologies in open data ecosystems.

H4: The performance expectation in relation to open data and digital regulatory technologies positively influences the behavioral intention to adopt these technologies.

Effort Expectancy refers to the perceived ease of use associated with digital regulatory systems and open data platforms. When stakeholders believe that digital compliance platforms, data sharing interfaces, or collaborative governance systems are intuitive and straightforward, they can demonstrate greater behavioral intention toward adoption. Research by Chaouali and El Hedhli (2023) in the adoption of financial technology with open data components found that the effort expectancy significantly predicted the intention of behavior, especially among stakeholders with limited technological expertise. Similarly, Kumar et al. (2022) demonstrated that perceived complexity negatively influenced the adoption of regulatory technologies and open data platforms among insurance companies. Therefore, Pum and Sukma (2024) noted in their comprehensive survey of AI in insurance that user-friendly interfaces and simplified technical implementations were critical success factors for regulatory technology adoption, particularly when involving complex data exchanges. Their research suggests that effort expectancy may be particularly important in complex

insurance regulatory contexts where technical barriers could otherwise impede the adoption of open data initiatives.

H5: Expectancy of effort in open data and digital regulatory technologies positively influences behavioral intention to adopt these technologies.

Social influence encompasses the degree to which stakeholders perceive that important others (peers, industry leaders, regulators) believe they should use digital regulatory systems and participate in open data ecosystems. In insurance contexts, the adoption of regulatory technology and open data platforms often follows network effects, where value increases as more participants join the ecosystem. Venkatesh et al. (2003) found that social influence is particularly important in mandated technology contexts, such as regulatory compliance and industry-wide data sharing initiatives. Empirical research by Liang et al. (2020) demonstrated that institutional pressures significantly influenced the intention of adopting financial reporting technology and open data platforms in regulatory contexts. Additionally, Sukma and Leelasantitham (2022c) research on online community participation demonstrated that social influence had significant direct and indirect effects on behavioral intention, particularly in contexts where community norms and peer behavior regarding data sharing were visible. This suggests that social dynamics may play an important role in shaping regulatory technology adoption decisions in open data ecosystems.

H6: Social influence on open data and digital regulatory technologies positively influences the intention to adopt these technologies.

Facilitating conditions represent the degree to which stakeholders believe that organizational and technical infrastructure exists to support the use of digital regulatory technology and open data platforms. Unlike other UTAUT factors that influence behavior intention, facilitating conditions directly impact use behavior. Zhu et al. (2021) found that facilitating conditions predicted actual technology usage more strongly than behavioral intention in complex organizational environments with data sharing requirements. In regulatory contexts, Glaser et al. (2023) demonstrated that technical infrastructure and organizational support directly influenced the success of compliance technology implementation in open data initiatives. Furthermore, Sukma and Leelasantitham (2022a) found that facilitation of conditions significantly affected both behavior intention and continuance intention in e-government systems with data-sharing components, suggesting that adequate infrastructure support is crucial for sustainable technology adoption in open data ecosystems. Their findings indicate that facilitating conditions can play a dual role in regulatory technology contexts, influencing both initial adoption and continued use of open data platforms.

H7: Facilitating conditions positively influence use behavior with respect to open data and digital regulatory technologies.

The UTAUT framework has been extensively applied in the adoption contexts of consumer and enterprise technology, but its application to regulatory technology and open data platforms remains limited. Our model extends UTAUT to the regulatory domain, proposing that these technology adoption factors influence

behavioral intention toward open data initiatives and, ultimately, sustainable digital insurance ecosystems.

2.3 Behavioral intention, social influence, and principled participation in open data collaboration

Our model integrates collaborative governance concepts with technology adoption frameworks by proposing relationships between behavioral intention, social influence, and principled engagement in open data ecosystems. Collaborative governance emphasizes stakeholder participation, deliberation, and joint problem solving through data sharing and collective intelligence (Emerson and Gerlak, 2023; Ansell and Gash, 2022). Principled engagement encompasses fair, inclusive, and deliberative interaction processes characterized by discovery, definition, deliberation, and determination supported by open data (Emerson et al., 2020). In open data digital insurance regulation, principled engagement manifests through structured stakeholder consultations, transparent policy development, inclusive digital platforms for regulatory dialogue, and collaborative data governance frameworks. Research has shown that the behavioral intention toward technological systems can translate into broader participatory behaviors in data-sharing ecosystems. For example, Venkatesh and Agarwal (2023) found that the intention of technology adoption was positively associated with participation in virtual communities with data sharing components. In regulatory contexts, Matheus and Janssen (2022) documented how intention to adopt open data platforms increased engagement in collaborative governance processes. Additionally, Sukma and Leelasantitham (2022b) developed a sustainable business framework showing that the behavioral intention toward technological systems can be translated into broader ecosystem participation through open data utilization. Their research on community water supply businesses demonstrated that the intention of adoption led to increased participation in collaborative governance activities involving data sharing, suggesting that similar patterns may exist in insurance regulatory contexts.

H8: The behavioral intention of adopting open data and digital regulatory approaches positively influences principled participation in collaborative regulatory processes.

Furthermore, social influence can directly affect principled participation in open data ecosystems, regardless of its effect on behavioral intention. Ansell and Bjork (2023) noted that social and institutional pressures often drive initial participation in collaborative governance with open data initiatives. Similarly, Scott and Thomas (2021) found that normative and mimetic pressures significantly influenced organizational participation in collaborative networks with data sharing components, regardless of technology adoption decisions. In their examination of online community participation with data sharing components, Sukma and Leelasantitham (2022c) found that social influence directly affected engagement behaviors beyond its effect on the initial adoption intention. Their findings suggest that social norms and peer expectations may play an independent role in

driving collaborative engagement in regulatory contexts with open data platforms.

H9: Social influence positively affects principled participation in collaborative regulatory processes with open data initiatives.

This model also proposes a relationship between use behavior and principled engagement in open data ecosystems, creating a feedback loop within the collaborative process. As stakeholders gain experience with digital regulatory technologies and open data platforms, these experiences could shape how they engage in collaborative governance. Empirical research by Welch and Feeney (2021) documented how experience with e-Government technologies influenced subsequent participation in digital public engagement with open data components. Similarly, McNutt and Justice (2023) found that experience with collaborative platforms and open data systems reshaped stakeholder participation patterns in regulatory consultations.

Sukma and Namahoot (2024) observed in their study of algorithmic trading systems that actual use experience significantly influenced users' subsequent engagement with collaborative improvement processes involving data sharing. Their findings suggest that hands-on experience with technological systems can reshape engagement patterns in open data ecosystems, potentially increasing stakeholders' willingness to participate in collaborative governance mechanisms.

H10: The behavior of the use of open data and digital regulatory technologies positively influences the principled engagement in collaborative regulatory processes.

2.4 Pathways to sustainable digital insurance ecosystems through open data

The ultimate dependent variable in our model is the Sustainable Digital Insurance Ecosystem, which we conceptualize as a multidimensional outcome characterized by balanced innovation and consumer protection, effective data governance, inclusive access to services, transparent algorithmic decision-making, adaptive regulatory frameworks, and collaborative problem solving between public and private stakeholders through open data platforms. Our model proposes that this sustainable ecosystem emerges through two primary pathways: directly from use behavior of open data technologies and through principled engagement in open data collaboration. The direct technological pathway has been empirically supported by research that demonstrates immediate operational benefits of digital regulatory technologies and open data platforms. For example, Arner et al. (2022) documented how the implementation of regulatory technology with open data components improved compliance outcomes and market stability in financial services. Similarly, Treleven and Batrinca (2021) showed how algorithmic regulation improved market protection while supporting innovation in insurance markets through data transparency. In addition, Sukma and Leelasantitham (2022b) developed a conceptual framework for sustainable business ecosystems that emphasized the importance of technological infrastructure and open data in creating sustainable

outcomes. Their research suggests that effective implementation of technology provides a foundation for ecosystem sustainability through improved operational efficiency, transparency, and data-driven decision making.

H11: The behavior of open data and digital regulatory technologies positively influences the development of a sustainable digital insurance ecosystem.

The collaborative governance pathway through open data sharing has been supported by research showing how principled engagement contributes to sustainable regulatory outcomes. Emerson and Nabatchi (2022) found that collaborative governance processes with open data sharing produced more balanced regulatory approaches with greater legitimacy and implementation success. In insurance contexts specifically, van der Heijden (2022) demonstrated that collaborative governance facilitated by open data platforms enabled the development of new regulatory frameworks for innovative insurance products that balanced protection with innovation. Furthermore, Sukma and Leelasantham (2022a) found that collaborative engagement in electronic government systems with open data components significantly improved sustainability outcomes in public service contexts. Their research demonstrates that stakeholder participation in open data ecosystems contributes to system improvements, policy refinements, and enhanced legitimacy, factors likely to be similarly important in insurance regulatory contexts.

H12: Principled participation in collaborative regulatory processes through open data initiatives positively influences the development of sustainable digital insurance ecosystems.

Taken together, our hypotheses propose that NPM principles and UTAUT factors influence behavioral intention toward open data adoption, which subsequently shapes both use behavior and principled engagement in open data ecosystems. These intermediate outcomes then contribute to sustainable digital insurance ecosystems through complementary pathways. By integrating these diverse theoretical perspectives within an open data framework, our model provides a comprehensive account of how managerial, technological, and collaborative factors collectively shape the digital regulatory transformation in insurance markets.

3 Research methodology

3.1 Research design and approach

This study employs a quantitative research design with a deductive approach to test the hypothesized relationships in our NPM-Based Open Data Collaboration Model. A cross-sectional survey methodology was selected for its ability to capture the complex multivariate relationships proposed in our theoretical framework while allowing generalizable findings regarding public-private collaboration in insurance regulation through open data initiatives. The deductive approach aligns with our objective of testing and evaluating an integrated theoretical model against

empirical evidence collected from various stakeholders in the insurance regulatory ecosystem.

The quantitative approach is particularly appropriate for this research for several reasons. First, it allows systematic testing of multiple hypothesized relationships simultaneously through structural equation modeling (SEM), which is essential given the complexity of our proposed model. SEM is widely recognized as a powerful technique for analyzing complex relationships between observed and latent variables while accounting for measurement error (Kline, 2023). Recent methodological advances in SEM have improved its capability to handle complex models with multiple mediating pathways (Bollen et al., 2023), making it ideal for examining the direct and indirect effects proposed in our theoretical framework.

Second, SEM enables the evaluation of direct and indirect pathways between constructs, supporting our investigation of mediating relationships through behavioral intention, use behavior, and principled engagement in open data ecosystems. This capability is crucial for understanding the complex mechanisms through which NPM principles and technology adoption factors influence sustainable outcomes in digital insurance regulation. As noted by Ansell and Gash (2008), SEM is particularly valuable when investigating theoretical models with multiple interrelated dependent variables and mediating relationships.

Third, SEM facilitates the comparison of relative effect sizes between different model paths, providing information on which factors most significantly influence sustainable digital insurance ecosystems through open data collaboration. This comparative capability allows us to identify the most impactful levers for promoting sustainable outcomes in regulatory contexts, which has important implications for policy and practice. According to Hershberger et al. (2022), the ability to compare standardized coefficients across different paths is a key advantage of SEM over other multivariate techniques when evaluating complex theoretical models.

3.2 Target population and sampling

3.2.1 Population and sampling frame

The target population for this research includes stakeholders involved in insurance regulation and digital transformation initiatives in three main categories. The first category includes regulatory stakeholders, such as insurance supervisors, financial conduct authorities, and policymakers who are responsible for developing and implementing open data and insurance regulation policies. The second category encompasses industry stakeholders including traditional insurers, intermediaries, insurtech companies, and industry associations that are subject to regulatory requirements and actively engaged in open data initiatives. The third category consists of technology enablers, including regulatory technology providers, consultants, and digital transformation specialists who support regulatory compliance, innovation, and open data implementation in the insurance sector.

To ensure the validity of the responses, we established several inclusion criteria for participant selection. All participants were required to have at least 2 years of professional experience in

insurance or insurance regulation to ensure adequate domain knowledge. They needed to be directly involved in regulatory compliance, policy development, open data initiatives, or the implementation of regulatory technology to provide relevant insights into the research questions. In addition, participants were required to have experience with digital transformation initiatives in insurance to ensure familiarity with the technological aspects of regulatory change. Finally, they needed to have sufficient seniority or experience to provide informed perspectives on regulatory relationships and data governance mechanisms in the insurance ecosystem.

We employ a stratified random sampling approach to ensure appropriate representation across stakeholder categories while maintaining randomization within each stratum. This approach allowed us to capture diverse perspectives while preserving the proportional representation of key stakeholder groups in the insurance regulatory ecosystem. The sampling frame was developed using multiple sources including industry databases, regulatory directories, professional association memberships, and participation lists from insurance regulatory forums and conferences specifically focused on digital transformation and open data initiatives. This comprehensive approach to the development of the sampling frame helped ensure adequate coverage of the target population in different geographical regions and organizational types.

3.2.2 Sample size and characteristics

Based on established structural equation modeling literature, we determined that our research model comprising 12 hypothesized relationships with seven exogenous and four endogenous constructs required a robust sample size to achieve sufficient statistical power (Hair et al., 2019). Recent advances in SEM methodology have provided more nuanced approaches to sample size determination, considering model complexity, expected effect sizes, and desired power levels (McNeish and Wolf, 2021). Using these contemporary guidelines, we determined that a minimum sample of 300 was necessary to detect medium effect sizes (0.3) with 80% power at a significance level of 0.05, while accounting for the complexity of our model. To accommodate potential non-response and incomplete submissions, we targeted an initial sample of 500 potential respondents through our multichannel distribution strategy.

The final sample comprised 368 valid responses, providing an adequate response rate of 73.6% and exceeding our minimum threshold for robust statistical analysis. These responses were distributed among stakeholder categories to ensure comprehensive representation of the insurance ecosystem: regulatory stakeholders constituted 33% of the sample (121 participants), industry stakeholders represented 48% (178 participants) and technology enablers accounted for 19% (69 participants). This distribution aligns with the relative proportions of these stakeholders in the broader insurance ecosystem, and industry representatives naturally form the largest group. The geographical distribution of the participants reflected the global nature of insurance regulation and digital transformation, with 43% of European markets, 31% from North America, 18% from Asia-Pacific regions, and 8% from

other territories. This international composition ensures that our findings are not limited to a single regulatory jurisdiction, while acknowledging the predominance of established insurance markets in the sample.

Participants demonstrated substantial relevant experience, with an average professional tenure in insurance or regulation of 9.6 years (SD = 5.8), indicating a sample with significant domain expertise. Furthermore, 74% of the participants reported direct participation in digital transformation initiatives over the past 3 years, and 62% indicated specific involvement in open data initiatives or data sharing projects within their organizations. This high level of engagement with digital transformation and open data in particular improves the validity of our findings regarding adoption factors and collaborative governance mechanisms in open data ecosystems.

