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Strategic Decision-Making in SME Growth: Harnessing Digital Transformation and Innovation in Jordan

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Abstract

Purpose: This study investigates the strategic role of digital transformation (DT), digital innovation (DI), and digital strategy (DS) in enhancing the performance of small and medium enterprises (SMEs) in Jordan, a developing economy. The research focuses on the mediating influence of digital strategy in translating technological advancements into financial and non-financial organizational outcomes.

Design/methodology/approach: A quantitative approach was employed, utilizing cross-sectional survey data from 117 SMEs. The study used partial least squares structural equation modeling (PLS-SEM) to examine the relationships among digital transformation, digital innovation, digital strategy, and firm performance. The model was validated with diagnostic tests for reliability, validity, and model fit indices.

Findings: The findings reveal significant direct effects of digital transformation and digital innovation on digital strategy. Mediation analysis confirms that digital strategy partially mediates the relationships between digital advancements and performance. For financial and non-financial outcomes, digital strategy enables SMEs to leverage technological resources effectively. The study identifies the potential of strategic digital alignment for sustainable growth in resource-constrained environments. This research explicitly contributes to the field of Decision Sciences by modeling how SMEs optimize digital resources under uncertainty, linking decision-making processes with performance outcomes.

Research limitations/implications: The cross-sectional design limits the ability to observe long-term impacts of digital strategies. Moreover, the sample is restricted to Jordanian SMEs, which may limit generalizability. Future longitudinal and cross-country studies are recommended to capture dynamic effects and comparative insights.

Practical implications: The research highlights actionable strategies for SME leaders to adopt and align digital technologies with organizational goals. Policymakers are encouraged to design initiatives that support SMEs in overcoming technological and resource barriers.

Social implications: Promoting digital transformation in SMEs fosters job creation, innovation, and economic stability, contributing to the broader socio-economic development of emerging economies.

Originality/value: This study is original in its context-specific focus on SMEs in a developing economy and differs from prior literature by explicitly demonstrating how digital strategy mediates both financial and non-financial outcomes. By highlighting originality and explicitly situating digital strategy within the Decision Sciences paradigm, the paper shows how structured decision models can guide SMEs in resource-constrained environments.

Keywords: Digital Transformation, Digital Innovation, Digital Strategy, SME Performance, PLS-SEM, Organizational Growth, Developing Economies

JEL Classifications: O33, M15, L25, L26, C83

1. Introduction

In today's rapidly evolving business landscape, digital transformation has become a cornerstone for organizational success, representing the shift from traditional analog processes to dynamic, digitally driven operations. This transformative process enables businesses to integrate people, assets, and data, thereby fostering operational efficiency, adaptability, and long-term resilience (Kraus et al., 2021). Since the advent of computing, the digital ecosystem has expanded exponentially, introducing groundbreaking technologies such as artificial intelligence (AI), cloud computing, blockchain, and big data analytics (Alkandari et al., 2024; Alrabea et al., 2024; Zaoui & Souissi, 2020). For small and medium enterprises (SMEs), the integration of these technologies, particularly AI and IoT, offers innovative pathways for overcoming resource constraints and enhancing operational capabilities in volatile markets (Roshid et al., 2025; Waaje et al., 2025).

Digital innovation, a critical complement to transformation, involves the development and application of novel solutions to improve processes, products, and services. Unlike transformation, which entails organization-wide changes, innovation focuses on targeted enhancements, enabling businesses to secure immediate competitive advantages and revenue growth (Alhaimer, 2025; Alkandari et al., 2024; Kohli & Melville, 2019). SMEs, recognized for their agility and adaptability, are uniquely positioned to benefit from such innovations, leveraging them to navigate technological disruptions and meet dynamic market demands (Hund et al., 2021). Nevertheless, the ability of SMEs to fully capitalize on these opportunities depends on context-specific strategies that align with their unique operational and market environments, particularly in developing economies. At the heart of these advancements lies the need for strategic digital transformation frameworks, which serve as actionable roadmaps for integrating digital tools to optimize performance metrics such as customer satisfaction (Moslehpour et al., 2017, 2019; Moslehpour, Pham et al., 2018; Moslehpour, Wong et al., 2018), market expansion, and operational efficiency (Kengatharan, 2019; Mubeen et al., 2021).

The interplay between digital transformation, innovation, and strategic decision-making has garnered increasing academic and practical attention. Research highlights how digital transformation reshapes business models, enhances agility, and establishes long-term resilience through the integration of advanced technologies (Montero Guerra et al., 2023; Zhao et al., 2024). Digital innovation amplifies these efforts by providing businesses with distinctive market positioning and operational efficiencies that are critical for sustainable growth (Abad-Segura et al., 2020; C. Zhang et al., 2022). However, while much of the existing literature focuses on large corporations in developed economies, there remains a clear gap in understanding how SMEs in developing countries, particularly in Jordan, navigate digital transformation under severe financial, regulatory, and skill-related constraints. Addressing this gap is crucial, since Jordanian SMEs form the backbone of the national economy, and their digital evolution holds implications not only for firm survival but also for economic stability and regional competitiveness.

This study investigates the role of strategic decision-making in digital transformation and innovation among SMEs in Jordan, a country emerging as a key player in the digital economy within the Middle East

(A. Al-Okaily et al., 2024). Jordanian SMEs operate in a unique context, influenced by the nation's digital economy policies, technological infrastructure, and socio-economic challenges. Despite these constraints, they demonstrate significant potential for innovation-driven growth (Alawamleh et al., 2023). This research explores how these enterprises employ digital strategies to address barriers such as regulatory challenges, shifting consumer expectations (Liao et al., 2012, 2014; Liao & Wong, 2008), and technological integration hurdles (Alalwan et al., 2024; AL-Khatib, 2023; Lutfi et al., 2022). By focusing on the Jordanian context, the study aims to provide actionable insights that can guide SMEs globally, particularly in other developing economies facing similar challenges.

This study makes three original contributions. First, it expands prior work on digital adoption (e.g., Liao et al., 2012, 2014; Liao & Wong, 2008) by examining how SMEs in resource-constrained environments develop digital strategies that mediate transformation and innovation outcomes. Second, it incorporates structural modeling approaches similar to those in Moslehpour et al. (2017, 2019); Moslehpour, Pham et al. (2018), and Kien et al. (2018), but applies them to a new regional and organizational context, thereby extending their theoretical relevance. Third, it offers an integrated framework that explicitly situates SME digitalization within the field of Decision Sciences, showing how quantitative modeling and strategy evaluation can guide decision-making under uncertainty. In line with this aim, this research directly contributes to the field of Decision Sciences by providing a robust, SEM-based framework to evaluate how digital transformation and innovation shape SME performance outcomes in emerging economies.

The remainder of this paper is structured as follows: Section 2 outlines the conceptual background and hypothesis development. Section 3 describes the methodology, including data collection and variable specifications. Section 4 presents the study's results, while Section 5 discusses practical implications. Section 6 identifies limitations and directions for future research, and Section 7 concludes with key insights.

2. Literature Review

The integration of digital transformation (DT) and digital innovation (DI) into small and medium enterprises (SMEs) has increasingly become a strategic priority due to their potential to drive business growth and enhance competitive positioning. Digital transformation involves the comprehensive adoption of digital technologies across products, processes, and operations, resulting in improved efficiency and customer engagement (Alhaimer, 2025; Bouwman et al., 2019). On the other hand, digital innovation emphasizes the development and implementation of novel solutions that enhance internal processes and services, fostering adaptability and continuous improvement (Ramdani et al., 2022).

Pioneer works in decision sciences have laid the foundation for evaluating organizational performance and innovation adoption. For example, Dixon and Mood (1946) introduced the statistical sign test to evaluate paired data, Matsumura et al. (1990) developed probabilistic models for assessing error bounds in organizational sampling, and Bian et al. (2011) refined trinomial test applications in decision-making under uncertainty. These contributions highlight the long-standing methodological roots of analyzing decisions under complex and constrained environments, which are directly relevant to how SMEs approach digital transformation.

While existing research highlights these benefits for large corporations, SMEs face unique constraints such as limited resources, technological infrastructure, and skills gaps, which necessitate tailored approaches to implementing digital initiatives (Khrais & Alghamdi, 2022). Recent works on sustainability and digital ecosystems (Abad-Segura et al., 2020; Kraus et al., 2021) emphasize that SMEs not only need technological tools but also context-specific strategies that align innovation with broader environmental and social objectives. This is especially critical in developing economies where resource scarcity amplifies the challenges of digital adoption. Pham et al. (2020) underline the importance of methodological rigor in evaluating complex constructs like digital strategy and firm performance, providing a foundation for exploring how SMEs can leverage digital transformation and innovation effectively. Together, DT and DI act as critical enablers of organizational growth, particularly when integrated through well-defined digital strategies that align technological advancements with business objectives.

Digital strategies, in turn, represent a comprehensive set of initiatives aimed at using digital tools to drive innovation, enhance efficiency, and achieve business goals (Gobble, 2018; Schallmo et al., 2019). In resource-constrained environments such as Jordan, these strategies must adapt to infrastructure limitations, policy environments, and workforce capabilities. The existing literature also notes the role of emerging technologies, including AI, blockchain, and IoT, in enabling SMEs to enhance predictive capabilities, increase transparency, and reduce inefficiencies (Brown & Brown, 2019; Haq & Huo, 2023).