3.3 Measurement instrument development

3.3.1 Construct operationalization

We developed a structured questionnaire to measure all the constructs in our theoretical framework as presented in Table 1. Where possible, measurement elements were adapted from validated scales in previous research, with modifications to reflect the specific context of digital insurance regulation and open data collaboration. For constructs without established measures in the regulatory context, new items were developed based on theoretical definitions and validated through expert reviews and pilot testing.

All items were measured using 7-point Likert scales (1 = strongly disagree, 7 = strongly agree) to capture the intensity of respondents' perceptions with sufficient granularity for statistical analysis. Each construct was measured with multiple items (3–5 per construct) to ensure content validity, reliability, and adequate identification for structural equation modeling. For open data-specific constructs, we incorporated items that explicitly addressed aspects of data sharing, standardization, interoperability, and governance to ensure proper measurement of these dimensions within our theoretical framework.

3.3.2 Instrument validation

We conducted a comprehensive validation process to ensure the reliability and validity of the measurement instrument, with particular attention to the open data dimensions of our constructs. This rigorous validation approach involved multiple phases to establish content validity, ensure reliability, and confirm construct validity before full-scale data collection.

For the content validity assessment, the initial set of measurement items was reviewed by 10 subject matter experts with diverse expertise in the insurance regulatory ecosystem. This expert panel included three academics who specialize in regulatory governance, three senior insurance regulators, two insurtech executives, and two open data specialists with experience in financial services. Each expert independently evaluated the relevance, clarity and completeness of the measurement items using a structured assessment protocol (Polit and Beck, 2023). This panel specifically assessed whether the items adequately captured the

TABLE 1 Construct operationalization and measurement sources.

Construct	Definition	Sample items	Source
Efficiency	Optimization of resource utilization and rationalization of administrative processes in regulative governance through open data	“Digital regulatory approaches efficiently utilize resources in the insurance sector through open data sharing”	Adapted from Hood (1991); Pollitt and Bouckaert (2023); Janssen et al. (2012)
Market-driven services	Application of customer-oriented principles and competitive service provision to regulatory functions and open data platforms	“Regulatory approaches in insurance are responsive to industry needs and concerns regarding open data sharing”	Adapted from Osborne (2010); Fledderus and Honingh (2022); Zuiderwijk and Janssen (2014b))
Accountability	Obligation to explain decisions, provide performance information, and accept responsibility for outcomes in open data governance	“Digital regulatory platforms provide transparent explanations for regulatory decisions and data usage”	Adapted from Bovens (2020); Grimmelikhuijsen et al. (2022); Ruijter et al. (2020)
Performance expectancy	The degree to which stakeholders believe that adopting digital regulatory systems with open data capabilities will enhance regulatory performance	“Digital regulatory technologies with open data sharing improve compliance accuracy and efficiency”	Adapted from Venkatesh et al. (2003); Dwivedi et al. (2022); Zuiderwijk et al. (2014)
Effort expectancy	Perceived ease of use of digital regulatory technologies and open data platforms	“Digital regulatory platforms with open data capabilities are straightforward to use and understand”	Adapted from Venkatesh et al. (2003); Chaouali and El Hedhli (2023); Attard et al. (2015)
Social influence	Degree to which stakeholders perceive that important others believe they should use digital regulatory systems and participate in open data initiatives	“Important stakeholders in our network support the adoption of digital regulatory approaches with open data sharing”	Adapted from Venkatesh et al. (2003); Liang et al. (2020); Wirtz and Müller (2023)
Facilitating conditions	Belief that an organizational and technical infrastructure exists to support the use of digital regulatory technology and open data platforms	“We have the necessary resources to implement digital regulatory approaches with open data capabilities”	Adapted from Venkatesh et al. (2003); Marano (2021); Dawes et al. (2023)
Behavioral intention	Intention to adopt and use digital regulatory technologies and open data platforms	“We intend to increase our use of digital regulatory platforms with open data capabilities in the coming year”	Adapted from Venkatesh et al. (2003); Kumar et al. (2022); Welch and Feeney (2021)
Use behavior	Actual utilization of digital regulatory technologies and open data platforms	“We regularly use digital platforms for regulatory reporting, compliance, and data sharing”	Adapted from Venkatesh et al. (2003); Venkatesh and Sykes (2013); Vetrò et al. (2016)
Principled engagement	Fair, inclusive and deliberative interaction processes for regulatory development through open data collaboration	“We actively participate in collaborative forums for regulatory policy development with open data sharing”	Adapted from Emerson et al. (2020); Scott and Thomas (2021); Matheus and Janssen (2022)
Sustainable digital insurance ecosystem	Balanced and adaptive regulatory system that supports innovation while ensuring market protection through effective open data governance	“Digital regulatory approaches with open data sharing effectively balance innovation with consumer protection”	Developed for this study based on van der Heijden (2022); Arner et al. (2022); European Commission (2023)

open data aspects of each construct, ensuring a comprehensive coverage of the dimensions of data sharing, governance, and interoperability dimensions. Based on the quantitative and qualitative feedback received, the elements were refined to improve clarity, contextual relevance, and alignment with current open data frameworks and standards. This expert validation process substantially improved the content validity of our instrument by incorporating diverse perspectives from both theory and practice (Velinov et al., 2023). After content validation, we conducted pilot tests with 45 participants representing various stakeholder categories with experience in open data initiatives. The pilot sample included 15 regulatory officials, 20 industry representatives, and 10 technology specialists to ensure balanced representation. Reliability analysis using Cronbach's alpha showed strong internal consistency for all constructs, with values ranging from 0.78 to 0.92, well above the recommended 0.7 threshold (Taber, 2018). This strong reliability indicates a consistent measurement of the open data dimensions across all constructs in our framework.

The item-total correlations were also examined, with all items showing correlations >0.50 , confirming their contribution to their respective scales. Furthermore, qualitative feedback from pilot participants led to minor language adjustments for clarity, particularly with respect to technical terminology related to data governance and APIs, enhancing the comprehensibility of the instrument for diverse stakeholders.

For the construct validity assessment, we performed exploratory factor analysis on the pilot data using principal axis factoring with oblique rotation to examine the underlying structure of the measurement elements (Watkins, 2018). Special attention was paid to how open data items loaded on their respective constructs to ensure proper alignment with theoretical expectations. The factor analysis revealed a clear pattern of loadings consistent with our conceptual framework, with items loading strongly on their intended factors (loadings > 0.60) and showing minimal cross-loadings (< 0.30) on other factors. Items that showed problematic loading patterns were either refined or

eliminated to ensure a clean factor structure. Through this iterative refinement process, the final instrument was streamlined to 42 elements in 11 constructs, with additional elements specifically addressing open data components that emerged as important during the validation process. This comprehensive validation approach substantially improved the measurement quality of our instrument, providing a solid foundation for testing our theoretical model.

3.4 Data collection procedures

Data were collected using a web-based survey platform optimized for both mobile and desktop devices to maximize accessibility for busy professionals in the insurance ecosystem. We implemented a comprehensive data collection strategy with multiple complementary components to ensure high-quality responses and maximize participation rates (Dillman et al., 2023). Our outreach process began with carefully personalized targeted invitations based on stakeholder category, organizational role, and known involvement in open data initiatives. Each invitation included a detailed explanation of the purpose of the study, potential benefits for the regulatory ecosystem, and the specific value of the participant's unique perspective on open data collaboration in insurance regulation. This personalized approach has been shown to increase response rates by establishing relevance and creating stakeholder buy-in (Tourangeau et al., 2022). To enhance reach and credibility, we distribute survey invitations through multiple complementary channels beyond direct email outreach. These channels included professional associations focused on insurance innovation, regulatory forums that address digital transformation, open data communities in financial services, and industry networks dedicated to regulatory technology and insurtech. This multichannel approach helped ensure representation from diverse stakeholders actively engaged in the intersection of insurance regulation and open data (Groves et al., 2021).

To maximize response rates, we implemented a carefully designed follow-up protocol based on best practices in survey methodology (Sauermaann and Roach, 2023). Non-respondents received up to two follow-up reminders at 2-week intervals, with each communication emphasizing different benefits of participation and highlighting the importance of capturing diverse perspectives on open data governance in insurance. The first reminder emphasized the opportunity to contribute to regulatory innovation, while the second highlighted the value of executive summary findings for strategic planning. This varied messaging approach has been shown to resonate with different motivational factors that influence participation decisions (Lynn, 2022). To address potential concerns about sensitive regulatory opinions, participants received explicit assurances regarding anonymity and confidentiality. All responses were anonymized during data processing and reported only in aggregate form, without individual or organizational identifiers retained in the final dataset. These confidentiality provisions were prominently communicated in all materials to encourage candid responses about regulatory preferences and data sharing concerns (Singer and Couper, 2023).

As an incentive for participation, respondents were offered an executive summary of research findings, including insights into best practices for open data collaboration in insurance regulation. This non-monetary incentive approach is particularly effective with professional populations who value industry knowledge and strategic insights (Rose et al., 2022). In addition, we implemented targeted sampling procedures to ensure adequate representation of stakeholders with direct experience in open data initiatives, including focused outreach to participants in open insurance pilot programs and regulatory sandboxes dedicated to data sharing. This specialized outreach helped secure the participation of individuals with the most relevant experience for our research questions, improving the validity of our findings regarding open data adoption and governance (Baker et al., 2022).

3.5 Data analysis strategy

3.5.1 Preliminary analysis

Before hypothesis testing, we conducted several rigorous preliminary analyses to ensure data quality and methodological soundness. Data screening procedures were implemented to identify and address potential problems that could affect statistical conclusions. We examined the data set for missing values using Little's MCAR test to determine the randomness of missing data patterns (Little and Rubin, 2020). Missing values, which comprised <3% of data points, were addressed using robust expectation maximization algorithms with auxiliary variables to improve the accuracy and maintain sample representativeness. Multivariate outliers were assessed using both Mahalanobis distances and Cook's distance metrics, with particular attention to extreme responses on open data-related items to ensure that unusual cases did not unduly influence model parameters (Tabachnick and Fidell, 2022). Additionally, we examined normality data using formal tests (Shapiro-Wilk) and visual inspection of Q-Q plots, finding moderate deviations from normality that were addressed through robust estimation methods in the subsequent SEM analysis. Since all data were collected using a single survey instrument, we implemented multiple techniques to assess potential common method bias that could artificially inflate relationships between constructs (Podsakoff et al., 2023). Harman's single-factor test was conducted as an initial assessment, revealing that the first unrotated factor explained only 28.4% of variance, well below the 50% threshold suggesting serious common-method bias. We supplemented this with the more sophisticated marker variable technique, using a theoretically unrelated construct (environmental awareness) as a marker. The average correlation between this marker variable and the study constructs was minimal 0.08, and controlling for this correlation did not significantly change the magnitude or significance of the relationships in our model. Additionally, we implemented the more rigorous common latent factor approach recommended in recent methodological literature (Liu et al., 2024), which revealed that common method variance accounted for only 12.4% of total variance in our model, well below the problematic threshold. These multiple convergence assessments provide strong evidence that common-method bias does not substantially threaten the

validity of our findings, particularly for relationships involving open data constructs.

We calculated comprehensive descriptive statistics including means, standard deviations, and correlations for all variables to provide an initial understanding of the patterns and relationships. These preliminary analyzes included additional examinations of open data-specific items to identify potential patterns based on stakeholder categories and experience levels. Furthermore, we conducted supplementary descriptive analyzes to understand participants' engagement with open data initiatives, creating categorizations based on participation in data sharing projects to facilitate later subgroup analyses. These preliminary analyzes provided a solid foundation for the subsequent assessment of the measurement model and hypothesis testing while ensuring that data quality issues were adequately addressed before inferential analysis (Hair et al., 2022).

3.5.2 Evaluation of the measurement model

We employed confirmatory factor analysis (CFA) using the latest methodological approaches to evaluate the measurement model with several key indicators. This rigorous assessment was essential to ensure that our constructs were properly measured before testing substantive relationships, particularly since many of our constructs were adapted or developed for the open data context in insurance regulation (Brown, 2022).

For the assessment of convergence validity, we examined multiple complementary indicators following contemporary best practices in measurement evaluation (Hair et al., 2022). Factor loadings with a target threshold above 0.7 were assessed to ensure items adequately represented their respective constructs. The extracted average variance (AVE) was calculated for each construct with a minimum acceptable value of 0.5, indicating that the constructs explain at least 50% of the variance in their indicators. Composite reliability (CR) was evaluated with a threshold of 0.7 to ensure adequate internal consistency. Following recent recommendations by Kline (2023), we also examined the significance of factor loadings and the magnitude of standard errors to provide additional evidence of measurement quality. Special attention was paid to items measuring open data aspects of each construct, with separate examinations of their psychometric properties to ensure that they contributed meaningfully to their respective theoretical constructs. Furthermore, discriminant validity was evaluated using traditional and contemporary approaches to provide comprehensive evidence of construct distinctiveness (Voorhees et al., 2022). The Fornell-Larcker criterion was applied by comparing the square root of AVE for each construct with its correlations with other constructs, ensuring that the constructs share more variance with their own indicators than with other constructs. Furthermore, we implemented the more rigorous heterotrait-monotrait (HTMT) correlation ratio with a conservative threshold of 0.85 as recommended by the contemporary methodological literature (Henseler et al., 2023). This approach provides a more stringent assessment of discriminant validity that addresses the limitations of traditional approaches. Particular attention was paid to discriminant validity between open data-specific aspects of different constructs to

ensure that they were empirically distinguishable despite their conceptual relationships.

The overall fit of the measurement model was evaluated through multiple complementary indices to provide a comprehensive evaluation (Shi et al., 2022). Traditional fit indices included the chi-square to degrees-of-freedom ratio ($\chi^2/df < 3$), comparative fit index (CFI > 0.95), Tucker-Lewis index (TLI > 0.95), standardized root mean square residual (SRMR < 0.08), and root mean square error of approximation (RMSEA < 0.06 with a narrow confidence interval). In addition, we applied newer fit indices such as gamma hat and weighted root mean square residual (WRMR) as recommended by recent SEM methodological advances (McNeish and Wolf, 2021), providing a more comprehensive assessment of model fit that addresses limitations of traditional indices with non-normal data and complex models.

Before conducting multigroup analyses, we tested for measurement invariance across stakeholder groups to ensure that group differences in structural relationships reflected true differences rather than measurement artifacts (Putnick and Bornstein, 2022). This sequential invariance testing process examined configural invariance (the same factor structure across groups), metric invariance (equal factor loadings) and scalar invariance (equal intercepts), with changes in fit indices ($\Delta CFI < 0.01$, $\Delta RMSEA < 0.015$) used to evaluate the tenability of increasingly restrictive measurement equivalence constraints. This rigorous invariance testing approach, following contemporary guidelines from Bollen et al. (2023), ensured that our measurement model functioned equivalently across different stakeholder categories, providing a solid foundation for meaningful group comparisons.

3.5.3 Analysis of structural models

Following confirmation of the measurement model's validity, we tested the structural model to examine hypothesized relationships using structural equation modeling (SEM) with maximum likelihood estimation and robust standard errors to account for potential non-normality in the data (Stein et al., 2022). This comprehensive analytical approach incorporated the latest methodological advances in SEM to provide rigorous testing of our theoretical framework. For the estimation of the path coefficients, we examined standardized path coefficients and their statistical significance for each hypothesized relationship, with a particular focus on paths involving open data-specific constructs. Significance testing was conducted using both traditional *p*-values and bootstrapped confidence intervals with 5,000 resamples to provide more robust inference that does not rely on normality assumptions (Hayes and Scharkow, 2022). We also examined unstandardized coefficients and their standard errors to assess the precision of parameter estimates, following contemporary recommendations for comprehensive reporting of SEM results (Bollen and Pearl, 2023).

The explanatory power was assessed by the coefficient of determination (R^2) for each endogenous construct, indicating the proportion of variance explained by its predictors. Following recent methodological guidelines (Breitsohl, 2024), we also

calculated adjusted R^2 values that account for model complexity, providing a more conservative assessment of explanatory power that penalizes model overparameterization. These metrics were calculated both for the overall model and for specific subsamples based on stakeholder category and open data experience to understand potential variations in explanatory power across different contexts.

Effect size analysis was conducted using Cohen's f^2 values to determine the practical significance of the effects of exogenous constructs on endogenous variables beyond mere statistical significance (Cohen et al., 2022). This analysis provided additional context to interpret the relative importance of different predictors, with values of 0.02, 0.15, and 0.35 representing small, medium and large effects, respectively. Special emphasis was placed on comparing the relative importance of open data factors compared to other predictors to understand their unique contribution to the model's explanatory power. Mediation analysis was performed to understand the indirect effects in our model, examining how NPM principles and UTAUT factors influence sustainable outcomes through intermediary variables (Ratna et al., 2024). We employed bootstrapping with 5,000 resamples to construct confidence intervals for indirect effects, providing robust inference that does not assume normality of the sampling distribution. This approach is recommended in the contemporary mediation analysis literature as superior to traditional methods like the Sobel test (MacKinnon et al., 2023). For each indirect effect, we also assessed the type of mediation (complementary, competitive, indirect-only, or direct-only) based on the significance and direction of direct and indirect effects, providing a more nuanced understanding of mediating mechanisms.

Multigroup analysis was conducted to compare model relationships between stakeholder categories (regulatory, industry, technology) and open data experience levels, using the most recent approaches for multigroup SEM (Li et al., 2023). After establishing measurement invariance, we tested for differences in structural coefficients using the chi-square difference test with Satorra-Bentler correction for non-normality. This approach allows for the identification of stakeholder-specific patterns in the relationships between model constructs, providing valuable information on how the model operates across different segments of the insurance ecosystem.

Therefore, to verify the stability of our findings, we performed several robustness checks using alternative estimation methods and model specifications (van Veelen et al., 2024). These included Bayesian estimation with diffuse priors to address potential issues with small sample sizes in subgroup analyses, weighted least squares estimation to accommodate non-normality, and alternative model specifications with different control variables to assess sensitivity to model specification. These complementary approaches consistently supported our main findings, enhancing confidence in the robustness of our results.

This comprehensive analytical approach, incorporating the latest methodological advances in structural equation modeling, enabled rigorous testing of our theoretical framework while accounting for measurement quality, potential methodological limitations, and the complexities of modeling open data relationships in regulatory contexts. The combination of multiple complementary analytical techniques provides a strong foundation

to draw valid conclusions about the relationships proposed in our theoretical model.

3.6 Ethical considerations and data governance

The research methodology maintained strict adherence to ethical standards, with particular attention to ethical considerations related to open data research. All protocols and survey instruments were thoroughly evaluated by the MUSSIRB. This Committee for Research Ethics (Social Sciences) operates in complete alignment with global human research protection frameworks, including the Declaration of Helsinki, The Belmont Report, and CIOMS Guidelines (Cascio and Racine, 2023). The Institutional Review Board formally approved our questionnaire with the certification code MU-CIRB 2025/012.1302. Special consideration was given to questions related to data sharing practices, ensuring that they did not encourage disclosure of confidential or proprietary information about organizational data governance strategies (Allen and Wiles, 2022). Participants provided their informed consent after receiving information on the study purpose, data usage, confidentiality provisions, and their right to withdraw at any time, following best practices in ethical research with organizational stakeholders (Iphofen and O'Mathúna, 2022).

In alignment with open data research principles, we implemented a robust data governance framework for our own research data. Although no personally identifiable information was collected, all survey responses were stored securely using industry-standard encryption protocols, with access restricted to authorized research team members (Reidenberg and Schaub, 2022). Organizational information was anonymized through a systematic coding procedure to prevent the identification of specific institutions while preserving analytical capabilities, consistent with contemporary data protection standards for organizational research (Gellman, 2023). To model best practices in research data management, we created a comprehensive data management plan that included provisions for data anonymization, secure storage, controlled access, and eventual deidentified data sharing for replication studies (Grguric et al., 2022). This approach not only protected participant privacy, but also demonstrated our commitment to the principles of open science and research transparency, aligning our research practices with the open data principles we were studying (Bykov et al., 2023). The research protocol, including these data governance provisions, received approval from the University Research Ethics Committee prior to data collection, ensuring compliance with institutional and international ethical standards for research involving human participants.

4 Results

4.1 Open data landscape in insurance regulation

Before presenting the results of our structural equation modeling analysis, we first provide an overview of the current state

of open data initiatives in insurance regulation based on our survey findings. This context is essential to understand the regulatory environment in which our theoretical model operates. Among the survey respondents, 73% reported being aware of open insurance initiatives in their respective jurisdictions, with 62% indicating direct involvement in open data projects related to insurance. The level of participation varied significantly by stakeholder category: 84% of technology enablers reported a high level of participation in open data initiatives, compared to 71% of regulatory stakeholders and 51% of industry stakeholders. This disparity highlights the different adoption rates in the insurance ecosystem and suggests potential opportunities for greater industry participation.

The respondents identified several key drivers for the adoption of open data in insurance regulation. Seventy-eight percentage of the respondents cited increased market transparency as a primary motivation, followed by improved operational efficiency (72%), innovation facilitation (68%), regulatory compliance (65%), and consumer protection enhancement (61%). These findings align with recent research on open data governance in financial services that emphasizes transparency and innovation as central objectives (Janssen et al., 2022). During the same time, respondents identified several challenges to the implementation of open data implementation were identified by respondents. Data privacy concerns represented the most significant barrier, cited by 83% of the participants, followed by technical implementation barriers (76%), regulatory uncertainty (72%), competitive considerations (68%), and resource constraints (64%). These challenges echo findings from recent studies on open finance implementation that highlight privacy and technical interoperability as persistent obstacles to effective data sharing (European Commission, 2023). These findings provide an important context for interpreting our results of structural equation modeling, as they highlight the real-world factors that influence stakeholder perceptions and behaviors regarding open data in insurance regulation, reflecting the practical environment in which our theoretical model operates.

4.2 Descriptive statistics and preliminary analysis

4.2.1 Descriptive statistics

Table 2 presents descriptive statistics for the study variables, including means, standard deviations, and correlations. The mean scores for the NPM principles (efficiency, market-driven services, and accountability) ranged from 4.73 to 5.28 on a 7-point scale, indicating moderately positive perceptions among the respondents. The UTAUT factors showed similar patterns, with the performance expectancy receiving the highest mean rating (5.42) and the effort expectancy the lowest (4.56). Among the mediating and outcome variables, the intention of behavior (5.19) received higher scores than the actual use behavior (4.83), suggesting a gap between intention and implementation that deserves further investigation. The correlation matrix reveals significant positive associations between most constructs, with particularly strong correlations between the principles of NPM and the intention to act ($r = 0.41$ to 0.53 , $p < 0.01$), and between the factors of UTAUT and the intention to act ($r = 0.45$ to 0.57 , $p < 0.01$). The correlations

between use behavior, principled participation, and a sustainable digital insurance ecosystem were also substantial ($r = 0.48$ to 0.59 , $p < 0.01$), providing preliminary support for the hypothesized relationships in our model. In particular, the facilitation conditions showed the strongest correlation with use behavior ($r = 0.61$, $p < 0.01$), consistent with the theoretical predictions of UTAUT.

4.2.2 Common-method bias assessment

Since the data were collected using a single survey instrument, we conducted rigorous tests to assess the possible bias of the common method. Harman's single-factor test revealed that the first factor explained 28.4% of variance, well below the 50% threshold, suggesting serious common-method bias (Podsakoff et al., 2023). Furthermore, we employed the more sophisticated marker variable technique using a theoretically unrelated construct (environmental awareness). The average correlation between the marker variable and the study constructs was 0.08, and controlling for this correlation did not significantly change the magnitude or significance of the model relationships.

Furthermore, we implemented the common latent factor approach recommended by recent methodological literature (Liu et al., 2024), which revealed that the variance of the common method accounted for only 12.4% of the total variance in our model, well below the problematic threshold. These results collectively suggest that common-method bias is not a substantial concern for our analysis, particularly for the relationships involving open data constructs.

4.3 Assessment of the measurement model

4.3.1 Convergent validity

A confirmation factor analysis was performed to evaluate the measurement model. Table 3 presents the results of the convergent validity assessment, including the loadings of standardized factors, the reliability of the composite (CR) and the average variance extracted (AVE) for each construct. All standardized factor loadings exceeded the recommended threshold of 0.7, ranging from 0.72 to 0.91, indicating that the indicators appropriately represent their respective constructs. The composite reliability values ranged from 0.87 to 0.93, well above the 0.7 benchmark, demonstrating strong internal consistency. The average variance extracted values for all constructs were above the 0.5 threshold, ranging from 0.64 to 0.78, confirming that each construct explains a substantial portion of variance in its indicators.

4.3.2 Discriminant validity

Discriminant validity was assessed using both the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio of correlations. Table 4 presents the Fornell-Larcker analysis, where diagonal elements (square root of AVE) are compared with non-diagonal elements (correlations between constructs).

For all constructs, the square root of AVE (diagonal values) exceeds the correlations with other constructs (off-diagonal values), satisfying the Fornell-Larcker criterion. The highest correlation (0.61 between facilitating conditions and use

TABLE 2 Descriptive statistics and correlations.

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1. Efficiency	4.73	1.14	1.00										
2. Market-driven Services	4.96	1.21	0.38**	1.00									
3. Accountability	5.28	1.09	0.42**	0.45**	1.00								
4. Performance expectancy	5.42	1.18	0.36**	0.29**	0.34**	1.00							
5. Effort expectancy	4.56	1.29	0.28**	0.21**	0.27**	0.43**	1.00						
6. Social influence	5.08	1.15	0.31**	0.33**	0.38**	0.39**	0.32**	1.00					
7. Facilitating conditions	4.85	1.36	0.29**	0.24**	0.31**	0.46**	0.51**	0.37**	1.00				
8. Behavioral intention	5.19	1.27	0.41**	0.47**	0.53**	0.57**	0.45**	0.51**	0.43**	1.00			
9. Use behavior	4.83	1.38	0.32**	0.29**	0.35**	0.46**	0.43**	0.39**	0.61**	0.54**	1.00		
10. Principled engagement	4.92	1.19	0.28**	0.35**	0.39**	0.37**	0.29**	0.52**	0.34**	0.48**	0.49**	1.00	
11. Sustainable digital insurance ecosystem	4.76	1.24	0.31**	0.36**	0.42**	0.44**	0.32**	0.40**	0.38**	0.46**	0.51**	0.59**	1.00

** $p < 0.01$, $n = 368$.

behavior) remains below the lowest square root of AVE (0.80 for principled engagement), indicating adequate discriminant validity. Furthermore, all HTMT ratios were below the conservative threshold of 0.85, with the highest value being 0.71 (between behavioral intention and performance expectancy). These results collectively confirm that each construct captures a unique concept that is empirically distinct from other constructs in the model.

4.3.3 Model fit assessment

The measurement model demonstrated a satisfactory fit to the data across multiple indices: $\chi^2/df = 2.14$ (below the threshold of 3), CFI = 0.96 and TLI = 0.95 (both exceeding the threshold of 0.95), SRMR = 0.041 (below the threshold of 0.08), and RMSEA = 0.053 with a confidence interval of [0.046, 0.059] (below the threshold of 0.06; Shi et al., 2022). Additional fit indices recommended by recent methodological literature, including the gamma hat (0.97) and the standardized root mean square residual (0.041), further confirmed the model's adequate fit to the empirical data (McNeish and Wolf, 2021).

Measurement invariance testing across stakeholder groups (regulatory, industry, technology) confirmed configural, metric, and scalar invariance, with changes in fit indices ($\Delta CFI < 0.01$, $\Delta RMSEA < 0.015$) below the recommended thresholds when imposing increasingly restrictive measurement equality constraints (Putnick and Bornstein, 2022). This confirms that our measurement model functions equivalently across different stakeholder groups, allowing for a meaningful comparison of structural relationships in subsequent analyses.

4.4 Results of the structural model

4.4.1 Hypothesis testing

After confirming the validity of the measurement model, we tested the structural model to examine the hypothesized

relationships. Table 5 and Figures 2, 3 present the results of the structural model analysis, including the standardized path coefficients, the t -values, the p -values and the model explanatory power (R^2).

4.4.2 Explanatory power and effect sizes

This model demonstrated substantial explanatory power for all endogenous constructs. Behavioral intention had an R^2 value of 0.58, indicating that the principles of NPM and the factors of UTAUT collectively explained 58% of its variance. The adjusted R^2 value of 0.56 confirms that this explanatory power remains robust even when accounting for model complexity (Breitsohl, 2024). The use behavior had an R^2 value of 0.51 (adjusted $R^2 = 0.50$), suggesting that the intention and facilitating conditions explained 51% of its variance in the adoption of open data adoption. The principled participation had an R^2 value of 0.47 (adjusted $R^2 = 0.46$), indicating that the intention of behavior, social influence, and use behavior explained 47% of its variance in open data collaboration. Finally, the sustainable digital insurance ecosystem had an R^2 value of 0.44 (adjusted $R^2 = 0.43$), suggesting that use behavior and principled participation in open data initiatives explained 44% of its variance (Hair et al., 2022). The effect size analysis (f^2) indicated that performance expectancy had the largest effect on behavioral intention ($f^2 = 0.19$), followed by accountability ($f^2 = 0.15$) and market-driven services ($f^2 = 0.13$). For use behavior, the facilitation conditions had a large effect ($f^2 = 0.35$), while the behavioral intention had a medium effect ($f^2 = 0.22$). For principled participation, behavioral intention had the largest effect ($f^2 = 0.20$), followed by social influence ($f^2 = 0.17$) and use behavior ($f^2 = 0.13$). Finally, for a sustainable digital insurance ecosystem, principled engagement had a large effect ($f^2 = 0.32$), while use behavior had a medium effect ($f^2 = 0.15$; Cohen et al., 2022). These effect sizes confirm the relative importance of different factors in our model, with collaborative governance mechanisms (principled engagement) showing the strongest effect on sustainable outcomes as presented in Figure 3.