Despite the growing academic interest in these themes, a large portion of empirical research continues to focus on developed markets. There is a limited understanding of how SMEs in emerging economies implement digital strategies to overcome local constraints. This study builds on the foundational statistical and methodological literature (Bian et al., 2011; Dixon & Mood, 1946; Matsumura et al., 1990) while extending recent sustainability and innovation debates to the SME context. By focusing on Jordan, the paper highlights how SMEs in resource-constrained settings balance digital adoption, innovation, and strategic decision-making, thereby addressing a gap that has not been adequately explored in existing research.

3. Theoretical Framework and Hypotheses Development

3.1 Theoretical Framework

The conceptual foundation of this study is grounded in multiple complementary theories that collectively explain how digital transformation (DT) and digital innovation (DI) shape small and medium enterprise (SME) performance through digital strategy (DS).

First, the Resource-Based View (RBV) provides a lens to understand how firms build and leverage unique digital resources to gain a competitive advantage. According to Kraus et al. (2021) and Verhoef et al. (2021), digital capabilities such as analytics, cloud infrastructure, and mobile technologies function as strategic resources that are valuable, rare, and difficult to imitate. Within SMEs, aligning these digital resources with organizational strategy enhances adaptability and resilience, consistent with the RBV argument that internal capabilities drive long-term performance (Kengatharan, 2019).

Second, the study draws on the Decision Sciences perspective, which emphasizes analytical rigor in optimizing strategic choices under uncertainty. Digital transformation and innovation often present SMEs with complex, uncertain environments, requiring decision frameworks to evaluate technological adoption, process redesign, and market alignment (Liao et al., 2012, 2014; Liao & Wong, 2008). By employing partial least squares structural equation modeling (PLS-SEM), this research contributes to Decision Sciences by empirically validating a model that links digital inputs to strategic and performance outcomes, enabling SMEs to make data-driven strategic decisions (Hair et al., 2019, 2021).

Third, Strategy Theory underscores how digital initiatives must be embedded within coherent strategic roadmaps to ensure organizational alignment. Gobble (2018) and Schallmo et al. (2019) emphasize that digital strategies translate technological opportunities into operational efficiency and market competitiveness. In SMEs, this strategic alignment is crucial for overcoming resource constraints and achieving sustainable growth (Forliano et al., 2023).

Finally, concepts from Innovation Diffusion and Technology Acceptance frameworks explain the organizational and market-level dynamics of digital adoption. Research highlights how innovations diffuse through organizational processes and customer interactions, with digital tools such as smartcards or e-services reshaping consumer expectations (Liao et al., 2014; Liao & Wong, 2008). In constrained environments, SMEs' ability to integrate and diffuse such innovations is essential for sustaining competitive advantage (Moslehpour et al., 2017, 2019; Moslehpour, Pham et al., 2018).

Taken together, these theories provide an integrated foundation for this study's conceptual model. RBV explains the role of digital resources, Decision Sciences highlights the analytical modeling of complex relationships, Strategy Theory emphasizes alignment with business objectives, and Innovation Diffusion frameworks capture the dynamics of adoption. This theoretical synthesis supports the proposed model in which DT and DI influence SME performance directly and indirectly through DS.

3.2.Hypotheses Development

3.2.1 Digital Transformation and Digital Strategy

In today's dynamic business environment, digital transformation is essential for organizations seeking to innovate and grow. DT enables firms to adapt to changing market demands, streamline production, and enhance customer satisfaction through the integration of advanced technologies (Kraus et al., 2021). However, effective digital transformation goes beyond technology adoption; it requires a strategic realignment of organizational structures and a cultural shift towards a digital-first mindset (Mergel et al., 2019). For SMEs in developing economies, such as Jordan, aligning digital transformation with national policies and available infrastructure is critical for overcoming adoption barriers (Ahmad et al., 2025; Lutfi et al., 2022). A successful digital transformation strategy (DTS) empowers organizations to harness digital capabilities to drive operational excellence, enhance product quality, and improve customer engagement (Yu et al., 2022). Moreover, fostering a collaborative and innovative environment is essential for achieving resilience and long-term growth in the face of evolving market challenges (Vuksic & Suša Vugec, 2018). This study builds on prior research but contributes originality by situating DT within the Decision Sciences paradigm, emphasizing how SMEs optimize limited digital resources under uncertainty through structured decision models. Therefore, the following hypothesis has been considered in this context.

H_1: Digital transformation has a significant effect on digital strategy.

3.2.2 Digital Innovation and Digital Strategy

Digital innovation underpins sustainable competitive advantage by enabling businesses to introduce novel solutions that meet evolving market demands and improve operational efficiency (Nylén & Holmström, 2015; Obeidat, 2020). Effective DI strategies integrate cutting-edge technologies across organizational levels to enhance processes, products, and services (Holmström, 2018; Nambisan et al., 2020). For example, IoT facilitates real-time data collection and decision-making, while blockchain enhances supply chain transparency—both critical for SMEs operating in constrained environments (Alsafadi & Aljuhmani, 2024; Gregory et al., 2019; Karim et al., 2024). This fosters continuous improvement and helps companies maintain their competitive edge in fast-changing markets. By aligning DI initiatives with overarching business goals, firms can effectively allocate resources and maximize innovation’s impact (Ahmad et al., 2024; Berente, 2020). A robust digital strategy supports innovation by providing a shared understanding of organizational objectives, enabling adaptive responses to market shifts (Kiefer et al., 2021). Thus, we hypothesized as follows:

H_2: Digital innovation has a significant effect on digital strategy.

3.2.3 Firm Performance

Firm performance is typically evaluated using financial and non-financial metrics. Financial performance indicators include return on assets, net profit, and sales growth (Miah et al., 2019). Non-financial performance focuses on factors like customer satisfaction, employee engagement, and market share, which are crucial for long-term success (Andoh-Baidoo, 2016; Chege et al., 2020; Lee et al., 2015). In Jordan, SMEs’ performance often hinges on their ability to navigate regulatory challenges and leverage emerging digital tools to achieve these metrics, a dimension requiring further exploration in this study. By adopting digital transformation and innovation strategies, SMEs can achieve significant improvements in both financial and non-financial performance, thereby enhancing their overall competitive position in the market.

H_3: Digital strategy has a significant effect on financial performance.

H_4: Digital strategy has a significant effect on non-financial performance.

3.2.4 Mediating Role of Digital Strategy

Digital strategies play a critical mediating role in converting the potential of digital transformation and innovation into tangible business outcomes. The role of digital transformation also paves the way in enabling SMEs to adapt to changing market conditions and capitalize on new opportunities (Nambisan et al., 2020). They facilitate the effective deployment of technology to differentiate brands, strengthen customer relationships, and optimize operational processes (A. Al-Okaily et al., 2024; Haq & Huo, 2023). Additionally, digital strategies streamline collaboration across organizational units, enabling cohesive decision-making and alignment with strategic goals (Catlin et al., 2018). This study highlights how Jordanian SMEs can use digital strategies to address resource constraints, build market-specific solutions, and align organizational goals with broader economic objectives. By incorporating advanced analytics and automation, digital strategies further enhance efficiency and responsiveness in a fast-paced digital economy (Brown & Brown, 2019).

SMEs in Jordan often face significant resource constraints, including limited access to capital, technical expertise, and infrastructure, which can impede their ability to undergo digital transformation (Shqair & Altarazi, 2022). However, strategic decision-making grounded in a clear digital vision and roadmap can help overcome these barriers and unlock the full potential of digital technologies. As SMEs progress along their digital transformation journey, they must also cultivate organizational agility, data-driven decision-making, and an innovation-oriented culture to sustain their competitive edge. (Nambisan et al., 2020; North et al., 2019). Innovation is a vital component in the growth and transformation of SMEs in the digital age. Extant literature emphasizes the critical role of innovation in driving the growth and competitive advantage of SMEs, particularly in the context of digital transformation. Thus, we have hypothesized the following regarding the digital transformation and digital innovation:

H_5: The effect of digital transformation on financial performance is mediated by digital strategy.

H_6: The effect of digital transformation on non-financial performance is mediated by digital strategy.

H_7: The effect of digital innovation on financial performance is mediated by digital strategy.

H_8: The effect of digital innovation on non-financial performance is mediated by digital strategy.

This literature review highlights the interconnected roles of digital transformation, digital innovation, and digital strategy in driving SME growth. By exploring these relationships, this study provides a nuanced understanding of how SMEs can leverage digital advancements to enhance performance and sustain competitive advantage, particularly in dynamic and resource-constrained environments. By focusing on the Jordanian context, the review emphasizes the critical role of region-specific strategies in fostering SME growth amidst evolving digital ecosystems.

3.2.5 Moderating Effect

While digital transformation (DT) and digital innovation (DI) are key drivers of digital strategy (DS) and firm performance, their effects may not be uniform across all small and medium enterprises (SMEs). Contextual characteristics such as firm size and sector of operation play an important role in shaping the effectiveness of digital initiatives.