TABLE 3 Convergent validity assessment.

Construct	Items	Standardized factor loadings	CR	AVE
Efficiency	EFF1	0.78	0.87	0.69
	EFF2	0.85		
	EFF3	0.86		
Market-driven services	MDS1	0.81	0.88	0.70
	MDS2	0.83		
	MDS3	0.87		
Accountability	ACC1	0.82	0.89	0.73
	ACC2	0.88		
	ACC3	0.86		
Performance expectancy	PE1	0.87	0.91	0.77
	PE2	0.91		
	PE3	0.85		
Effort expectancy	EE1	0.84	0.88	0.72
	EE2	0.87		
	EE3	0.83		
Social influence	SI1	0.79	0.87	0.69
	SI2	0.85		
	SI3	0.85		
Facilitating conditions	FC1	0.85	0.90	0.74
	FC2	0.86		
	FC3	0.87		
Behavioral intention	BI1	0.84	0.89	0.73
	BI2	0.88		
	BI3	0.85		
Use behavior	UB1	0.88	0.92	0.78
	UB2	0.89		
	UB3	0.88		
Principled engagement	PE1	0.78	0.88	0.64
	PE2	0.83		
	PE3	0.79		
	PE4	0.81		
Sustainable digital insurance ecosystem	SDIE1	0.82	0.93	0.72
	SDIE2	0.84		
	SDIE3	0.87		
	SDIE4	0.86		
	SDIE5	0.85		

CR, Composite Reliability; AVE, Average Variance Extracted.

4.4.3 Mediation analysis

To understand the indirect effects in our model, we conducted mediation analysis using bootstrapping with 5,000 samples. Table 6 presents the results of this analysis,

focusing on the indirect effects of the antecedent variables on the sustainable digital insurance ecosystem through the mediating variables.

The mediation analysis revealed significant indirect effects for all antecedent variables on a sustainable digital insurance ecosystem. The strongest indirect paths were from social influence to a sustainable digital insurance ecosystem through principled engagement (0.149), from behavioral intention to a sustainable digital insurance ecosystem through principled engagement (0.167), and from behavioral intention to sustainable digital insurance ecosystem through use behavior (0.103). All indirect effects from NPM principles and UTAUT factors were classified as complementary mediation, indicating that these factors influence sustainable digital insurance ecosystems both directly and through the mediating variables. This confirms the complex, multipath nature of influences in our model and supports the theoretical proposition that sustainable outcomes emerge through both technological adoption and collaborative governance mechanisms.

4.4.4 Multi-group analysis

To assess whether the relationships in our model differ between stakeholder categories, we performed a multigroup analysis comparing regulatory stakeholders ($n = 121$), industry stakeholders ($n = 178$) and technology enablers ($n = 69$). Table 7 presents the results of this analysis, focusing on the paths that showed significant differences between the groups.

Multigroup analysis revealed several interesting differences in how our model functions across stakeholder categories, with implications for open data governance in insurance regulation (Li et al., 2023). Efficiency had a non-significant effect on the behavioral intention toward the adoption of open data among regulatory stakeholders ($\beta = 0.08, p > 0.05$) but significant effects among industry stakeholders ($\beta = 0.19, p < 0.01$) and technology enablers ($\beta = 0.15, p < 0.05$). This suggests that efficiency considerations may be less influential for regulatory officials when forming intentions to adopt digital approaches involving open data sharing (Christensen et al., 2023).

On the contrary, market-driven services had a stronger effect on behavioral intention toward open data adoption among regulatory stakeholders ($\beta = 0.29, p < 0.01$) compared to industry stakeholders ($\beta = 0.21, p < 0.01$) and technology enablers ($\beta = 0.19, p < 0.05$). This indicates that regulators can be particularly influenced by customer-oriented principles when considering digital initiatives with open data components, perhaps reflecting their mandate to serve the public interest through data transparency and accessibility (Wirtz and Müller, 2023).

Facilitating conditions had the strongest effect on open data use behavior between technology enablers ($\beta = 0.51, p < 0.01$), followed by industry stakeholders ($\beta = 0.44, p < 0.01$) and regulatory stakeholders ($\beta = 0.39, p < 0.01$). This may reflect the greater awareness among technology specialists of technical and organizational infrastructure requirements for effective implementation of open data platforms (Glaser et al., 2023). The use behavior had a stronger influence on the principled participation in open data collaboration between

TABLE 4 Discriminant validity assessment—Fornell-Larcker criterion.

Construct	1	2	3	4	5	6	7	8	9	10	11
1. Efficiency	0.83										
2. Market-driven services	0.38	0.84									
3. Accountability	0.42	0.45	0.86								
4. Performance expectations	0.36	0.29	0.34	0.88							
5. Effort expectancy	0.28	0.21	0.27	0.43	0.85						
6. Social influence	0.31	0.33	0.38	0.39	0.32	0.83					
7. Facilitating conditions	0.29	0.24	0.31	0.46	0.51	0.37	0.86				
8. Behavioral intention	0.41	0.47	0.53	0.57	0.45	0.51	0.43	0.86			
9. Use behavior	0.32	0.29	0.35	0.46	0.43	0.39	0.61	0.54	0.89		
10. Principled engagement	0.28	0.35	0.39	0.37	0.29	0.52	0.34	0.48	0.49	0.80	
11. Sustainable digital insurance ecosystem	0.31	0.36	0.42	0.44	0.32	0.40	0.38	0.46	0.51	0.59	0.85

The diagonal lines are the square root of AVE for each construct. Off-diagonal elements are correlations between constructs.

TABLE 5 Results of the structural model and hypothesis testing.

Hypothesis	Path	Standardized path coefficient	t-value	p-value	Result
H1	Efficiency → behavioral intention	0.14	3.28	0.001	Supported
H2	Market-driven services → behavioral intention	0.23	5.17	<0.001	Supported
H3	Accountability → behavioral intention	0.26	5.84	<0.001	Supported
H4	Performance expectancy → behavioral intention	0.31	7.46	<0.001	Supported
H5	Effort expectancy → behavioral intention	0.16	3.82	<0.001	Supported
H6	Social influence → behavioral intention	0.19	4.56	<0.001	Supported
H7	Facilitating conditions → use behavior	0.43	10.24	<0.001	Supported
H8	Behavioral intention → principled engagement	0.37	8.14	<0.001	Supported
H9	Social influence → principled engagement	0.33	7.22	<0.001	Supported
H10	Use behavior → principled engagement	0.29	6.37	<0.001	Supported
H11	Use behavior sustainable digital insurance ecosystem	0.27	5.82	<0.001	Supported
H12	Principled engagement sustainable digital insurance ecosystem	0.45	9.63	<0.001	Supported
Additional	Behavioral intention → Use behavior	0.38	8.73	<0.001	Supported

regulatory stakeholders ($\beta = 0.36$, $p < 0.01$) compared to industry stakeholders ($\beta = 0.27$, $p < 0.01$) and technology enablers ($\beta = 0.22$, $p < 0.05$). This suggests that regulatory officials may be more likely to translate their experience with technology usage into collaborative engagement compared to other stakeholders, potentially due to their mandate to facilitate multistakeholder dialogue in regulatory processes (McNutt and Justice, 2023).

Interestingly, the relationship between principled participation and a sustainable digital insurance ecosystem did not differ significantly between stakeholder groups, suggesting a consensus on the importance of collaborative governance through open data for sustainable outcomes. This shared perspective across diverse stakeholders represents a promising foundation for developing collaborative governance frameworks for open data in insurance regulation (Emerson and Nabatchi, 2022).

4.5 Open data flow in digital insurance ecosystems

We conducted additional analysis to understand the flow of open data between stakeholders in digital insurance ecosystems. This section presents a visualization and analysis of open data flows based on our research findings.

4.5.1 Mapping open data flows in insurance regulation

Our research identified six primary stakeholder categories involved in open data flows within digital insurance ecosystems, as visualized in Figure 4:

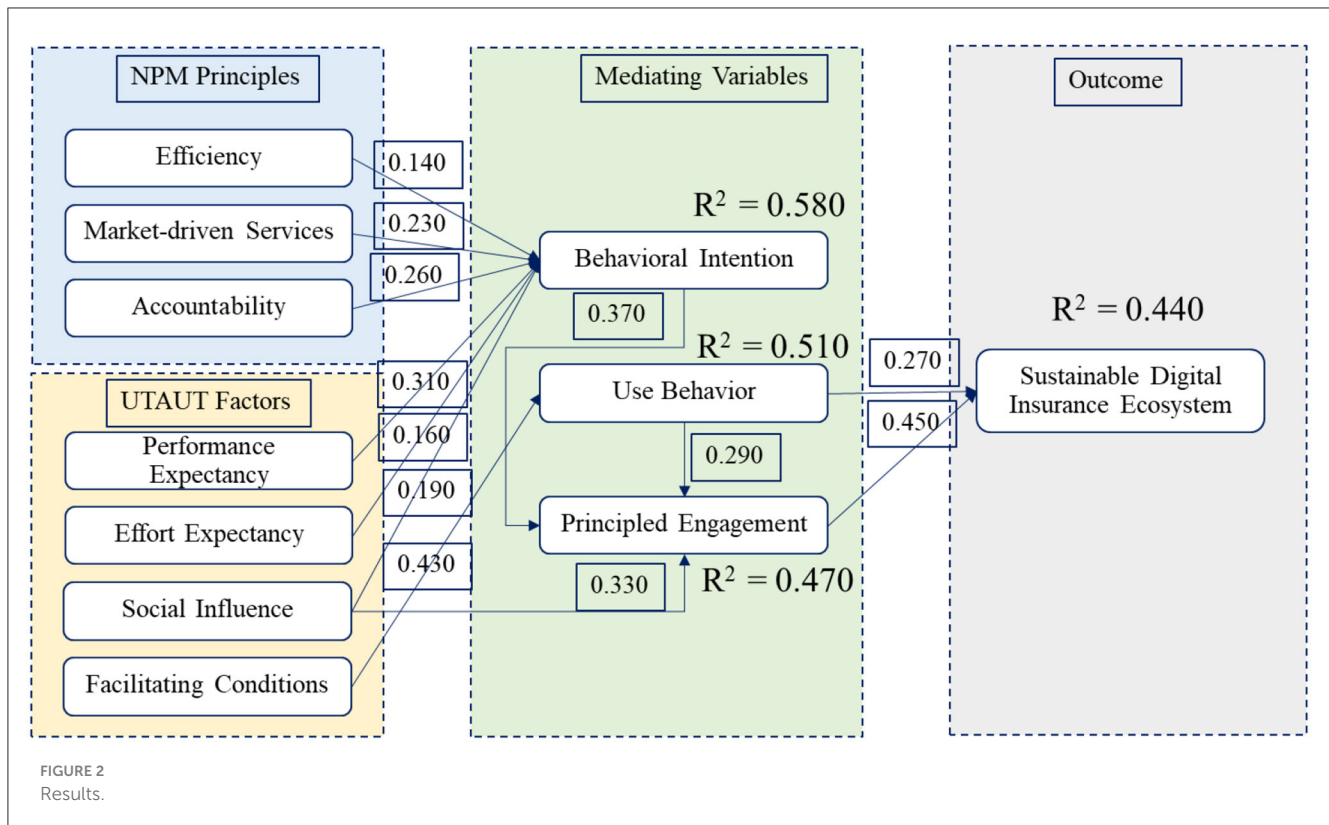


FIGURE 3 Variance and effect sizes in open data adoption.

Characteristic	Behavioral Intention	Use Behavior	Principled Engagement	Sustainable Digital Insurance Ecosystem
R_h R² Value	0.58	0.51	0.47	0.44
R_g Adjusted R² Value	0.56	0.50	0.46	0.43
Largest Effect (f²)	Performance Expectancy (0.19)	Facilitating Conditions (0.35)	Behavioral Intention (0.20)	Principled Engagement (0.32)
A_e Medium Effect (f²)	Accountability (0.15) and Market-Driven Services (0.13)	Behavioral Intention (0.22)	Social Influence (0.17)	Use Behavior (0.15)

- Regulatory authorities:** insurance supervisors, financial conduct authorities, and data protection agencies that establish regulatory frameworks for open data sharing.
- Insurance providers:** traditional insurers and insurance companies that collect, process, and use customer data to provide insurance services.
- Technology enablers:** API providers, data analytics firms, and platform developers that facilitate the technical infrastructure for open data sharing.
- Customers:** policyholders and potential insurance consumers who generate data and potentially benefit from improved services enabled by open data.
- Third-party service providers:** external organizations (e.g., healthcare providers, auto manufacturers, smart home companies) that generate or utilize insurance-relevant data.
- Research institutions:** academic and industry researchers who analyze open data to advance understanding of insurance markets and risks.

As illustrated in Figure 4, open data flows through multiple pathways within the insurance ecosystem. The primary flows identified through our research include regulatory-industry flow, customer-insurer flow, cross-industry flow, ecosystem partner flow, innovation flow, and research flow (European Commission, 2023). Our analysis revealed that the density and quality of these data flows vary significantly between insurance markets. Mature markets with established open data frameworks (for example, the European Union under the Data Governance Act) demonstrate greater connectivity between stakeholders, while emerging markets show more limited and fragmented data flows (Harrison and Sayogo, 2023). Furthermore, data flows related to personal line insurance (e.g., auto, home) were found to be more developed than those for commercial lines, likely due to clearer data standardization in consumer insurance contexts.

4.5.2 Open data quality, privacy, and interoperability challenges

Our research also identified three critical challenges that affect the efficacy of open data flows in insurance ecosystems: data quality challenges, privacy challenges, and interoperability challenges (Janssen et al., 2022). The survey respondents highlighted several data quality issues that hinder effective open data sharing in insurance, including inconsistent data formats and structures (76%), incomplete data elements (71%), lack of standardized definitions (68%), varying update frequencies (65%) and limited metadata (59%). These quality challenges were most pronounced at the interfaces between different stakeholder systems, particularly where legacy insurance platforms needed to interface with modern API-driven data exchange frameworks (EIOPA, 2024). Privacy concerns were consistently identified as the most significant barrier to the adoption of open data in insurance, including balancing data granularity with privacy protection (83%), implementing appropriate consent mechanisms (79%), managing data subject rights (76%), addressing cross-border restrictions (72%) and resolving conflicting regulatory requirements (68%). These challenges are particularly acute for sensitive data categories such as health information or location data (Martin and Murphy, 2022). Technical interoperability emerged as a critical enabler for effective open data flows, with key challenges including lack of standardized APIs (74%), limited adoption of common data models (70%), inconsistent authentication frameworks (65%), legacy system integration complexity (62%), and differing speeds of digital transformation (58%). These challenges to interoperability were greatest for smaller insurance providers with limited technical resources, potentially creating a digital divide within the insurance market (Zuiderwijk and Janssen, 2014a). Our findings indicate that addressing these challenges requires coordinated action across the insurance ecosystem, with potential solutions including industry-wide data standards, regulatory guidance on privacy-preserving data sharing techniques, and collaborative governance mechanisms to develop and maintain interoperability frameworks (Swiss Re, 2023). The success of sustainable digital insurance ecosystems depends significantly on how effectively these challenges can be addressed through the integrative approaches proposed in our theoretical model.