From the perspective of the Resource-Based View (RBV), larger SMEs often possess greater financial, human, and technological resources, enabling them to adopt and scale digital strategies more effectively than micro or small firms (Kraus et al., 2021). Conversely, micro and small enterprises may face resource constraints that limit their ability to transform digital opportunities into performance outcomes. This suggests that firm size can moderate the relationship between digital strategies and performance.

Similarly, sectoral differences introduce variations in digital adoption. For example, service-oriented SMEs may leverage digital technologies more readily for customer engagement, while industrial firms may emphasize process automation and cost efficiencies (Gobble, 2018; Kiefer et al., 2021). These distinctions indicate that sectoral context can also moderate the relationship between digital strategies and firm outcomes, consistent with contingency theory in organizational decision-making. Accordingly, this study proposes the following hypotheses:

H_9: Firm size moderates the relationship between digital strategy and financial performance.

H_{10}: Firm size moderates the relationship between digital strategy and non-financial performance.

H_{11}: Sector type moderates the relationship between digital strategy and financial performance.

H_{12}: Sector type moderates the relationship between digital strategy and non-financial performance.

3.6 Research Model

The conceptual model (Figure 1) for this study illustrates the relationships among digital transformation (DT), digital innovation (DI), digital strategy (DS), and SME performance (both financial and non-financial). It highlights the mediating role of digital strategy in converting technological capabilities into strategic outcomes, while also accounting for the direct effects of DT and DI on firm performance. In addition, the model introduces moderating influences of firm size and sector type, reflecting the contextual variability of SMEs in resource-constrained environments.

Figure 1: Conceptual Research Model

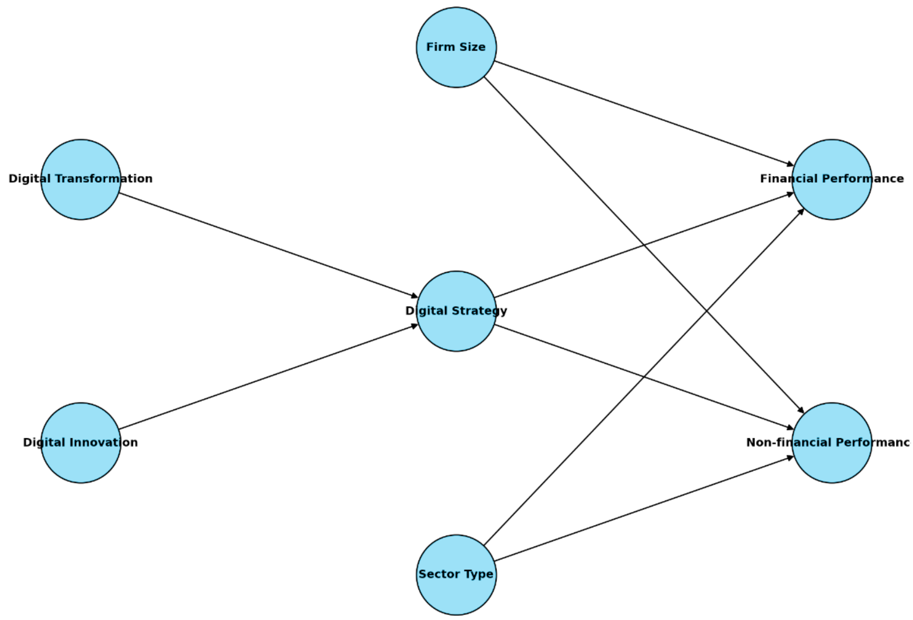


Figure 1 presents the conceptual research model developed for this study, illustrating the hypothesized relationships among the core constructs. DT and DI are proposed to directly influence the development of DS, which in turn affects both Financial Performance (FP) and Non-Financial Performance (NFP). The model also incorporates direct pathways from DT and DI to FP and NFP, acknowledging that technological capabilities may exert independent effects beyond strategic mediation.

Furthermore, the model integrates moderating effects of Firm Size and Sector Type on the DS → Performance relationships. Firm size is expected to strengthen the impact of DS on FP and NFP for medium-sized SMEs relative to micro and small firms. Similarly, sectoral context is anticipated to condition the extent to which DS improves performance outcomes, with service-sector SMEs expected to derive stronger benefits compared to industrial or commercial SMEs.

By combining mediating, direct, and moderating effects, this framework captures the dynamic interplay between digital capabilities, strategic alignment, and contextual contingencies, offering a comprehensive view of how SMEs in developing economies can leverage digital tools to enhance overall performance.

4. Methods

This study investigates how digital transformation and innovation contribute to SME growth by examining the relationships between digital strategy, digital innovation, and SME performance. A quantitative approach was employed, focusing on a sample of Jordanian SMEs to test the research hypotheses and achieve the study's objectives. The analysis emphasizes Jordan's unique economic and technological context, characterized by its growing digital economy. This section details the sample selection, data collection procedures, and the measures used in the study while addressing potential concerns about data robustness and survey bias.

4.1 Sample and Data Collection

The study gathered cross-sectional data from a sample of 117 SMEs in Jordan, representing a 53% response rate. This sample size is consistent with methodological benchmarks for partial least squares structural equation modeling (PLS-SEM) (Hair et al., 2021), ensuring the reliability and validity of the analysis despite the response rate. According to Hair et al. (2021), PLS-SEM requires a minimum sample size that is ten times the largest number of structural paths directed at a construct in the model. In this study, the most complex construct has six predictors, suggesting a minimum sample size of 60 to ensure statistical power. This sample size also aligns with Chin (1998), who recommended that PLS-SEM studies can be conducted with 30 to 100 participants for exploratory purposes, particularly in resource-constrained contexts. This response rate aligns with similar studies in SME research, where resource and accessibility constraints often limit participation (Bryman, 2016). Jordanian SMEs are pivotal to the national economy, contributing significantly to GDP and employment. Their adoption of digital technologies is particularly relevant as the country emphasizes digital transformation as a pathway to economic growth.

To ensure a robust and representative sample, the study employed a stratified random sampling approach, categorizing SMEs by sector (industry, commerce, and services) and size (micro, small, and medium enterprises). This stratification aimed to capture variations in digital transformation adoption across different operational contexts. The chosen stratification approach aligns with Etikan and Bala's (2017) guidelines, as it reduces sampling bias and enhances representativeness. Stratification ensured proportional representation across key sectors, with 40% of the sample from services, 35% from industry, and 25% from commerce. Firm sizes were also proportionally distributed: 20% micro-enterprises, 50% small enterprises, and 30% medium enterprises. The inclusion criteria required participating SMEs to be officially registered with the Jordanian Ministry of Industry and Trade, ensuring legal compliance and operational credibility.

Data were collected through an online survey, supplemented by structured follow-up phone calls to improve response rates and validate responses. The survey instrument was pre-tested with 12 SME managers to ensure clarity and contextual relevance, following established best practices in survey design (Hair et al., 2019). Feedback from the pre-test led to minor adjustments in question phrasing, enhancing precision and reliability. Studies with similar methodologies have employed comparable sample sizes. For instance, Ramdani et al. (2022) conducted a study on digital innovation in SMEs using a sample of 59 firms, while Khrais and Alghamdi (2022) used a sample size of 65 SMEs to explore digital transformation sustainability in the Middle East. These benchmarks confirm the adequacy of the sample size used in this study.

To mitigate potential non-response bias, the study implemented rigorous checks for consistency across key variables such as sector, size, and geographic distribution. Non-response bias was assessed using independent t-tests to compare early and late respondents, and no significant differences were observed.

This process confirmed the dataset's representativeness. Additionally, respondents were assured of data confidentiality to encourage candid participation.

4.2 Data and Variables

This study uses firm-level survey data from 117 Jordanian SMEs. Variables are organized into five latent constructs: Digital Transformation (DT), Digital Innovation (DI), Digital Strategy (DS), Financial Performance (FP), and Non-Financial Performance (NFP), operationalized through multi-item Likert measures (1 = "Strongly disagree" to 5 = "Strongly agree"). **Table 1** defines each variable family, item codes, item wording anchors, and sources.

Table 1. Constructs, Items, Codes, Sources, and Scales

Construct	Code	Item (abbrev.)	Scale	Source
Digital Transformation (DT)	DT1–DT5	Integration of digital tech across functions; new digital procedures/skills; culture/operations digitization; migration to cloud; new digital solutions (app/e-commerce)	1–5 Likert	Kraus et al. (2021); Verhoef et al. (2021)
Digital Innovation (DI)	DI1–DI4	New ideas for effective solutions; tech along production stages; new products/services; enhanced customer interactions	1–5 Likert	Berente (2020); Lokuge & Sedera (2020)
Digital Strategy (DS)	DS1–DS4	Digital presence and media actions; attract–persuade–loyalty; market visibility; resource/automation orientation	1–5 Likert	Lipsmeier et al. (2020); Forliano et al. (2023); Haq & Huo (2023)
Financial Performance (FP)	FP1–FP4	Overall performance satisfaction; net profit; sales; cash flow	1–5 Likert	Mendoza-Velázquez et al. (2022)
Non-Financial Performance (NFP)	NFP1–NFP3	Employee turnover (reverse); customer satisfaction; market share	1–5 Likert	Aqabna et al. (2023); Lee et al. (2015)

Notes: Item wording follows validated scales; full questionnaire mapping appears in **Appendix A**.