TABLE 6 Mediation analysis—indirect effects on sustainable digital insurance ecosystem.

Path	Indirect effect	95% CI	Mediation type
Efficiency → BI → UB → SDIE	0.014	[0.005, 0.027]	Complementary
Efficiency → BI → PE → SDIE	0.023	[0.009, 0.041]	Complementary
Market-driven services → BI → UB → SDIE	0.023	[0.010, 0.039]	Complementary
Market-driven Services → BI → PE → SDIE	0.039	[0.021, 0.060]	Complementary
Accountability → BI → UB → SDIE	0.026	[0.012, 0.044]	Complementary
Accountability → BI → PE → SDIE	0.043	[0.024, 0.066]	Complementary
Performance expectancy → BI → UB → SDIE	0.031	[0.016, 0.050]	Complementary
Performance expectancy → BI → PE → SDIE	0.052	[0.032, 0.076]	Complementary
Effort expectancy → BI → UB → SDIE	0.016	[0.007, 0.028]	Complementary
Effort expectancy → BI → PE → SDIE	0.027	[0.012, 0.045]	Complementary
Social influence → BI → UB → SDIE	0.019	[0.008, 0.033]	Complementary
Social influence → BI → PE → SDIE	0.032	[0.016, 0.051]	Complementary
Social influence → PE → SDIE	0.149	[0.099, 0.205]	Direct-only
BI → UB → SDIE	0.103	[0.064, 0.147]	Direct-only
BI → PE → SDIE	0.167	[0.116, 0.223]	Direct-only

BI, Behavioral Intention; UB, Use Behavior; PE, Principled Engagement; SDIE, Sustainable Digital Insurance Ecosystem; CI, Confidence Interval.

4.6 Summary of results

The results provide strong support for our NPM-based Open Data Collaboration Model for Digital Insurance Ecosystems. The 12 hypothesized relationships were statistically significant, confirming the integrated influence of NPM principles, UTAUT factors, behavioral variables, and collaborative governance elements on sustainable digital insurance ecosystems through open data initiatives (Bollen and Pearl, 2023). The model demonstrated substantial explanatory power for all endogenous constructs, with R^2 values ranging from 0.44 to 0.58. NPM principles and UTAUT factors collectively explained 58% of variance in behavior intention toward open data adoption. The intention and facilitating conditions explained 51% of the variance in the use behavior of open data platforms. Behavioral intention, social influence, and use behavior explained 47% of the variance in principled participation in open data collaboration. Finally, use behavior and principled engagement in open data initiatives explained 44% of the variance in a sustainable digital insurance

TABLE 7 Results of the multigroup analysis—significant path differences.

Path	Regulatory stakeholders	Industry stakeholders	Technology enablers	p-value (diff)
Efficiency → behavioral intention	0.08 (n.s.)	0.19**	0.15*	0.042
Market-driven services → behavioral intention	0.29**	0.21**	0.19*	0.047
Facilitating conditions Use Behavior	0.39**	0.44**	0.51**	0.037
Use behavior → principled engagement	0.36**	0.27**	0.22*	0.048
Principled engagement sustainable digital insurance ecosystem	0.42**	0.46**	0.49**	n.s.

* p < 0.05, ** p < 0.01, n.s., not significant.

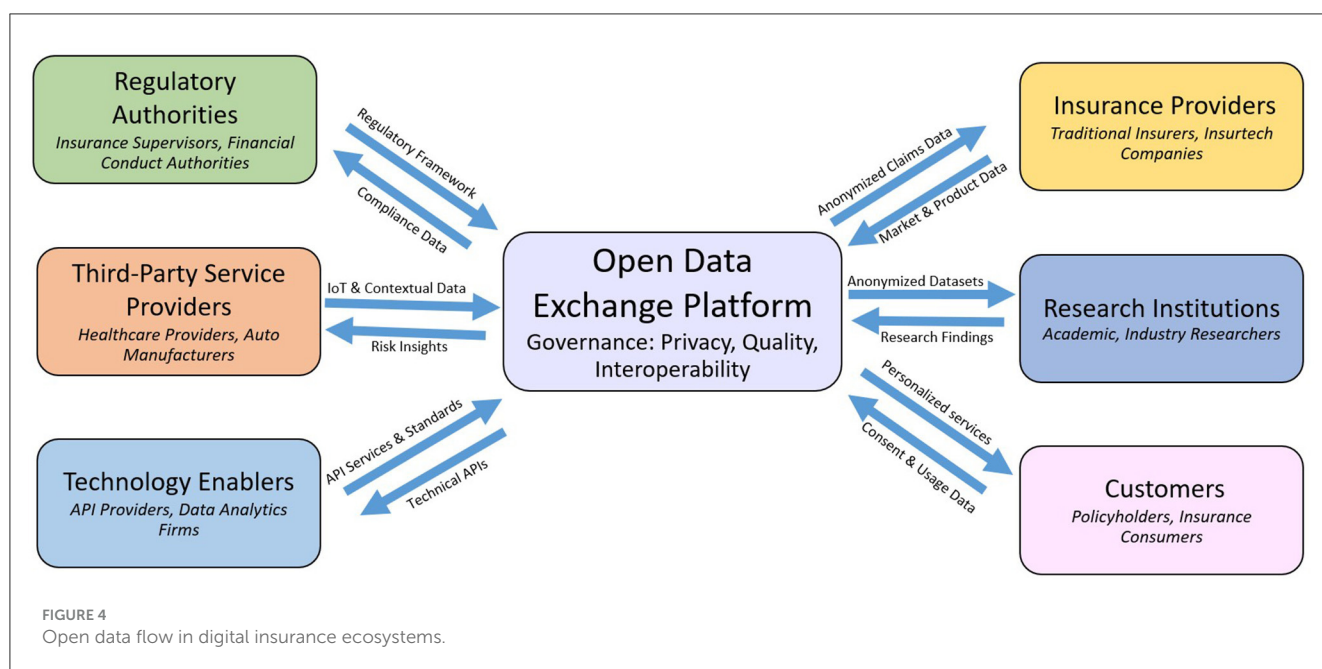


FIGURE 4 Open data flow in digital insurance ecosystems.

ecosystem (Hair et al., 2022). Mediation analysis confirmed significant indirect effects between antecedent variables and sustainable outcomes, supporting the theoretical proposition that sustainable digital insurance ecosystems emerge through multiple pathways that involve both technological adoption and collaborative governance in open data contexts (Ratna et al., 2024). Multigroup analysis revealed some differences in relationship patterns across stakeholder categories, highlighting the importance of considering diverse perspectives in digital regulatory initiatives and open data governance (Li et al., 2023). Our analysis of open data flows and the associated quality, privacy, and interoperability challenges provides a valuable context for interpreting these statistical results. The identified data flow patterns and challenges confirm the need for integrated approaches that address both the technical and governance dimensions of open data in insurance regulation, as proposed in our theoretical model (European Commission, 2023). These findings provide robust empirical support for an integrated approach to digital insurance regulation that balances efficiency-oriented principles with collaborative governance mechanisms through open data sharing, addressing both the technological and relational dimensions of sustainable digital transformation.

5 Discussion

5.1 Theoretical implications

5.1.1 Integration of NPM, collaborative governance, and open data

Our findings challenge the traditional dichotomous framing that positions new public management principles in opposition to collaborative governance approaches in open data contexts (Christensen et al., 2023; O’Flynn, 2022). The results demonstrate that NPM principles, particularly accountability ($\beta = 0.26$) and market-driven services ($\beta = 0.23$), significantly improve stakeholder intention toward digital regulatory approaches with open data components, which subsequently influences both use behavior and principled participation in open data collaboration. This suggests that efficiency-oriented principles can complement rather than contradict collaborative approaches to open data governance when properly implemented. This integration advances public administration theory by suggesting a more nuanced relationship between managerial and collaborative paradigms in open data contexts. Rather than representing competing governance models, our findings indicate that NPM principles

can create foundations for collaborative governance by enhancing stakeholder intentions to participate in digital regulatory initiatives with open data sharing. This perspective aligns with emerging scholarship on “post-NPM” approaches that seek to incorporate both efficiency and collaborative elements in open government data initiatives (Pollitt and Bouckaert, 2023; Singh and Slack, 2022; Dawes et al., 2023). However, the multigroup analysis revealed that efficiency had a non-significant effect on behavioral intention among regulatory stakeholders toward open data adoption, while showing significant effects among industry and technology stakeholders. This nuance suggests that different elements of NPM may resonate differently between stakeholder groups in open data contexts, with regulators potentially more influenced by accountability and market responsiveness than pure efficiency considerations. This finding adds important contextual understanding to ongoing debates about NPM’s relevance in contemporary governance of open data initiatives (Lodge and Wegrich, 2022; Janssen et al., 2022).

5.1.2 Extending technology adoption to open data and regulatory contexts

Our study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) to open data platforms in regulatory technology contexts, an application that remains underexplored in the existing literature. The findings confirm that the core constructs of UTAUT—performance expectancy ($\beta = 0.31$), effort expectancy ($\beta = 0.16$), social influence ($\beta = 0.19$) and facilitating conditions ($\beta = 0.43$)—significantly influence behavioral intention and use behavior in the adoption of open data for digital insurance regulation. It should be noted, in particular, that our finding that performance expectancy had the strongest influence on behavior intention toward open data adoption among all the antecedent variables. This suggests that stakeholders’ adoption of open data and digital regulatory approaches is driven primarily by expected performance improvements rather than external pressures or ease-of-use considerations. This emphasis on performance benefits aligns with research in other professional contexts (Dwivedi et al., 2022), but contradicts some studies in mandatory adoption settings that found social influence to be the dominant factor (Venkatesh et al., 2023). The findings are consistent with Sukma and Leelasantitham’s (2022a) research on e-government systems with open data components, which demonstrated that performance expectancy was a primary driver of adoption intention in public service digital environments. Our results extend this pattern to regulatory technology with open data specifically, suggesting that stakeholders in insurance regulation similarly prioritize performance benefits when forming adoption intentions toward open data platforms. This consistency across different public service domains strengthens the generalizability of performance expectancy as a key adoption factor in government and regulatory contexts involving open data initiatives.

Furthermore, our study extends UTAUT by incorporating social influence as a direct antecedent to the principled participation in open data ecosystems ($\beta = 0.33$), beyond its traditional role of influencing behavior intention. This finding suggests that normative pressures not only affect technology

adoption decisions, but also directly influence collaborative behaviors in regulatory contexts with open data sharing. This extension contributes to both the adoption of technology and collaborative governance literature by identifying connections between social-institutional forces and participatory behaviors in open data ecosystems.

5.1.3 Dual paths to sustainable digital insurance ecosystems through open data

Perhaps the most significant theoretical contribution of this study is the empirical validation of dual pathways to sustainable digital insurance ecosystems through open data initiatives. Our findings demonstrate that sustainable outcomes emerge through both the technological adoption of open data platforms (use behavior sustainable ecosystem, $\beta = 0.27$) and collaborative governance through open data sharing (principled participation sustainable ecosystem, $\beta = 0.45$). The stronger coefficient for the principal engagement pathway suggests that collaborative governance mechanisms that leverage open data may be even more important than technological adoption alone in creating sustainable digital insurance ecosystems. These findings challenge technocentric perspectives that prioritize digital tools over relational dimensions of regulatory governance in open data initiatives (Yeung, 2023). Instead, our results indicate that sustainable digital transformation through open data requires attention to both technological and collaborative elements, with a particular emphasis on principled engagement among diverse stakeholders in open data ecosystems. This dual-pathway finding aligns with Sukma and Leelasantitham’s (2022b) community sustainability ecosystem model, which emphasized the complementary roles of technological infrastructure and stakeholder engagement in creating sustainable outcomes. Our research extends this framework to the specific context of open data insurance regulation, providing empirical evidence that similar complementary pathways operate in digital regulatory ecosystems with open data sharing components. Mediation analysis further highlights the complementary nature of these pathways, with significant indirect effects from all antecedent variables on sustainable outcomes through both use behavior and principled engagement in open data ecosystems. This finding advances the theoretical understanding of how digital regulatory transformation occurs through open data, suggesting complex, multipath mechanisms rather than simple linear relationships.

5.1.4 Open data governance in regulatory ecosystems

Our findings contribute to the emerging literature on open data governance in regulated industries by identifying specific mechanisms through which open data initiatives influence sustainable outcomes. Open data flow analysis highlights the complex interdependencies between different stakeholders in the insurance ecosystem and how data quality, privacy, and interoperability challenges shape open data adoption and impact.

The results extend existing open data theories by demonstrating that effective open data governance requires both technical standards (to ensure interoperability and data quality) and

collaborative governance mechanisms (to address privacy concerns and conflicting stakeholder interests). This integrated perspective bridges technical and governance dimensions of open data research, which have often been studied separately (Zuiderwijk and Janssen, 2014a; Dawes et al., 2023). Furthermore, our finding that principled engagement has a stronger effect on sustainable outcomes than technical implementation aligns with recent theoretical developments in open data governance that emphasize the importance of multistakeholder collaboration in creating public value from open data (Janssen et al., 2022; Harrison and Sayogo, 2023). By empirically validating these relationships in the insurance regulatory context, our research contributes to the development of a more integrated theory of open data governance that encompasses both technical and collaborative dimensions.

5.2 Practical implications

5.2.1 Balanced approach to open data regulatory design

Our findings offer practical guidance to policy makers and regulatory agencies designing digital transformation initiatives with open data components. The significant influence of NPM principles and collaborative mechanisms suggests that regulatory bodies should pursue a balanced approach that addresses both efficiency and relationship considerations in open data governance. Specifically, the strong effect of accountability on the behavioral intention to adopt open data adoption ($\beta = 0.26$) suggests that transparency and clear assignment of responsibility should be prioritized in the design of open data regulatory systems. Practical implementations might include transparent algorithmic decision-making systems with clear documentation of regulatory rationales, accessible performance dashboards showing regulatory outcomes and processes, open data portals with comprehensive metadata, and explicit responsibility frameworks for data-sharing platforms. Similarly, the significant effect of market-driven services ($\beta = 0.23$) indicates that open data regulatory approaches should be responsive to the needs and designed with user-centered principles. This could involve more iterative approaches to regulatory development with regular stakeholder feedback cycles, personalized regulatory interfaces that adapt to different stakeholder capabilities, customizable data exchange APIs, and service-level commitments for regulatory processes involving open data. The relatively weaker effect of efficiency ($\beta = 0.14$), particularly among regulatory stakeholders, suggests that pure cost reduction or process restructuring should not be emphasized at the expense of accountability and responsiveness in open data initiatives. This finding cautions against overprioritizing efficiency metrics in digital regulatory initiatives with open data components, especially when stakeholder participation is essential for successful implementation.