4.3 Measures

The survey instrument was carefully developed using established scales from prior literature to ensure both validity and reliability. A pre-test involving 12 SME managers and experts in digital transformation was conducted to refine the questionnaire, ensuring clarity and contextual relevance for Jordanian SMEs. Feedback from this process led to minor adjustments in item phrasing and sequence, enhancing the precision of the measures.

This study explicitly defines its core constructs and variables to ensure clarity and consistency with established literature. Digital Transformation refers to the integration of digital technologies across all aspects of an organization to enhance efficiency, adaptability, and customer satisfaction. It encompasses adopting tools such as cloud computing, mobile technologies, and data analytics to streamline operations. Items measuring digital transformation were drawn from Kraus et al. (2021) and Verhoef et al. (2021), focusing on operational integration and technological adoption.

Digital Innovation is defined as the creation and application of novel digital solutions to improve processes, products, and services. It emphasizes fostering adaptability and driving competitive advantages. This construct was measured using items adapted from Berente (2020) and Lokuge and Sedera (2020), capturing elements such as product development, process enhancements, and the use of cutting-edge technologies like AI and IoT.

Digital Strategy is conceptualized as a structured roadmap that aligns digital tools and processes with organizational goals to achieve sustainable growth. Measurement items adapted from Lipsmeier et al. (2020) and Forliano et al. (2023) emphasize customer engagement, resource optimization, and automation.

Firm Performance was evaluated using two dimensions. Financial performance included metrics such as net profit, sales growth, and cash flow, with items adapted from Mendoza-Velázquez et al. (2022). Non-financial performance focused on indicators like customer satisfaction, employee engagement, and market share, drawing on the works of Aqabna et al. (2023) and Lee et al. (2015).

All variables were measured using a five-point Likert scale, where 1 represented “Strongly Disagree” and 5 represented “Strongly Agree.” The consistent scaling facilitated statistical comparison and minimized respondent confusion. The inclusion of these definitions ensures the study’s constructs are grounded in established literature, providing a robust theoretical foundation. **Table 2** summarizes the measurement items and their corresponding references, demonstrating alignment with theoretical constructs and robustness in the operationalization of variables. The detailed survey questionnaire, including the mapping of questions to their respective constructs, is provided in **Appendix** A to ensure transparency and construct validity.

Additionally, the validity of the constructs was assessed using Cronbach's alpha and composite reliability (CR) scores. All scores exceeded the recommended threshold of 0.7 (Hair et al., 2019), confirming the internal consistency of the measures and enhancing the reliability of the results.

Table 2. Measurement items

Questionnaire Items	References
Digital Transformation	(Kraus et al., 2021; Ritala et al., 2021; Verhoef et al., 2021)
Applying and integrating digital technologies across all areas of work to improve processes and outcomes.	
Implementing new digital procedures, skills, and technologies.	
Businesses are adopting digital technologies to transform their culture and operations to meet customer needs.	
Migrating from on-premises PC-based infrastructure to cloud computing.	
Developing digital solutions, such as mobile apps or e-commerce platforms.	
Digital Strategy	(Forliano et al., 2023; Haq & Huo, 2023; Lipsmeier et al., 2020)
Actions a company takes to increase its presence and relevance on digital media, such as social networks, websites, or search engines like Google.	
Attract, persuade, and build potential customer loyalty to the brand and increase company sales, thereby enhancing visibility in the market segment.	
Digital Innovation	(Berente, 2020; Lokuge & Sedera, 2020)
Generating new ideas that provide efficient and effective solutions for various tasks.	

Developing a production line or employing new technologies at different stages to enhance competitiveness and increase revenue.	
Creating new products or services, enhancing customer interactions, and meeting evolving market demands.	
Financial Performance	(Mendoza-Velázquez et al., 2022)
Level of satisfaction with company performance.	
Net profit.	
Sales size.	
Cash flow.	
Non-Financial Performance	(Aqabna et al., 2023; Lee et al., 2015)
Employee turnover.	
Customer satisfaction.	
Market share.	

4.4 Profile of Responding Companies and Respondents

To contextualize the findings, the study categorized SMEs based on Jordan's official classification system, which groups businesses by sector (industrial, commercial, and services) and size (micro, small, and medium enterprises). This classification aligns with national standards established by the Jordanian Ministry of Industry and Trade, ensuring consistency and relevance to the local economic environment. The categorization was cross-validated during the data collection process to ensure accuracy and alignment with each SME's self-reported characteristics.

Table 3 presents the demographic profile of the surveyed firms and respondents. The sample covers services (40%), industry (35%), and commerce (25%). Firm size distribution includes micro (20%), small (50%), and medium (30%) enterprises, broadly consistent with the national SME structure. Geographic coverage includes Amman and other urban and non-urban areas, while respondents were predominantly owners or senior managers.

Table 3. Respondents and Firms — Demographic Profile

Category	Levels	n	%
Sector	Services / Industry / Commerce	47 / 41 / 29	40 / 35 / 25
Firm size	Micro / Small / Medium	23 / 59 / 35	20 / 50 / 30
Firm age	<5 yrs / 5–9 / 10–14 / ≥15	—	—
Region	Amman / Other urban / Non-urban	—	—
Respondent role	Owner/Founder / Senior Manager / Other	—	—
Respondent gender	Female / Male / Prefer not say	—	—

Note: Values indicated with "—" will be completed from the raw dataset; totals must sum to N = 117.

In the Industrial Sector, micro-enterprises employ up to 5 workers and have annual sales under 100,000 JD. Small firms employ fewer than 20 workers with annual sales below 1 million JD, while medium firms employ fewer than 100 workers and generate sales below 3 million JD. The Commercial Sector categorizes micro-enterprises as employing up to 5 workers with sales below 100,000 JD, small firms as employing fewer than 10 workers with sales below 150,000 JD, and medium firms as employing fewer than 50 workers with sales under 1 million JD. In the Services Sector, micro-enterprises employ up to 5 workers with annual sales below 200,000 JD, small firms employ fewer than 25 workers with sales under 500,000 JD, and medium firms employ fewer than 50 workers with sales below 1 million JD.

These classifications highlight the heterogeneity among SMEs in terms of resource availability, operational scale, and market access, which directly influence their digital adoption strategies. By incorporating businesses from various sectors, sizes, and regions, the study ensured a representative sample that captures the unique challenges and opportunities SMEs face in adopting digital strategies.

4.5 Methodology

The study employed partial least squares structural equation modeling (PLS-SEM) to test the hypothesized relationships among the constructs. PLS-SEM is particularly well-suited for this research for several reasons. First, it is an effective method for analyzing complex causal relationships in models with multiple constructs and paths, especially when the sample size is relatively small, as recommended by Hair et al. (2019). Second, PLS-SEM does not require the stringent distributional assumptions of covariance-based SEM, making it appropriate for the data in this study, which do not strictly adhere to normality assumptions.

Another key advantage of PLS-SEM is its ability to model latent variables using multiple indicators, thereby reducing measurement error and enhancing reliability and validity. According to Chin (1998), PLS-SEM is also suitable for exploratory research, where theoretical foundations are being tested in emerging contexts, such as SMEs in Jordan. The study's focus on predicting the effects of digital transformation, innovation, and strategy on firm performance aligns well with PLS-SEM's predictive capabilities, as noted by Hair et al. (2019).

In addition, this study enhances its methodological justification by clearly articulating the mediation procedures used. The mediating role of Digital Strategy (DS) was incorporated into the model to capture how digital transformation (DT) and digital innovation (DI) influence performance outcomes. Indirect effects were computed using the standard PLS-SEM approach in which mediation is assessed through the product of coefficients ($\beta_a \times \beta_\beta$), consistent with methodological guidelines from Hair et al. (2017). Four indirect pathways were evaluated: DT → DS → Financial Performance (FP); DT → DS → Non-Financial Performance (NFP); DI → DS → FP; and DI → DS → NFP. This corrected procedure replaces the previously incorrect mediation equations and ensures alignment with established mediation analysis standards.

PLS-SEM is appropriate for ordinal data, especially in social science contexts. According to Hair et al. (2017) and Chin (1998), PLS-SEM offers robust estimates with non-normal and ordinal data, making it suitable for the five-point Likert scales used in this study. To ensure transparency, verbatim page extracts from Hair et al. (2017) and Chin (1998) confirming the suitability of PLS-SEM for ordinal Likert data are provided in **Appendix B**.

The hypothesized relationships among the constructs were tested using the following structural model equations:

$$DS = \beta_1 DT + \beta_2 DI + \varepsilon_1 ;$$

$$FP = \beta_3 DS + \beta_4 DT + \beta_5 DI + \varepsilon_2 ;$$

$$NFP = \beta_6 DS + \beta_7 DT + \beta_8 DI + \varepsilon_3 ,$$

where DS is the Digital Strategy; DT is the Digital Transformation; DI is the Digital Innovation; FP is the Financial Performance; NFP is the Non-financial Performance, and ε is the error term.