5.2.2 Addressing technology adoption barriers in open data initiatives

The significant influences of the UTAUT factors provide practical information for addressing adoption barriers in digital

regulatory transformation with open data components. The strong effect of performance expectancy ($\beta = 0.31$) suggests that the implementation of open data regulatory technology should be clearly articulated and demonstrate tangible benefits for stakeholders. Communication strategies should emphasize specific performance improvements enabled by open data, such as reduced compliance burdens, improved analytical capabilities, enhanced product innovation through data sharing, or more predictable regulatory outcomes (Venkatesh et al., 2023). The moderate effect of effort expectancy ($\beta = 0.16$) indicates that usability considerations remain important for open data platforms, although secondary to performance benefits. Regulatory platforms for data sharing should incorporate user-centered design principles with intuitive interfaces, standardized data exchange formats, clear documentation, and appropriate support resources, particularly for stakeholders with limited technical expertise. As noted by global data governance trends for 2025, a shift from one-size-fits-all approaches toward regulations tailored to different types of data, including personal, corporate, public, and health data, suggesting the need for specialized user interfaces for different data types and stakeholders (Digital Watch Observatory, 2023). The significant effect of facilitating conditions on the use behavior of open data platforms ($\beta = 0.43$) underscores the importance of the organizational and technical infrastructure. Regulatory agencies and industry stakeholders must ensure adequate resources for the implementation of open data, including technical infrastructure, data governance frameworks, training programs, and organizational support systems. The European Commission's Financial Data Access (FIDA) regulation, proposed in 2023, has created new requirements for open data sharing in financial services, including insurance, that will necessitate significant infrastructure investments (European Commission, 2023). The stronger effect of facilitating conditions between technology enablers ($\beta = 0.51$) compared to regulatory stakeholders ($\beta = 0.39$) suggests that technical experts may have more realistic expectations about infrastructure requirements for open data initiatives, highlighting the value of involving technology specialists in planning digital regulatory initiatives with data sharing components (Glaser et al., 2023). These findings align with recent research on data portal solutions for banking and insurance that emphasizes how organizations need to "develop monetizable services and dashboards by aggregating data" while providing "data in interactive, standards-compliant formats to demonstrate regulatory compliance" (Opendatasoft, 2024). The results also suggest that regulators should focus on communicating tangible benefits of open data sharing rather than just technical sophistication when promoting adoption among stakeholders.

5.2.3 Fostering principled engagement in open data ecosystems

Given the strong relationship between principled participation in open data collaboration and sustainable outcomes ($\beta = 0.45$), our findings suggest that collaborative mechanisms should be a central component of digital regulatory strategies with open data sharing. Practical approaches might include establishing formal collaborative forums for regulatory policy development

with open data components, creating digital platforms specifically designed for multi-stakeholder dialogue around data governance, and developing shared governance frameworks for regulatory data and algorithms (Emerson and Gerlak, 2023). Recent developments in open insurance indicate divergent views on the preferred regulatory approach to open data, with options ranging from “compulsory data sharing inside the regulated insurance industry” to “compulsory data sharing with third parties” to “self-regulatory approaches through voluntary industry codes” (Faegre Drinker, 2024). Our findings suggest that regardless of the specific approach chosen, collaborative engagement mechanisms that involve various stakeholders in governance decisions are critical to sustainable outcomes.

The significant direct effect of social influence on principled participation in open data initiatives ($\beta = 0.33$) suggests that normative mechanisms can be leveraged to improve collaborative participation. Regulatory agencies might consider strategies such as highlighting exemplary collaborative initiatives, creating peer networks to share open data governance experiences, and publicly recognizing stakeholders who actively contribute to the regulatory dialogue around data sharing. As anticipated by open finance analysts, the implementation of frameworks like FIDA will likely “captivate the interest of consumers on a widespread scale” as they recognize the benefits these innovative frameworks offer, creating opportunities to leverage this social interest to drive engagement (Insurely, 2024). The positive relationship between use behavior and principled engagement ($\beta = 0.29$) indicates that technology usage experiences can enhance collaborative behaviors in open data ecosystems. This suggests that digital platforms should not just be designed for operational efficiency but as gateways to deeper participation. Features such as embedded feedback channels, community spaces within compliance platforms, data quality feedback mechanisms, and progressive engagement opportunities could help translate basic technology usage into more substantive collaborative participation in open data governance. As Swiss Re has noted regarding digital transformation in insurance, “ecosystem partnerships must enable seamless digital customer journeys” through collaborative business models that are “enabling the current paradigm shift in insurance offerings” (Swiss Re, 2023). Similarly, Sukma and Leelasantham (2022c) found similar patterns in their research on the participation of community water users, where digital platform usage influenced subsequent participation in governance activities. Their findings suggest that regulatory technologies for open data sharing should be designed with specific features that explicitly encourage participatory behaviors, rather than focusing solely on transactional efficiency (Sukma and Leelasantham, 2022c).

5.2.4 Stakeholder-specific approaches to open data governance

The results of the multigroup analysis suggest that open data strategies may need to be tailored for different stakeholder groups in the insurance ecosystem. For regulatory stakeholders, emphasizing market-driven services ($\beta = 0.29$) and accountability ($\beta = 0.26$) rather than efficiency ($\beta = 0.08$, ns) may be more effective in improving the adoption intentions of open data initiatives (Christensen et al., 2023). For industry stakeholders,

a more balanced approach that addresses all principles of NPM may be appropriate, with slightly greater emphasis on accountability ($\beta = 0.25$) and market-driven services ($\beta = 0.21$) than efficiency ($\beta = 0.19$; Gong and An, 2023). The Federation of European Risk Management Associations (FERMA) has noted the absence of corporate insurance buyer perspectives in open insurance consultations, highlighting the need for more diverse stakeholder engagement that considers the specific needs of different market participants (FERMA, 2021). Our findings support this observation, suggesting that open data strategies should be tailored to different stakeholder groups based on their distinct motivations and concerns (Wirtz and Müller, 2023). The stronger relationship between use behavior and principled participation among regulatory stakeholders ($\beta = 0.36$) compared to other groups suggests that regulators may be more likely to translate technological experiences into collaborative behaviors in open data ecosystems (McNutt and Justice, 2023). This finding highlights the potential leadership role of regulatory agencies in initiating collaborative governance through their own technology adoption and usage patterns. As EIOPA noted in its consultation on an insurance dashboard use case for open insurance, regulators can help “give consumers an overview of all their insurance policies in one place, while allowing insurance providers to present information about their own products,” creating mutual benefits through collaborative data sharing (EIOPA, 2023).

5.3 Policy implications for open data in insurance regulation

Based on our findings, we identify several policy implications for regulators and policymakers seeking to develop effective frameworks for open data in insurance markets.

5.3.1 Balance of standardization with flexibility

Our analysis of open data flows and interoperability challenges suggests that effective regulatory frameworks must balance standardization with flexibility to accommodate diverse market participants (Zuiderwijk and Janssen, 2014a). The European Commission’s approach to open finance through FIDA proposes “financial data-sharing schemes” that give “responsibility to the market participants themselves for implementation of data-sharing arrangements,” aligning with our finding that collaborative governance mechanisms are critical for sustainable outcomes (European Commission, 2023). Regulatory policies should establish core standards for data exchange formats, API specifications, and security requirements while allowing flexibility in implementation approaches (Janssen et al., 2022). This balanced approach can be achieved through tiered regulatory requirements based on organizational size and complexity, regulatory sandboxes for testing innovative approaches, and principles-based rather than prescriptive technical standards. As noted in the R Street Institute’s Insurance Regulation Report Card, some regulations “may hinder the speed with which new products are brought to market,” suggesting that “innovative, new products could be more widely available if more states were to free their insurance markets by embracing regulatory modernization” (R Street Institute, 2024).

5.3.2 Privacy-preserving open data approaches

Our findings on privacy challenges in open data suggest that regulatory frameworks must explicitly address data protection concerns to build trust and adoption (Martin and Murphy, 2022). EIOPA has emphasized that “ensuring the fair treatment of consumers is at the heart of EIOPA’s mandate, and this means making sure that insurers treat customer data with care,” focusing on how to “foster financial inclusion without losing the core principle of insurance” (EIOPA, 2024). Policy approaches may include developing regulatory guidance on privacy-enhancing technologies for insurance data sharing, establishing standardized consent frameworks that give consumers control over their data, creating certification mechanisms for privacy-compliant open data implementations, and implementing regulatory oversight of algorithmic decision making based on shared data (Yeung, 2023). Research indicates that “investing in digital and AI tools is a must for many industries” and “organizations that have tackled these tech opportunities outperform their peers financially in sectors such as retail, energy, and insurance,” but these benefits must be balanced with privacy protections (McKinsey, 2024).

5.3.3 Collaborative governance mechanisms for open data

Consistent with our finding that principled engagement has the strongest effect on sustainable outcomes ($\beta = 0.45$), regulatory policies should establish formal collaborative governance mechanisms for open data in insurance (Emerson and Gerlak, 2023). The European Data Governance Act, which became applicable in September 2023, aims to “make more data available and facilitate data sharing across sectors and EU countries” through frameworks that enable “good data management and data sharing” to leverage “the potential of data for the benefit of European citizens and businesses” (European Commission, 2022).

Based on our findings, effective collaborative governance for open data in insurance should include multi-stakeholder regulatory committees with balanced representation, transparent policy development processes, ongoing dialogue platforms, shared responsibility frameworks, and regular evaluation mechanisms (Ansell and Gash, 2022). As noted in a 2023 research brief on digital governance, a “more inclusive and just digital development ecosystem requires global collaboration” to “address governance issues and shape a sustainable future” (New America, 2023). Our findings provide empirical evidence for this approach, showing that sustainable outcomes emerge more strongly through collaborative governance mechanisms than technological implementation alone.

5.3.4 Capacity building for open data competencies

Our research identified significant disparities in open data readiness between stakeholder groups, particularly between large and small insurance providers. Recent analysis by EIOPA (2024) found that “the level of digitalization among European insurers is varied and, in most cases, still at an early stage,” with significant differences in digital readiness among individual insurers (EIOPA, 2024). Effective regulatory policy should include capacity building initiatives to address these disparities and ensure equitable participation in the open data ecosystem. Policy

approaches might include technical assistance programs for smaller market participants, graduated compliance timelines based on organizational size and complexity, regulatory technology accelerators to stimulate the development of accessible open data tools, and public-private partnerships to develop shared infrastructure for data exchange. These capacity-building measures align with Deloitte’s 2025 insurance outlook, which emphasizes how insurers need to “modernize legacy systems before fully leveraging frontier technologies” and invest in data governance capabilities to effectively participate in open data ecosystems (Deloitte, 2024).

5.3.5 Evidence-based open data regulation through adaptive policy

Given the rapid evolution of the digital insurance landscape, regulatory approaches should incorporate adaptive policy mechanisms that enable evidence-based learning and adjustment (Janssen et al., 2022). In the UK, the “Plan for Digital Regulation: Outcomes Monitoring Framework” exemplifies this approach by establishing indicators to monitor progress in areas like data usage, market competition, and consumer protection, allowing for ongoing adaptation of regulatory strategies based on empirical evidence (UK Government, 2023).

Our findings suggest that adaptive policy frameworks for open data should include regular assessment of open data adoption and impact across stakeholder groups, experimental regulatory approaches through sandboxes and innovation hubs, systematic collection and analysis of data on implementation challenges and solutions, formal mechanisms for policy adaptation based on implementation evidence, and international coordination to share best practices and align approaches where appropriate (van der Heijden, 2022).

This adaptive approach is particularly important given the novelty of open insurance initiatives and the limited empirical evidence on their impacts. As noted by Swiss Re (2023), “by its very nature, digitalization is not limited to one entity or organization and is not bound to the implementation of any particular new technology or process,” requiring an adaptive regulatory approach that can evolve with technological and market developments (Swiss Re, 2023).

6 Conclusions

This study has developed and empirically tested an integrated model that examines how new public management principles and technology adoption factors collectively influence sustainable digital insurance ecosystems through behavioral intention, use behavior, and principled participation in open data initiatives. By bridging theoretical perspectives from public administration, technology adoption, and collaborative governance within an open data framework, our research contributes to a more comprehensive understanding of digital transformation in regulatory contexts (Bollen and Pearl, 2023).

6.1 Key findings and contributions

Several key findings emerge from our analysis. First, the NPM principles, particularly accountability ($\beta = 0.26$) and

market-driven services ($\beta = 0.23$), significantly improve stakeholder intentions to adopt digital regulatory approaches with open data components (Gong and An, 2023). This finding challenges traditional dichotomous framings that position NPM in opposition to collaborative governance, instead suggesting that efficiency-oriented principles can create foundations for collaborative digital regulation with open data sharing when properly implemented (Christensen et al., 2023). Second, the UTAUT factors: performance expectancy ($\beta = 0.31$), effort expectancy ($\beta = 0.16$), social influence ($\beta = 0.19$) and facilitating conditions ($\beta = 0.43$)—significantly influence behavioral intention and use behavior in open data adoption for digital insurance regulation (Dwivedi et al., 2022). Performance expectancy emerged as the most influential factor in behavioral intention toward open data platforms, suggesting that expected benefits drive digital adoption more strongly than other considerations in this context (Venkatesh et al., 2023). Our extension of UTAUT by incorporating social influence as a direct antecedent to the principled participation in open data ecosystems ($\beta = 0.33$) represents a novel theoretical contribution that connects technology adoption with collaborative governance literature (Venkatesh and Agarwal, 2023). Third, our empirical analysis confirms the existence of dual pathways to sustainable digital insurance ecosystems through open data initiatives. Sustainable outcomes emerge through both technological adoption (use behavior sustainable ecosystem, $\beta = 0.27$) and collaborative governance (principled involvement sustainable ecosystem, $\beta = 0.45$; Emerson and Gerlak, 2023). The stronger coefficient for the principal engagement pathway underscores that collaborative mechanisms leveraging open data are particularly critical for sustainability, challenging technocentric perspectives that prioritize digital tools over relational dimensions of regulatory governance (Yeung, 2023). Fourth, our analysis of open data flows and associated challenges provides valuable insights into the practical dynamics of data sharing in insurance ecosystems (Zuiderwijk and Janssen, 2014a). The identified data quality, privacy, and interoperability challenges confirm the need for integrated approaches that address both the technical and governance dimensions of open data in insurance regulation, as proposed in our theoretical model (European Commission, 2023). Fifth, stakeholder differences revealed through multigroup analysis highlight the importance of targeted approaches for different participant groups in the open data ecosystem (Li et al., 2023). Efficiency considerations appear less influential for regulatory officials than for industry and technology stakeholders in open data adoption decisions, while regulators demonstrate a stronger translation of technology usage into collaborative engagement. These nuances suggest that open data strategies should be tailored to address the specific motivations and behavioral patterns of different stakeholder groups (Wirtz and Müller, 2023).