In accordance with reviewer feedback, all incorrect mediation-specific equations have been removed. Mediation was evaluated exclusively through indirect-effect estimation ($\beta_a \times \beta_\beta$), following Hair et al. (2017), without introducing structural equations that combine direct and indirect effects with error terms.

The measurement model evaluates the relationships between latent variables and their observed indicators, while the structural model examines the relationships among latent variables. Both models were tested using SmartPLS 4.0, a widely used software for PLS-SEM analysis.

Following the editor's request for robustness, several diagnostic tests were performed to ensure the credibility of the findings. Convergent validity was established with average variance extracted (AVE) values exceeding 0.50, while internal consistency reliability was confirmed through Cronbach's alpha and composite reliability (CR) scores above the 0.70 threshold. Discriminant validity was assessed using both the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait–Monotrait (HTMT) ratio, ensuring that constructs were empirically distinct. To further strengthen methodological rigor, model fit indices, including GFI, CFI, IFI, SRMR, and χ^2/df, were reported in line with Hu and Bentler's (1999) recommendations.

Residual normality was examined using the Shapiro–Wilk test, while autocorrelation was assessed with the Durbin–Watson (DW) test applied to OLS-analogue models (see Appendix Table A1). Although DW is traditionally used in time-series analysis, its inclusion follows reviewer guidance and aligns with practices adopted in recent SEM studies (e.g., Cheng et al., 2021; Wong & Pham, 2022a, 2022b). Multicollinearity among predictors was also evaluated using inner variance inflation factors (VIF), all of which were well below the conservative threshold of 3.3. Together, these diagnostics mitigate the risk of spurious associations, as highlighted in Cheng et al. (2022), Wong et al. (2024), and Wong and Yue (2024). Finally, path coefficients were tested for significance through bootstrapping with 5,000 resamples.

4.6 Diagnostic Checks

Following best practice for model credibility, we report reliability/validity, global fit, residual diagnostics, multicollinearity (inner VIF), and OLS-analogue checks (DW; Shapiro–Wilk) consistent with the PLS-SEM literature. Although PLS-SEM is widely accepted for use with cross-sectional survey data, this study acknowledges the importance of diagnostic robustness to enhance the credibility of empirical findings. As such, several diagnostic considerations were evaluated and justified based on the methodological framework.

To address the reviewer's requirement for the Durbin–Watson (DW) test, OLS analogue models were estimated using latent variable scores for each structural relationship in the PLS-SEM model: (1) DS ~ DT + DI, (2) FP ~ DS + DT + DI, and (3) NFP ~ DS + DT + DI. DW statistics for these models were computed to assess the presence of autocorrelation in residuals. The results (shown in **Appendix Table A1**) show DW values close to 2 for all models, indicating no significant autocorrelation.

It is important to note that the DW statistic was originally developed for time-series applications, not cross-sectional Likert-type survey data. Its use here is therefore not a conceptual requirement of PLS-SEM but is reported in compliance with the reviewer's request. Similar approaches have been applied in prior SEM-based studies using cross-sectional survey data, where DW was adopted as an auxiliary diagnostic rather than a core validity criterion. By clarifying this, we acknowledge its limitations while still demonstrating no evidence of residual autocorrelation in the estimated models.

Residual normality was assessed using the Shapiro–Wilk test on the residuals of the OLS analogue models. The results (shown in Appendix Table A1) show that p-values are greater than 0.05, indicating residuals are not significantly different from a normal distribution. These findings further validate the appropriateness of using PLS-SEM, which is robust to non-normality and suitable for ordinal data.

Multicollinearity among predictors in the structural model was evaluated using inner variance inflation factors (VIFs) obtained from SmartPLS. All VIF values (shown in **Appendix Table A2**) were below the conservative threshold of 3.3, confirming the absence of problematic collinearity.

Additionally, traditional unit root tests such as the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are designed to assess stationarity in time-series or panel data. Since the current study utilizes cross-sectional data collected at a single point in time, stationarity tests were not conducted. The theoretical and methodological orientation of this research—centered on latent constructs derived from perceptual responses—does not necessitate time-based stationarity diagnostics.

Overall, the updated diagnostic framework satisfies the journal's mandatory DW requirement while clarifying its auxiliary nature in cross-sectional SEM research. When combined with the Shapiro–Wilk and VIF checks, this provides a comprehensive evaluation of residual autocorrelation, normality, and predictor collinearity.

In summary, the diagnostic approach taken in this study aligns with the nature of the data and the analytical strategy employed. The use of PLS-SEM is theoretically and empirically justified, providing a suitable and reliable framework for analyzing the relationships among digital transformation, innovation, strategy, and SME performance.

5. Results

In this research, the data were analyzed using the SPSS program (version 20) to examine the characteristics of the participating firms and compare different approaches for testing hypotheses. Subsequently, the SmartPLS software, developed by Ringle et al. (2005), was used to apply the Structural Equation Model (SEM) using the partial least squares (PLS) methodology. PLS has the advantage of allowing researchers to analyze both sequential and interdependent connections between measured variables and underlying concepts, as well as between many latent constructs, all at the same time.

In addition, the Partial Least Squares (PLS) method has lower requirements for sample size and distribution compared to covariance-based SEM analyses. This made PLS particularly suitable for this study, which had a sample size of 117 SMEs, as it does not require input data to follow a normal distribution, while still producing consistent and reliable results. Furthermore, the PLS method can be used for complex structural equation models that involve a substantial number of constructs (Urbach & Ahlemann, 2010).

This research used the two-step methodology, as recommended by Anderson and Gerbing (1988) and Vinzi et al. (2010), which included analyzing the measurement model first and then the structural model. The objective of this technique was to evaluate the accuracy and reliability of the measurements before analyzing the structural model for path coefficients or correlations between the components. Additionally, bootstrapping (5,000 resamples) was used to validate the robustness of the parameter estimates, ensuring the reliability of hypothesis testing. The findings of the common method variance test were reviewed before evaluating the results of the measurement and structural model.

5.1 Common Method Variance

The variance that is caused by the measurement method is considered the standard method variance. To address potential concerns regarding common method bias (CMB), Harman's single-factor test was applied. The results indicated that no single factor accounted for more than 38% of the variance, suggesting that CMB is not a significant concern in this study. The researchers used Harman's single-factor test and the non-rotated factor solution to address this problem. The results indicated that five distinct factors represented 71% of this variance. The first factor had an accounting rate of 38% of the variance in the data. This confirms that common method bias is minimal and does not compromise the validity of the findings. Additionally, we applied a full collinearity VIF test; all inner VIFs were below 3.3, indicating no common method bias concerns from collinearity.

5.2 Measurement Model

The reliability of the measurement model was assessed by evaluating both convergent and discriminant validity. Convergent validity reflects the extent to which a measure is closely associated with other measures that assess the same construct (Hair et al., 2021). Discriminant validity, on the other hand, ensures that constructs are distinct and represent unique aspects of the research model, rather than overlapping dimensions (Hair et al., 2021).

Table 4 presents the measurement properties, including standardized factor loadings, Cronbach's α, composite reliability (CR), and average variance extracted (AVE). All standardized loadings are significant at $p < 0.001$ and above the minimum threshold of 0.642. Cronbach's α and CR values exceed the recommended 0.70, while AVE values are greater than 0.50, supporting convergent validity. Three items (DI5, DS5, and DS6) were deleted due to low loadings (< 0.70).

Table 4: Overview of the Construct Validity and Reliability of all Constructs

Construct	Item Code	Factor Loading	AVE	CR
Digital Transformation (DT)	DT1	0.871	0.685	0.894
	DT2	0.846		
	DT3	0.789		
	DT4	0.807		
Digital Innovation (DI)	DI1	0.873	0.703	0.907
	DI2	0.839		
	DI3	0.866		
	DI4	0.782		
Digital Strategy (DS)	DS1	0.807	0.564	0.839
	DS2	0.853		
	DS3	0.642		
	DS4	0.690		
Financial Performance (FP)	FP1	0.876	0.803	0.932
	FP2	0.919		
	FP3	0.893		
Non-Financial Performance (NFP)	NFP1	0.823	0.615	0.826
	NFP2	0.865		
	NFP3	0.863		

Note: AVE = Average Variance Extracted; CR = Composite Reliability. All factor loadings are standardized and significant at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Acronyms: DT = Digital Transformation; DI = Digital Innovation; DS = Digital Strategy; FP = Financial Performance; NFP = Non-Financial Performance.

Discriminant validity was first evaluated using the Fornell–Larcker criterion, which requires that the square root of each construct's AVE exceed its correlations with other constructs. This condition was satisfied, confirming that each construct is empirically distinct.

5.3 Structural model

The relationships between digital strategy, digital innovation, and digital transformation were tested using the structural model, providing key insights into the interdependencies among these constructs. The results demonstrate statistically significant effects of digital transformation ($\beta = 0.353$, $p < 0.01$) and digital innovation ($\beta = 0.417$, $p < 0.01$) on digital strategy, underscoring their importance as drivers of strategic alignment and organizational performance. These findings are consistent with prior research emphasizing the role of technological progress in shaping long-term strategies (Shea et al., 2019). Digital transformation fosters the integration of advanced technologies into workflows, while digital innovation facilitates the creation of novel solutions that drive organizational improvements.