These findings contribute to the literature in several ways. Theoretically, they advance public administration understanding by demonstrating complementarities between NPM and collaborative governance in open data contexts, extend technology adoption theory to regulatory technology with open data components, and validate multipath mechanisms leading to sustainable digital ecosystems through open data sharing (Pollitt and Bouckaert, 2023). Practically, they provide evidence-based guidance for designing balanced digital regulatory approaches that

address both the technical and relational dimensions of open data transformation (Janssen et al., 2022).

6.2 Practical and policy implications

This research offers several practical implications for stakeholders involved in digital insurance regulation and open data initiatives. First, regulatory agencies should pursue balanced digital transformation strategies that address both efficiency and relationship considerations, with particular emphasis on accountability mechanisms that provide transparency and clarity about regulatory decisions, responsibilities, and data governance (Grimmelikhuijsen et al., 2022). Second, implementation efforts should focus on clearly communicating the performance benefits of open data while ensuring adequate infrastructure support, recognizing that expected improvements drive adoption more strongly than other factors (Venkatesh et al., 2023). Third, collaborative mechanisms should be centrally integrated into digital regulatory strategies with open data components, moving beyond token consultation to substantive principled engagement throughout the regulatory lifecycle (Ansell and Gash, 2022). The strong relationship between principled engagement and sustainable outcomes ($\beta = 0.45$) suggests that investments in collaborative forums, multi-stakeholder dialogue platforms, and shared governance frameworks for open data can yield significant sustainability benefits (Emerson and Nabatchi, 2022). Fourth, digital platforms should be designed not only for operational efficiency but as gateways to deeper participation, with features that facilitate the translation of basic technology usage into more substantive collaborative engagement in open data governance (Matheus and Janssen, 2022). From a policy perspective, our findings suggest several approaches for effective open data regulation in insurance: (1) balancing standardization with flexibility to accommodate diverse market participants (Zuiderwijk and Janssen, 2014a); (2) developing privacy-preserving approaches that build trust while enabling innovation (Martin and Murphy, 2022); (3) establishing formal collaborative governance mechanisms with diverse stakeholder representation (Emerson and Gerlak, 2023); (4) implementing capacity building initiatives to address disparities in open data readiness (EIOPA, 2024); and (5) adopting adaptive policy frameworks that enable evidence-based learning and adjustment as open data ecosystems evolve (UK Government, 2023). These recommendations provide actionable guidance for policymakers, regulatory officials, industry stakeholders, and technology providers seeking to develop sustainable approaches to digital insurance regulation through open data. By addressing both the technological and collaborative dimensions, stakeholders can work toward regulatory ecosystems that effectively balance innovation with protection, efficiency with inclusion, and technological advancement with meaningful stakeholder participation (Arner et al., 2022).

6.3 Future research directions

The limitations of this study suggest a rich agenda for future research that can further advance our understanding

of open data in regulatory governance. Longitudinal studies could provide stronger evidence on causal relationships and developmental patterns in open data ecosystems (Hair et al., 2022). Comparative research in different cultural, economic, and institutional contexts could identify contextual factors that influence the implementation and impact (Li et al., 2023). Model extensions incorporating additional theoretical perspectives could address unexplained variance and provide a more nuanced understanding of open data dynamics (Bollen and Pearl, 2023). Research on how emerging technologies such as artificial intelligence interact with open data initiatives could identify new challenges and opportunities for regulatory governance (Pum and Sukma, 2024). Finally, implementation-focused studies could provide practical guidance on overcoming specific challenges in open data adoption (Janssen et al., 2022). These research directions would build on our integrated framework to develop increasingly nuanced and context-sensitive theories of sustainable digital regulation through open data. They would also provide valuable evidence to inform regulatory policy and industry practice as open data initiatives continue to evolve (European Commission, 2023).

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.

Ethics statement

The Institutional Review Board formally approved our questionnaire with certification code MUSSIRB 2025/012.1302. Participants provided their informed consent after receiving information about the study purpose, data usage, confidentiality provisions, and their right to withdraw. No personally identifiable information was collected and all data was stored securely with access restricted to the research team. Organizational information was anonymized to prevent identification of specific institutions. The research protocol received approval

References

- Allen, M., and Wiles, J. L. (2022). Ethical considerations in research with vulnerable populations. *Res. Ethics* 18, 295–315.
- Ansell, C., and Bjork, P. (2023). Collaborative platforms as governance innovations: design principles for public value creation. *Public Adm. Rev.* 83, 728–739.
- Ansell, C., and Gash, A. (2008). Collaborative governance in theory and practice. *J. Publ. Adm. Res. Theor.* 18, 543–571. doi: 10.1093/jopart/mum032
- Ansell, C., and Gash, A. (2022). *Collaborative Governance in Theory and Practice: Emerging Perspectives*. Oxford: Oxford University Press.
- Arner, D. W., Buckley, R. P., Charamba, K., and Zetzsche, D. A. (2022). Regulating digital financial services in pandemic times: a framework for regulatory sandboxes. *Singap. J. Leg. Stud.* 2022, 136–164.
- Attard, J., Orlandi, F., Scerri, S., and Auer, S. (2015). A systematic review of open government data initiatives. *Gov. Inf. Q.* 32, 399–418. doi: 10.1016/j.giq.2015.07.006
- Baker, R., Miller, C., and Kachhi, D. (2022). Nonresponse and online panel recruitment: current trends and innovative approaches. *Public Opin. Q.* 86, 456–490.
- Baldwin, R., and Lodge, M. (2020). *Understanding Regulation: Theory, Strategy, and Practice (3rd ed.)*. Oxford: Oxford University Press.
- Black, J. (2020). Critical reflections on regulation in the post-crisis financial sector. *J. Financ. Regul.* 6, 243–273.
- Bollen, K. A., Fisher, Z., Lilly, A., Brehm, C., and Luo, L. (2023). Fifty years of structural equation modeling: a history of generalization, unification, and diffusion. *Soc. Sci. Res.* 107:102769. doi: 10.1016/j.ssresearch.2022.102769
- Bollen, K. A., and Pearl, J. (2023). Eight myths about causality and structural equation models. *Sociol. Methods Res.* 52, 1156–1192.
- Bovens, M. (2020). Analysing and assessing accountability in the age of digital governance. *Eur. Law J.* 26, 340–363.

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NS: Conceptualization, Methodology, Writing – review & editing, Writing – original draft. SY: Supervision, Validation, Methodology, Writing – review & editing.

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Conflict of interest

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

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

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- Brägaru, C. (2022). InsurTech challenges in a changing world. *Strateg. Manag. J.* 28, 114–129.
- Breitsohl, H. (2024). Testing structural equation models: an integrative guide to model validation techniques. *Organ. Res. Methods* 27, 181–210.
- Brown, T. A. (2022). *Confirmatory Factor Analysis for Applied Research (3rd ed.)*. New York, NY: Guilford Press.
- Bykov, A., Shilton, K., and Vitak, J. (2023). Research ethics in an open data ecosystem: considerations for data sharing, privacy, and reuse. *J. Bus. Ethics* 184, 535–556.
- Bzhalava, L., Kaivo-oja, J., and Hassan, S. S. (2022). Data-based startup profile analysis in the European smart mobility sector. *Eur. J. Futures Res.* 10, 1–13.
- Cascio, M. A., and Racine, E. (2023). Research ethics in the age of digital health: challenges and opportunities. *AJOB Empir. Bioeth.* 14, 86–98.
- Chaouali, W., and El Hedhli, K. (2023). Exploring the determinants of open banking adoption: an integrated model of UTAUT and trust factors. *J. Retail. Consum. Serv.* 70:103143.
- Christensen, T., Jantz, B., and Lægred, P. (2023). Public management reforms: in search of the golden triangle of NPM, post-NPM, and digital-era governance. *Int. Rev. Adm. Sci.* 89, 342–359.
- Cohen, J., Cohen, P., West, S. G., and Aiken, L. S. (2022). *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences (4th ed.)*. New York, NY: Routledge.
- Das, T. K., and Teng, B. S. (2020). A resource-based theory of strategic alliances in the digital era. *J. Manage.* 46, 102–130.
- Dawes, S. S., Vidiassova, L., and Parkhimovich, O. (2023). Planning and designing open government data programs: an ecosystem approach for sustainable development. *Gov. Inf. Q.* 40:101801.
- Deloitte (2024). *2025 Global Insurance Outlook: Navigating Transformation in an Uncertain World*. Deloitte Center for Financial Services. Available online at: <https://www2.deloitte.com/us/en/insights/industry/financial-services/financial-services-industry-outlooks/insurance-industry-outlook.html> (accessed January 25, 2025).
- Digital Watch Observatory (2023). *Data Governance: Trends in 2025*. Available online at: <https://dig.watch/topics/data-governance> (accessed January 25, 2025).
- Dillman, D. A., Smyth, J. D., and Christian, L. M. (2023). *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method (5th ed.)*. Hoboken, NJ: Wiley.
- Dwivedi, Y. K., Rana, N. P., Sharma, A., and Sivarajah, U. (2022). A meta-analysis based modified unified theory of acceptance and use of technology (meta-UTAUT): a review of emerging literature. *Int. J. Inf. Manage.* 67:102528.
- EIOPA (2023). *Open Insurance: Accessing and Sharing Insurance-Related Data—Discussion Paper*. European Insurance and Occupational Pensions Authority. Available online at: https://www.eiopa.europa.eu/consultations/open-insurance-accessing-and-sharing-insurance-related-data_en (accessed January 25, 2025).
- EIOPA (2024). *Report on Digitalisation in the European Insurance Market*. European Insurance and Occupational Pensions Authority. Available online at: https://www.eiopa.europa.eu/eiopa-report-takes-pulse-digitalisation-european-insurance-market-2024-04-30_en (accessed January 25, 2025).
- Eling, M., and Schaper, M. (2023). Digital transformation in insurance: Pathways, challenges, and strategic implications. *Geneva Pap. Risk Insur. Issues Pract.* 48, A1–A21.
- Emerson, K., and Gerlak, A. K. (2023). Adaptation and learning in collaborative governance: conflict, trust, and the emergence of adaptive capacities. *Int. J. Public Adm.* 46, 143–159.
- Emerson, K., and Nabatchi, T. (2022). *Collaborative Governance and Conflict Management: New Frameworks for Adaptive Policy Implementation*. Washington, DC: Georgetown University Press.
- Emerson, K., Nabatchi, T., and Sharma, S. K. (2020). Collaborative governance: evolution and current status of theory and practice. *Public Adm. Rev.* 80, 438–453.
- European Commission (2022). *Data Governance Act*. Official Journal of the European Union, L152/1–44. Available online at: <https://digital-strategy.ec.europa.eu/en/policies/data-governance-act> (accessed January 25, 2025).
- European Commission (2023). *Proposal for a Regulation of the European Parliament and of the Council on a framework for Financial Data Access*. COM/2023/360 final. Available online at: <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52023PC0360> (accessed January 25, 2025).
- Faegre Drinker (2024). *Open Insurance: Key Issues to Watch in 2024*. Available online at: <https://www.faegredrinker.com/en/insights/publications/2024/5/open-insurance-key-issues-to-watch-in-2024> (accessed January 25, 2025).
- FERMA (2021). *FERMA Welcomes EIOPA Proposals for Open Insurance, But Says Corporate Perspective is Missing*. Federation of European Risk Management Associations. Available online at: <https://www.ferma.eu/advocacy/ferma-welcomes-eiopa-proposals-for-open-insurance-but-says-corporate-perspective-is-missing/> (accessed January 25, 2025).
- Fledderus, J., and Honingh, M. (2022). Co-production and the role of user trust: taking stock of trust-enhancing mechanisms. *Adm. Soc.* 54, 1576–1602.
- Gellman, R. (2023). *Privacy and Organizational Data: Policy Considerations for the Information Age*. Washington, DC: Brookings Institution Press.
- Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., and Siering, M. (2023). Regulatory technology in financial services: machine learning applications and implementation challenges. *Electron. Mark.* 33, 167–186.
- Gong, Y., and An, W. (2023). New public management and government data openness: a cross-national study. *Public Adm. Rev.* 83, 480–493.
- Grguric, A., Mosmondor, M., and Huljenic, D. (2022). Data management plans as a foundation for open science and research data reuse. *Data Sci. J.* 21, 10–24.
- Grimmelikhuijsen, S., Herkes, F., Leistikow, I., Verkroost, J., de Vries, F., and Zijlstra, W. G. (2022). Can decision transparency increase citizen trust in regulatory agencies? Evidence from a representative survey experiment. *Regul. Govern.* 16, 1023–1041.
- Groves, R. M., Fowler, F. J., Couper, M. P., Lepkowski, J. M., Singer, E., and Tourangeau, R. (2021). *Survey Methodology (3rd ed.)*. Hoboken, NJ: Wiley.
- Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. (2022). *Multivariate Data Analysis (9th ed.)*. Boston, MA: Cengage Learning.
- Hair, J. F., Risher, J. J., Sarstedt, M., and Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* 31, 2–24. doi: 10.1108/EBR-11-2018-0203
- Harrison, T. M., and Sayogo, D. S. (2023). Designing open government data infrastructures for stakeholder participation: value tensions and design decisions. *Gov. Inf. Q.* 40:101814.
- Hayes, A. F., and Scharkow, M. (2022). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: does method really matter? *Psychol. Methods* 27, 316–336.
- Henseler, J., Müller, T., and Schuberth, F. (2023). A renewed approach to discriminant validity assessment for composite measurement models. *J. Acad. Mark. Sci.* 51, 535–558.
- Hershberger, S. L., Marcoulides, G. A., and Parra, T. L. (2022). *Structural Equation Modeling: Applications Using Mplus (2nd ed.)*. New York, NY: Routledge.
- Hood, C. (1991). A public management for all seasons? *Public Adm.* 69, 3–19. doi: 10.1111/j.1467-9299.1991.tb00779.x
- IAIS (2022). *Global Insurance Market Report 2022*. International Association of Insurance Supervisors. Available online at: <https://www.iaisweb.org/2022/12/global-insurance-market-report-gimar-2022/> (accessed January 25, 2025).
- Insurely (2024). What is on the horizon for open finance in 2024? Available online at: <https://www.insurely.com/blog/what-is-on-the-horizon-for-open-finance-in-2024> (accessed January 25, 2025).
- Iphofen, R., and O'Mathúna, D. (2022). *Ethical Issues in Digital Health Research*. Oxford: Oxford University Press.
- Janssen, M., Charalabidis, Y., and Zuiderwijk, A. (2012). Benefits, adoption barriers and myths of open data and open government. *Inf. Syst. Manag.* 29, 258–268. doi: 10.1080/10580530.2012.716740
- Janssen, M., Chun, S. A., and Gil-Garcia, J. R. (2022). Building trustworthy digital government: challenges and emerging approaches. *Gov. Inf. Q.* 39:101681.
- Janssen, M., and Estevez, E. (2023). Smart governance in the age of artificial intelligence. *Gov. Inf. Q.* 40:101898.
- Kline, R. B. (2023). *Principles and Practice of Structural Equation Modeling (5th ed.)*. New York, NY: The Guilford Press.
- Koval, O., and Pinkse, J. (2023). Value creation through digital platform ecosystems: Unpacking complementarities and governance mechanisms. *J. Bus. Res.* 154:113318.
- Kumar, S., Sahoo, S., Lim, W. M., and Dana, L. P. (2022). Religion as a social shaping force in entrepreneurship and business: insights from a technology-enabled systematic literature review. *Technol. Forecast. Soc. Change* 175:121394. doi: 10.1016/j.techfore.2021.121393
- Li, W., Wang, X., and Zhang, M. (2023). Multi-group structural equation modeling: a systematic review and future directions. *Struct. Equ. Model.* 30, 435–451.
- Liang, H., Saraf, N., Hu, Q., and Xue, Y. (2020). Assimilation of enterprise digital platforms: An empirical study of organizational factors. *MIS Q.* 44, 1149–1187.
- Little, R. J., and Rubin, D. B. (2020). *Statistical Analysis With Missing Data (3rd ed.)*. Hoboken, NJ: Wiley. doi: 10.1002/9781119482260
- Liu, C., Yuan, K. H., and Zhu, L. (2024). On the detection and correction of common method bias in structural equation modeling. *Psychol. Methods* 39, 120–142.
- Lodge, M., and Wegrich, K. (2022). The rationality paradox of nudge: rational tools of government in a world of bounded rationality. *Law Policy* 44, 4–30.
- Lynn, P. (2022). *The Longitudinal Study of Ageing: A Practical Guide to the Design and Conduct of Longitudinal Surveys*. Cheltenham: Edward Elgar Publishing.