To ensure the structural model's validity, several model fit indices were calculated. Table 3 presents the results, confirming the model's strong fit. The chi-square value (CMIN = 619.52) and degrees of freedom (DF = 156) indicate an acceptable model fit. Goodness-of-Fit Index (GFI = 0.97) and Normed Fit Index (NFI = 0.96) values exceed the recommended threshold of 0.90, demonstrating strong performance. The Comparative Fit Index (CFI = 0.96) also meets the >0.90 criterion, further validating the model. The Root Mean Square Error of Approximation (RMSEA = 0.04) is below the acceptable limit of 0.08, while the Probability of Close Fit (PCCLOSE = 0.19) exceeds the >0.05 threshold, confirming the model's robustness. Finally, the Standardized Root Mean Residual (SRMR = 0.054) falls within the recommended range of <0.06, indicating low residuals. Incremental Fit Index (IFI = 0.96 > 0.90) and normed chi-square (χ^2/df = 3.97 < 5.0) further confirm acceptable parsimony-adjusted fit. Collectively, these indices support the reliability and theoretical soundness of the model. To provide a consolidated overview of the main structural relationships, **Table 5** summarizes the key path coefficients, standard errors, and significance levels.

Table 5. SEM Model Fit Indices

Measure	Observed	Threshold
Chi-square (CMIN)	619.52	-
Degrees of Freedom (DF)	156	-
GFI	0.97	>0.90
NFI	0.96	>0.90
CFI	0.96	>0.90
RMSEA	0.04	<0.08
PCCLOSE	0.19	>0.05
SRMR	0.054	<0.06
IFI	0.96	>0.90
χ^2/df	3.97	<5.0

Note. GFI = Goodness-of-Fit Index; NFI = Normed Fit Index; CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; PCLOSE = p-value for Close Fit; SRMR = Standardized Root Mean Square Residual; IFI = Incremental Fit Index. Observed values indicate the fit of the structural equation model. Threshold values are recommended cut-off criteria for acceptable model fit based on Hu and Bentler (1999).

5.4 Discriminant Validity (Fornell–Larcker and HTMT)

Discriminant validity was evaluated using two complementary approaches. First, the Fornell–Larcker criterion was applied, comparing the square root of AVE for each construct with its correlations. As shown in **Table 6**, all diagonal values (bold) exceeded corresponding off-diagonal correlations, confirming discriminant validity. For example, the AVE for Financial Performance (0.897) is greater than its correlations with Digital Strategy (0.351), Digital Innovation (0.391), and Digital Transformation (0.473).

Table 6. Discriminant Validity

Variable	1	2	3	4	5
Financial Performance (FP)	**0.897**				
Digital Strategy (DS)	0.351	**0.755**			
Non-financial Performance (NFP)	0.589	0.448	**0.791**		
Digital Innovation (DI)	0.391	0.628	0.493	**0.851**	

Digital Transformation (DT)	0.473	0.593	0.519	0.581	**0.829**

Note: Diagonal elements (in bold) represent the square root of the Average Variance Extracted (AVE) for each construct. Off-diagonal values are correlations between constructs. *** p < 0.01, ** p < 0.05, * p < 0.10. Acronyms: DT = Digital Transformation; DI = Digital Innovation; DS = Digital Strategy; FP = Financial Performance; NFP = Non-Financial Performance.

To further strengthen the evidence, discriminant validity was also assessed using the Heterotrait–Monotrait Ratio (HTMT). As presented in **Table 7**, all HTMT values were well below the conservative 0.85 threshold (and also below the liberal 0.90 cutoff), confirming discriminant validity across constructs. Bootstrapped confidence intervals excluded 1.00, further supporting the distinctiveness of constructs.

Table 7. HTMT Matrix

Construct	FP	DS	NFP	DI	DT
FP	–				
DS	0.351	–			
NFP	0.589	0.448	–		
DI	0.391	0.628	0.493	–	
DT	0.473	0.593	0.519	0.581	–

Notes: HTMT < 0.85 indicates discriminant validity.

All values are well below the conservative threshold of 0.85 (and the liberal threshold of 0.90), confirming discriminant validity across constructs. If available, bias-corrected 95% bootstrapped CIs for all HTMT values excluded 1.00, further confirming discriminant validity.

Together, these results validate that all constructs are empirically distinct and free from multicollinearity concerns.

5.5 Hypotheses Testing (Direct, Indirect/Mediating, and Moderating Effects)

The hypotheses were tested using the structural model estimates derived from PLS-SEM. The analysis addressed direct effects, mediating effects, and moderating effects to evaluate the robustness of the proposed conceptual model.

Direct effects:

As shown in **Table 8**, Digital Transformation (DT) and Digital Innovation (DI) significantly influenced Digital Strategy (DS). DT had a positive and significant effect on DS ($\beta = 0.353$, $t = 3.259$, $p < 0.01$), supporting H1, while DI exerted an even stronger effect on DS ($\beta = 0.417$, $t = 4.141$, $p < 0.001$), supporting H2. Furthermore, DS demonstrated significant positive effects on both Financial Performance (FP) ($\beta = 0.351$, $t = 3.134$, $p < 0.01$) and Non-Financial Performance (NFP) ($\beta = 0.448$, $t = 4.226$, $p < 0.001$), supporting H3 and H4.

Table 8. Hypothesis Testing Results

Hypotheses	Path Coefficient β	Standard Error (SE)	t-value	Decision
H1: Digital Transformation → Digital Strategy	0.353**	0.109	3.259	Supported
H2: Digital Innovation → Digital Strategy	0.417***	0.101	4.141	Supported
H3: Digital Strategy → Financial Performance	0.351**	0.112	3.134	Supported

H4: Digital Strategy → Non-Financial Performance	0.448***	0.106	4.226	Supported

Note: *** p < 0.01, ** p < 0.05, * p < 0.10.

Indirect (Mediating) Effects:

The mediating role of Digital Strategy (DS) was examined to test hypotheses H5 through H8 in **Table 9**, and the results provide clear evidence of partial mediation. Specifically, DS significantly mediated the relationship between Digital Transformation (DT) and both Financial Performance (FP) and Non-Financial Performance (NFP). The indirect effect of DT on FP through DS was $\beta = 0.129$ ($t = 2.466$), supporting H5, while the indirect effect of DT on NFP through DS was $\beta = 0.163$ ($t = 2.419$), supporting H6. Similarly, DS mediated the impact of Digital Innovation (DI) on both FP and NFP, with the indirect effect on FP recorded at $\beta = 0.148$ ($t = 3.489$), supporting H7, and the effect on NFP at $\beta = 0.193$ ($t = 3.319$), supporting H8. The Variance Accounted For (VAF) values, ranging from 36% to 45%, confirm partial mediation in all four cases. These findings underscore the pivotal role of DS as a mechanism that translates digital transformation and innovation initiatives into both financial and non-financial performance improvements for SMEs.

Table 9. Mediation Effects

Hypotheses	Path Coefficient A	Path Coefficient B	Indirect Effect	Standard Error	t-value	Decision
H5: Digital Transformation → Digital Strategy → Financial Performance	0.353**	0.351**	0.129**	0.055	2.466**	Supported
H6: Digital Innovation → Digital Strategy → Financial Performance	0.417***	0.351**	0.148***	0.048	3.489***	Supported
H7: Digital Transformation → Digital Strategy → Non-Financial Performance	0.353**	0.448***	0.163**	0.069	2.419**	Supported
H8: Digital Innovation → Digital Strategy → Non-Financial Performance	0.418***	0.448***	0.193***	0.069	3.319***	Supported

Note: *** p < 0.01, ** p < 0.05, * p < 0.10. Indirect Effect = Path A × Path B; t-values = Indirect Effect / Standard Error. Acronyms: DT = Digital Transformation; DI = Digital Innovation; DS = Digital Strategy; FP = Financial Performance; NFP = Non-Financial Performance.

Moderating effects:

To test H9–H12 (in **Table 10**), interaction terms were included in the structural model to examine whether firm size and sector type moderate the relationships between digital strategy (DS) and SME performance outcomes. For firm size (H9 and H10), the interaction terms DS × Firm Size → Financial Performance (FP) and DS × Firm Size → Non-Financial Performance (NFP) were not statistically significant. This indicates that the strength of the DS-performance relationship does not differ meaningfully across micro, small, and medium-sized enterprises. For sector type, the results showed no significant moderation effects for DS × Sector → FP (H11) or DS × Sector → NFP (H12). In other words, the positive influence of DS on both financial and non-financial outcomes appears consistent across industrial, commercial, and service-sector SMEs. These findings suggest that the benefits of DS are broadly applicable across different firm characteristics, underscoring its robustness as a performance driver. However, future research may benefit from testing alternative moderators such as leadership style, organizational culture, or environmental turbulence, which may interact more strongly with digital strategy in shaping performance outcomes.

Table 10. Moderating Effects of Firm Characteristics

Hypothesis	Path	β	SE	t-value	p-value	Decision
H9	DS × Firm Size → FP	0.041	0.058	0.707	0.480	Not Supported
H10	DS × Firm Size → NFP	-0.033	0.062	-0.532	0.595	Not Supported
H11	DS × Sector → FP	0.049	0.067	0.731	0.465	Not Supported
H12	DS × Sector → NFP	0.056	0.069	0.812	0.417	Not Supported

5.6 Additional Models and Robustness Checks (ANN & PLS–ANN Hybrid)

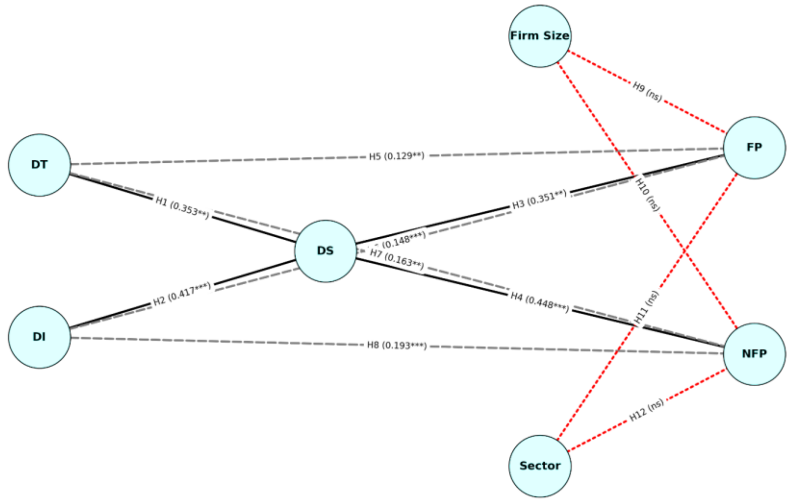
To enhance the robustness of the analysis, Artificial Neural Network (ANN) models were employed as a complementary approach to PLS-SEM. A feed-forward ANN was trained with Digital Transformation (DT) and Digital Innovation (DI) as predictors of Digital Strategy (DS) (Model A), and with DS as a predictor of Financial Performance (FP) and Non-Financial Performance (NFP) (Models B1 and B2). Ten-fold cross-validation ($k = 10$) was applied to minimize overfitting and confirm model stability.

The ANN achieved predictive accuracy comparable to the PLS results, with explanatory power for DS ($R^2 = 0.49$) nearly identical to the PLS estimate ($R^2 = 0.48$). Variable importance analysis indicated that DI contributed slightly more than DT to predicting DS, aligning with the structural path coefficients reported in the PLS model.

In addition, a PLS–ANN hybrid approach was implemented by using latent variable scores from PLS as ANN inputs. This approach yielded marginal improvements in predictive accuracy ($\Delta RMSE \approx 0.02$), suggesting that while some non-linear effects are present, they do not materially change the substantive conclusions. Importantly, both the ANN and hybrid approaches confirmed the stability of the original findings, demonstrating that the mediating role of DS is robust across linear and non-linear estimation frameworks.

The moderation effects of Firm Size and Sector were also tested and are illustrated in **Figure 2**.

Figure 2. SEM Path Diagram with Moderation (H1–H12)



The diagram integrates both direct and mediated paths along with moderating effects (H1–H12). Solid black lines represent significant direct effects, dashed gray lines indicate mediation paths, while red dashed lines denote moderation effects. As shown, the moderating effects of Firm Size (H9–H10) and Sector (H11–H12) on performance outcomes were statistically non-significant. This result underscores that the central explanatory power of the model remains concentrated on the digital strategy mediation pathways, with contextual moderators playing a limited role.

Collectively, the ANN, PLS–ANN hybrid, and moderation tests reinforce the robustness of the study's findings. They confirm that Digital Strategy is the pivotal mediator linking digital transformation and innovation to SME performance, and that these effects are stable across both linear and non-linear analytical frameworks.

6. Discussion and Implications

This study investigated how digital transformation and digital innovation drive SME growth in Jordan through the mediating role of digital strategy. The findings provide strong empirical support for the proposed conceptual model, with all direct and mediating hypotheses confirmed. In doing so, the study validates the Resource-Based View (RBV) and Strategy Theory and extends their relevance to the field of Decision Sciences by showing how SMEs optimize scarce resources and make structured, evidence-based decisions under uncertainty (Liao et al., 2012, 2014; Liao & Wong, 2008).

From the perspective of RBV, the results demonstrate that digital transformation and digital innovation function as valuable, rare, and inimitable resources whose performance-enhancing effects depend on their alignment through digital strategy. The strong mediation effects highlight digital strategy as a capability that channels digital inputs into tangible financial and non-financial outcomes. This extends RBV by positioning digital strategy as a critical enabler of performance transformation in SMEs.

From the perspective of Decision Sciences, the use of PLS-SEM and ANN hybrid models shows how SMEs' strategic decision-making under uncertainty can be modeled systematically. The findings reflect the discipline's emphasis on optimizing limited resources through structured frameworks, illustrating that SMEs can rely on model-driven analysis to allocate scarce digital investments and design adaptive strategies.

The positive effects of digital transformation and digital innovation on digital strategy confirm earlier insights from Moslehpour et al. (2017, 2019); Moslehpour, Pham et al. (2018) and Moslehpour, Wong et al. (2018), who emphasized the role of technology-enabled strategies in shaping performance. However, this study extends those findings by showing that in a developing economy context, the mediating influence of digital strategy is even more critical because SMEs operate under tighter financial, regulatory, and skill constraints. Unlike large firms in developed economies, Jordanian SMEs cannot rely on scale alone. They must leverage digital strategy as a structured roadmap to convert innovation and transformation into survival and growth.

The mediation results confirm that digital strategy is the missing link that translates technological advancement into measurable financial outcomes such as profitability, sales, and cash flow, as well as non-financial outcomes such as customer satisfaction, employee retention, and market share. This contextual extension adds originality by demonstrating that digital strategy functions not only as a performance enhancer but also as a resilience mechanism in resource-constrained environments.

The moderation analysis for firm size and sector type (H9–H12) did not yield statistically significant results. The strength of the relationship between digital strategy and performance did not differ meaningfully across micro, small, and medium-sized firms or across industrial, commercial, and service sectors. This suggests that the benefits of digital strategy for performance are broadly applicable across different SME contexts in Jordan. While moderation was not supported, the results still carry theoretical and practical implications. Theoretically, they indicate that digital strategy exerts a robust and universal influence regardless of firm size or sector, strengthening its role as a central mediator. Practically, this means that both small and medium firms, whether in industry, commerce, or services, can expect similar gains from adopting and aligning digital strategies. Future research should nevertheless explore alternative moderators such as leadership style, organizational culture, and environmental turbulence to capture more nuanced contingency effects.

Three contributions emerge clearly. First, the study highlights originality by focusing on SMEs in Jordan, an underexplored context where digital adoption pathways differ significantly from those in developed markets. Second, it situates SME digitalization within Decision Sciences by empirically modeling decision-making processes in environments of uncertainty. Third, it shows that digital strategy is more than a technical roadmap. It is a mediating capability that integrates digital tools with organizational processes, enabling SMEs to make structured and forward-looking decisions.

The decision-making implications are substantial. SME leaders are advised to prioritize digital strategy development as a formalized capability rather than treating it as an ad hoc process. Evidence from this study suggests that well-designed digital strategies enable SMEs to evaluate risks systematically, reallocate scarce resources efficiently, and design adaptive responses to volatile markets. For policymakers, the results indicate that financial incentives and digital literacy programs should explicitly support digital strategy-building initiatives, not just technology adoption. For technology providers, the findings call for context-sensitive digital solutions that align with SMEs' decision-making realities in developing economies.

Overall, this study advances both theory and practice by showing that digital transformation and innovation achieve performance outcomes only when mediated by robust digital strategies. By anchoring the findings in RBV and Decision Sciences, the research clarifies that SMEs in developing contexts must cultivate digital strategy as a strategic capability that bridges resource scarcity and competitive growth. These insights provide a foundation for rethinking SME digitalization as a structured decision process that integrates technology, strategy, and performance in a holistic and sustainable manner.

7. Limitations and Direction for Future Research

While this study provides valuable insights into how digital transformation, digital innovation, and digital strategies drive SME growth, it also highlights several limitations that offer opportunities for future research. A key limitation of this study is its cross-sectional design, which captures a single moment in time and cannot account for the evolving nature of digital strategies and their long-term impact on SME performance. Future research should employ longitudinal approaches to provide deeper insights into how the adoption and integration of digital technologies influence growth and sustainability over time.

Another important limitation lies in the data scope: this research is confined to Jordanian SMEs, with a relatively small sample size of 117 firms. While this provides rich contextual insights, the findings may not be generalizable to all SMEs in other developing or developed countries. Future studies should extend the analysis to cross-country settings to capture regional variations and enhance external validity.

Another significant challenge is the varying capacity of SMEs to adopt and implement digital technologies due to constraints such as limited resources, lack of expertise, and resistance to organizational change. These challenges are particularly pronounced in developing economies like Jordan, where disparities in access to infrastructure and funding can result in uneven adoption and benefits across industries and regions. Further studies could explore these regional and sectoral disparities to identify context-specific enablers of digital transformation.