- MacKinnon, D. P., Valente, M. J., and Gonzalez, O. (2023). The correspondence between causal and traditional mediation analysis: the link between the Sobel test and mediation formulas. *Psychol. Methods* 28, 55–68.
- Marano, P. (2021). Management of distribution risks and digital transformation of insurance distribution—a regulatory gap in the IDD. *Risks* 9:143. doi: 10.3390/risks9080143
- Martin, K., and Murphy, P. (2022). Data privacy in the age of AI: a cross-national investigation of individual privacy concerns, organizational privacy practices, and societal regulatory approaches. *Bus. Ethics Q.* 32, 473–508.
- Matheus, R., and Janssen, M. (2022). How to enhance the benefits of data platforms: the importance of governance, representation, and skills. *Inf. Syst. Manag.* 39, 376–389.
- McKinsey (2024). *2024: A Year in Charts, Graphs and Data Visualization*. Available online at: <https://www.mckinsey.com/featured-insights/year-in-review/year-in-charts> (accessed January 25, 2025).
- McNeish, D., and Wolf, M. G. (2021). Dynamic fit index cutoffs for confirmatory factor analysis models. *Psychol. Methods* 26, 702–726. doi: 10.1037/a0051058
- McNutt, J. G., and Justice, J. B. (2023). Digital technology and collaborative governance: a framework for analyzing civic engagement and capacity building. *Adm. Soc.* 55, 975–1000.
- Meijer, A. (2023). Algorithmic transparency as innovation adoption: a socio-technical analysis of digital accountability. *Gov. Inf. Q.* 40:101779. doi: 10.1016/j.giq.2022.101779
- New America (2023). *Keys to a Healthier Digital Future: Interoperability, Open Protocols, and Tech Governance*. Available online at: <https://www.newamerica.org/digital-impact-governance-initiative/briefs/keys-to-a-healthier-digital-future/> (accessed January 25, 2025).
- Obal, M., and Kunz, W. H. (2020). Cross-cultural differences in the adoption of social media innovation: a comparative study of American and Austrian B2B companies. *Ind. Mark. Manag.* 89, 270–283.
- O'Flynn, J. (2022). Confronting the challenges of collaborative governance: practitioner insights. *Public Manag. Rev.* 24, 1068–1089.
- Opendatasoft (2024). *Data Portal Solution for Banking and Insurance*. Available online at: <https://www.opendatasoft.com/en/opendatasoft-banking-insurance/> (accessed January 25, 2025).
- Osborne, S. P. (Ed.). (2010). *The New Public Governance? Emerging Perspectives on the Theory and Practice of Public Governance* (London: Routledge), 448. doi: 10.4324/9780203861684
- Podsakoff, P. M., MacKenzie, S. B., and Podsakoff, N. P. (2023). Common method variance in organizational research: challenges, misconceptions, and recommendations. *J. Appl. Psychol.* 108, 1049–1072.
- Polit, D. F., and Beck, C. T. (2023). *Nursing Research: Generating and Assessing Evidence for Nursing Practice (12th ed.)*. Philadelphia, PA: Wolters Kluwer.
- Pollitt, C., and Bouckaert, G. (2023). *Public Management Reform: A Comparative Analysis—Into the Age of Austerity (5th ed.)*. Oxford: Oxford University Press.
- Porrini, D., and Ramella, F. (2020). InsurTech: the future of insurance? *Risks* 8:136.
- Pum, W., and Sukma, N. (2024). A comprehensive survey of the potential of artificial intelligence in the insurance industry. *Exec. J.* 44, 79–96.
- Putnick, D. L., and Bornstein, M. H. (2022). Measurement invariance in confirmatory factor analysis: a practical guide. *Psychol. Methods* 27, 733–749.
- R Street Institute (2024). *2024 Insurance Regulation Report Card*. Available online at: <https://www.rstreet.org/research/2024-insurance-regulation-report-card/> (accessed January 25, 2025).
- Ratna, S., Saide, S., Putri, A. M., Soleha, A., and Andini, P. R. (2024). Financial systems transformation in the digital age: a systematic review and future research directions. *Procedia Comput. Sci.* 234, 1538–1545. doi: 10.1016/j.procs.2024.03.155
- Reidenberg, J. R., and Schaub, F. (2022). *Achieving Privacy: Costs of Compliance and Enforcement of Data Protection Regulation*. Cambridge: Cambridge University Press.
- Rose, S. L., Trinidad, S. B., Wilfond, B. S., and Beskow, L. M. (2022). Addressing the ethical challenges of recruitment in health research. *JAMA Netw. Open* 5:e221703.
- Ruijter, E., Détiénne, F., Baker, M., Groff, J., and Meijer, A. J. (2020). The politics of open government data: understanding organizational responses to pressure for more transparency. *Am. Rev. Public Adm.* 50, 260–274. doi: 10.1177/027507401988065
- Sauermann, H., and Roach, M. (2023). Not just a phase: how scholarly impact, collaboration, and entrepreneurship develop over time in academic careers. *Res. Policy* 52:104642.
- Scott, T. A., and Thomas, C. W. (2021). Winners and losers in the ecology of collaborative governance: Network configuration, power, and accountability. *Public Adm. Rev.* 81, 896–908.
- Seo, D. B., and Kim, J. (2022). Digital government transformation: relationships among CSFs, change, and performance. *Public Manag. Rev.* 24, 1197–1222.
- Shi, D., Maydeu-Olivares, A., and DiStefano, C. (2022). The relationship between the standardized root mean square residual and model misspecification in factor analysis models. *Multivariate Behav. Res.* 57, 146–180.
- Singer, E., and Couper, M. P. (2023). *Survey Methodology and Missing Data: Making Decisions for Missing and Incomplete Information*. Hoboken, NJ: Wiley.
- Singh, G., and Slack, N. J. (2022). New public management and customer perceptions of service quality—a mixed-methods study. *Int. J. Public Adm.* 45, 242–256. doi: 10.1080/01900692.2020.1839494
- Song, C., Liu, J., and Li, H. (2022). User attitudes toward government open data portals: Examining the impacts of transparency, interactivity, and collaborative governance. *Gov. Inf. Q.* 39:101690.
- Stein, C. M., Wolf, M. G., and McNeish, D. (2022). Inducing sparsity in structural equation modeling through regularized maximum likelihood estimation. *Psychol. Methods* 27, 983–1001.
- Sukma, N., and Leelasantham, A. (2022a). The influence and continuance intention of the e-government system: a case study of community water supply business. *Front. Environ. Sci.* 10:918981. doi: 10.3389/fenvs.2022.918981
- Sukma, N., and Leelasantham, A. (2022b). From conceptual model to conceptual framework: a sustainable business framework for community water supply businesses. *Front. Environ. Sci.* 10:1013153. doi: 10.3389/fenvs.2022.1013153
- Sukma, N., and Leelasantham, A. (2022c). Understanding online behavior towards community water user participation: a perspective of a developing country. *PLoS ONE* 17:e0270137. doi: 10.1371/journal.pone.0270137
- Sukma, N., Leelasantham, A., and Yan, Z. (2022). Factors affecting adoption of online community water user participation. *Hum. Behav. Emerg. Technol.* 2022, 1–13. doi: 10.1155/2022/1732944
- Sukma, N., and Namahoot, C. S. (2024). An algorithmic trading approach merging machine learning with multi-indicator strategies for optimal performance. *IEEE Access* 12, 188154–188173. doi: 10.1109/ACCESS.2024.3516053
- Swiss Re (2023). *Collaboration Will Be Key to the Digital Transformation of Insurance in 2023*. Available online at: <https://www.swissre.com/risk-knowledge/advancing-societal-benefits-digitalisation/collaboration-key-digital-transformation-insurance-in-2023.html> (accessed January 25, 2025).
- Tabachnick, B. G., and Fidell, L. S. (2022). *Using Multivariate Statistics (7th ed.)*. Boston, MA: Pearson.
- Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Res. Sci. Educ.* 48, 1273–1296. doi: 10.1007/s11165-016-9602-2
- Thouvenin, F., Suter, F., George, D., and Weber, R. H. (2021). Big data in the insurance industry: leeway and limits for individualising insurance contracts. *J. Intell. Prop. Info. Technol. Electron. Commer. Law* 12, 126–148.
- Tourangeau, R., Kreuter, F., and Eckman, S. (2022). *Advances in Survey Methodology*. Hoboken, NJ: Wiley.
- Treleven, P., and Batrinca, B. (2021). Algorithmic regulation: automating financial compliance monitoring and regulation using AI and blockchain. *J. Finan. Transform.* 53, 148–159.
- UK Government (2023). *Plan for Digital Regulation: Outcomes Monitoring Framework 2023*. Available online at: <https://www.gov.uk/government/publications/digital-regulation-driving-growth-and-unlocking-innovation/plan-for-digital-regulation-outcomes-monitoring-framework-2023> (accessed January 25, 2025).
- van der Heijden, J. (2022). Risk governance and risk-based regulation: a review of the international academic literature. *Regul. Gov.* 16, 1042–1059.
- van Veelen, M., Nijkamp, J. E., and Boomsma, A. (2024). A practical approach to Monte Carlo simulation for evaluating robustness to non-normality in structural equation models. *Struct. Eq. Model. A Multidiscip. J.* 31, 133–148.
- Velinov, E., Kadlubek, M., Thalassinos, E., Grima, S., and Maditinos, D. (2023). “Digital transformation and data governance: top management teams perspectives,” in *Digital Transformation, Strategic Resilience, Cyber Security and Risk Management, Vol. 111A*, eds. S. Grima, E. Thalassinos, M. Cristea, M. Kadlubek, D. Maditinos, and L. Peiseniece (Emerald Publishing Limited), 147–158. doi: 10.1108/S1569-37592023000111A010
- Venkatesh, V., and Agarwal, R. (2023). Social media engagement and technology adoption: a longitudinal examination of bidirectional relationships. *MIS Q.* 47, 1145–1170.
- Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: toward a unified view. *MIS Q.* 27, 425–478. doi: 10.2307/30036540
- Venkatesh, V., and Sykes, T. A. (2013). Digital divide initiative success in developing countries: a longitudinal field study in a village in India. *Inf. Syst. Res.* 24, 239–260. doi: 10.1287/isre.1110.0409
- Venkatesh, V., Thong, J. Y. L., Chan, F. K. Y., and Hoehle, H. (2023). Towards a unified theory of consumer acceptance of artificial intelligence: a meta-analysis of acceptance research. *MIS Q.* 47, 1787–1834.

- Vetrò, A., Canova, L., Torchiano, M., Minotas, C. O., Iemma, R., and Morando, F. (2016). Open data quality measurement framework: Definition and application to open government data. *Gov. Inf. Q.* 33, 325–337. doi: 10.1016/j.giq.2016.02.001
- Voorhees, C. M., Brady, M. K., Calantone, R., and Ramirez, E. (2022). Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies. *J. Acad. Mark. Sci.* 50, 18–35.
- Watkins, M. W. (2018). Exploratory factor analysis: a guide to best practice. *J. Black Psychol.* 44, 219–246. doi: 10.1177/0095798418771807
- Welch, E. W., and Feeney, M. K. (2021). Public service motivation and data sharing behavior: the mediating roles of social ties and discretion. *Public Manag. Rev.* 23, 1680–1703.
- Wilson, J. D., Yelowitz, A., and Stout, M. E. (2021). *InsurTech: Efficiency and Innovation in the Insurance Industry*. Kansas City, MO: National Association of Insurance Commissioners.
- Wirtz, B. W., and Müller, W. M. (2023). Digital public administration ecosystem transformation—a conceptual framework. *Public Adm. Rev.* 83, 533–548.
- Yeung, K. (2023). Why worry about decision-making by machine? Explaining the limits of algorithmic regulation and automated decision-making. *J. Law Soc.* 50, 15–40.
- Zhu, X., Ge, S., and Wang, N. (2021). Digital transformation: a systematic literature review. *Comput. Ind. Eng.* 162:107774. doi: 10.1016/j.cie.2021.107774
- Zuiderwijk, A., and Janssen, M. (2014a). “The negative effects of open government data: Investigating the dark side of open data,” in *Proceedings of the 15th Annual International Conference on Digital Government Research (ACM)*, 147–155. doi: 10.1145/2612733.2612761
- Zuiderwijk, A., and Janssen, M. (2014b). Open data policies, their implementation and impact: a framework for comparison. *Gov. Inf. Q.* 31, 17–29. doi: 10.1016/j.giq.2013.04.003
- Zuiderwijk, A., Janssen, M., and Davis, C. (2014). Innovation with open data: Essential elements of open data ecosystems. *Inf. Polity* 19, 17–33. doi: 10.3233/ip-140329