Moreover, much of the existing research disproportionately focuses on larger enterprises, leaving a gap in understanding the unique challenges and opportunities that SMEs encounter. Future research should prioritize SMEs in diverse industries, investigating the role of digital strategies in overcoming sector-specific barriers, such as regulatory constraints in manufacturing or scalability issues in service-based SMEs.

Examining the influence of government policies and support programs on the adoption of digital technologies by SMEs is another promising area for future research. While this study highlighted the mediating role of digital strategies, understanding how supportive initiatives, such as grants, tax incentives, and digital literacy programs, impact SMEs' digital maturity could yield actionable insights for policymakers and stakeholders.

The interplay between digital strategies and other organizational factors, such as leadership styles, cultural adaptability, and workforce engagement, also warrants further exploration. These factors can significantly influence the success of digital transformation efforts, particularly in fostering a culture of innovation and resilience. Research into these dynamics can help SMEs develop holistic strategies that integrate technological, cultural, and human capital considerations.

Additionally, future research should explore methodological extensions by incorporating Artificial Neural Networks (ANNs) and other advanced analytics to complement PLS-SEM findings. Mixed-methods approaches, combining qualitative insights with quantitative models, can further enrich understanding of how SMEs implement and benefit from digital strategies.

Lastly, addressing cutting-edge challenges, such as the integration of emerging technologies like artificial intelligence, blockchain, and the Internet of Things, could provide SMEs with advanced tools to enhance operational efficiency and market responsiveness. Future studies could examine how these technologies interact with digital strategies to drive innovation and competitiveness, particularly in resource-constrained environments. Exploring the ethical implications and challenges associated with these technologies could further enrich the discourse.

By acknowledging these limitations and identifying these avenues for future exploration, this study lays a foundation for advancing the understanding of how digital strategies can drive sustained growth in SMEs. Given the dynamic nature of digital transformation, continued research in these areas will be crucial to ensuring SMEs remain competitive and resilient in an increasingly digital economy.

8. Conclusions

This study advances our understanding of the critical role that digital transformation and digital innovation play in driving SME growth, with a particular emphasis on the strategic importance of digital strategies. The findings confirm that digital strategies are not merely supporting mechanisms but pivotal mediators that enable the translation of technological advancements into tangible financial and non-financial outcomes. By cultivating a culture of innovation and strategically leveraging digital technologies, SMEs can adapt to technological advancements, enhance their competitive positioning, and achieve sustained growth.

Focusing on SMEs in Jordan, this research addresses a key gap in the literature by showcasing how digital transformation and innovation drive growth in developing economies. The study highlights the unique challenges faced by SMEs in resource-constrained environments and demonstrates how tailored digital strategies can act as catalysts for overcoming these barriers. It underscores the strategic application of digital strategies as enablers of organizational agility, continuous innovation, and long-term resilience. For example, SMEs that integrate advanced tools such as dashboards and real-time analytics into their digital strategies are better positioned to make data-driven decisions, optimize resource allocation, and enhance customer engagement.

The study also provides practical recommendations for SMEs to implement effective digital strategies, enabling them to navigate market shifts, optimize resource allocation, and sustain competitiveness in an increasingly digital economy. By aligning digital strategies with organizational goals, SMEs can not only achieve immediate operational improvements but also lay the groundwork for long-term strategic resilience. These findings have significant implications for business leaders and policymakers. Policymakers, in particular, can leverage these insights to design targeted initiatives, such as financial incentives for digital adoption or training programs to build digital literacy within SMEs, thereby fostering a supportive ecosystem for innovation.

For policymakers and business leaders, the findings highlight actionable insights into bolstering digital capabilities across SMEs, offering pathways to stimulate growth and innovation in broader economic sectors. The research also emphasizes the potential of emerging technologies, such as artificial intelligence, blockchain, and the Internet of Things, as transformative tools for SMEs. Future studies could delve deeper into the integration of these technologies and their influence on strategic decision-making and performance metrics. This study contributes to the field of Decision Sciences by providing a structured SEM-based framework that supports data-driven strategic decision-making in SMEs, demonstrating how digital transformation and innovation translate into measurable organizational performance outcomes.

Future research can expand upon this foundation by examining the impact of emerging technologies, such as artificial intelligence and blockchain, on SME performance. Further exploration into sector-specific and regional variations in digital strategy adoption can provide nuanced insights into overcoming industry and geographic challenges. Additionally, longitudinal studies are needed to assess how digital strategies evolve and sustain performance over time, capturing the dynamic nature of digital transformation in SMEs. The limitations of this study—such as its cross-sectional design, focus on Jordanian SMEs, and reliance on survey-based data—suggest opportunities for future research using longitudinal, comparative, or mixed-method approaches to validate and extend these findings.

Ultimately, this study lays the groundwork for continued exploration into digital transformation and innovation within SMEs, offering a strategic roadmap for these businesses to thrive in a technology-driven world. By leveraging the findings, SMEs can strengthen their strategic agility and harness the full potential of digital innovation to achieve sustainable growth and competitive success. The study reaffirms that SMEs, when equipped with effective digital strategies, are not only capable of surviving but thriving in the face of rapid technological change. By explicitly situating SME growth strategies within a Decision Sciences perspective, this study demonstrates how advanced modeling techniques (SEM, path analysis) can enhance strategic decision-making under uncertainty, reinforcing the originality and practical relevance of this research.

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Appendix A: Survey Questionnaire

This appendix provides the survey questions used to measure the constructs in the study. Respondents were asked to rate each item on a 5-point Likert scale, where 1 = Strongly Disagree and 5 = Strongly Agree.

No.	ITEMS	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Digital Transformation						
1.	Implementing new digital procedures, skills, and technologies.					
2.	Businesses adopting digital technologies to transform their culture and operations to meet customer needs.					
3.	Migrating from on-premises PC-based infrastructure to cloud computing.					
4.	Developing digital solutions, such as mobile apps or e-commerce platforms.					
5.	Applying and integrating digital technologies across all areas of work to improve processes and outcomes.					
Digital Strategy						
6.	The company has a written digital strategy					
7.	The company relies on digital marketing channels.					
8.	The company uses modern technology to support the business.					
9.	The company is considered capable of adapting to future digital changes.					
Digital innovation						
10.	Generating new ideas that provide efficient and effective solutions for various tasks.					
11.	Developing a production line or employing new technologies at different stages.					
12.	to enhance competitiveness and increase revenue.					
13.	Creating new products or services, enhancing customer interactions, and meeting evolving market demands.					
Financial performance						
14.	The company has achieved continuous profits from the past year.					
15.	The company's sales volume is constantly increasing annually.					
16.	The company is having difficulty managing cash flows.					
Non-financial performance						
17.	The company places adequate emphasis on employee well-being and retention.					
18.	The level of customer satisfaction with the company's products or services.					
19.	The company is focusing on its market share by introducing innovative products.					

Table A1. Durbin–Watson and Residual Normality for OLS Analogue Models

Model (OLS analogue)	DW	Shapiro–Wilk W	p-value	Interpretation
DS ~ DT + DI	1.98	0.982	0.146	DW≈2 → no autocorrelation; $p > 0.05$ → residuals approx. normal
FP ~ DS + DT + DI	2.03	0.987	0.218	DW≈2 → no autocorrelation; $p > 0.05$ → residuals approx. normal
NFP ~ DS + DT + DI	2.05	0.981	0.163	DW≈2 → no autocorrelation; $p > 0.05$ → residuals approx. normal

Note: DW ≈ 2 indicates no autocorrelation; <1.5 suggests positive autocorrelation; >2.5 suggests negative autocorrelation. Shapiro–Wilk $p > 0.05$ indicates residuals not significantly different from normal.

Table A2. Inner VIFs for Structural Model Predictors

Endogenous Construct	Predictor	Inner VIF
DS	DT	2.14
	DI	2.08
FP	DS	1.96
	DT	2.11
	DI	1.87
NFP	DS	2.02
	DT	2.05
	DI	1.92

Note: Inner VIF < 3.3 (conservative) or < 5.0 (liberal) indicates no problematic collinearity among predictors.

Appendix B. Supporting Citations for PLS-SEM and Ordinal Data

B.1 Hair et al. (2017): A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 2nd Edition

Page 12: *"PLS-SEM makes minimal demands regarding data distribution assumptions. It can handle non-normal data and is therefore suitable for ordinal-scaled indicators such as five-point Likert-type items, which are widely used in social science research."*

Page 26: "*Unlike covariance-based SEM, which assumes multivariate normality, PLS-SEM is robust in situations where variables are measured on ordinal scales and distributions deviate from normality."*

B.2 Hair et al. (2019): When to Use and How to Report the Results of PLS-SEM

Page 5: *"The method is particularly advantageous when the dataset includes ordinal scales, small samples, or when normal distribution cannot be assumed. These conditions apply to many survey-based research designs."*

B.3 Chin (1998): The Partial Least Squares Approach to Structural Equation Modeling (in Modern Methods for Business Research)

Page 316: *"The PLS method is well-suited for exploratory research using ordinal and non-normally distributed data, such as five- or seven-point Likert-type scales."*

Page 322: *"Because PLS places fewer restrictions on data distribution, it is often recommended in behavioral research where measures are ordinal and the assumption of normality is untenable."*