Scientific African 31 (2026) e03157

Contents lists available at ScienceDirect

Scientific African

journal homepage: www.elsevier.com/locate/sciaf

Dynamic managerial capabilities, digital innovation and perceived financial performance in the banking sector

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ARTICLE INFO

Editor: DR B Gyampoh

Keywords:
Managerial human capital
Digital innovation
Managerial social capital
Perceived financial performance
Managerial cognition

ABSTRACT

The contemporary digital economy requires businesses to utilise creative skills to boost their performance. Utilising the Dynamic Managerial Capability (DMC) theory, we examine the influence of managerial capabilities—human capital (MHC), social capital (MSC), and cognition (MC) —on digital innovation (DI) and perceived financial performance (PFP) within the banking sector. The mediating influence of MC and DI on the link among MSC, MHC, and PFP was assessed. To achieve this, 728 bankers in Ghana were purposefully sampled, adopting a seven-point Likert scale for data collection regarding managers and employees. The analysis was conducted using the Partial Least Squares – Structural Equation Modelling (PLS-SEM). The results demonstrate that managerial cognition influences the interaction among managerial social capital, managerial human capital, digital innovation, and performance, with digital innovation not serving as a mediator. Managerial cognition serves as a conduit to human managerial capital, impacting perceived financial performance. The findings compel managers and policymakers to integrate DMC's initiatives to enhance banks' digital innovation, which is essential in the contemporary dynamic and digital landscape. The assessment has expanded the framework of dynamic capability theory in nascent communities, underscoring the influence of DMC on advancing digital innovation within the banking sector.

Introduction

The evolving competitive environment, characterised by changes in consumer preferences, experiences, and satisfaction, coupled with significant advancements in digital technologies, compels organisations to implement initiatives that address consumer demands and enhance their competitive advantage, growth, and sustainability. This requires organisations to be efficient and innovative, and to maintain productivity in this dynamic and constantly evolving environment. Organisations, in their pursuit of these objectives, have adopted digital innovation (DI). DI is widely recognised as a strategic transformation that elevates organisations and enhances performance [1–3]. Due to its broad impact on organisations, DI in the digital economy has become a significant topic in academic research. Organisational structures, strategies, procedures, performance, and competitiveness can all be profoundly influenced by DI [3,4]. According to Nambisan et al. [5], DI indicates the extent to which digital technology is utilised across a broad range of

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https://doi.org/10.1016/j.sciaf.2025.e03157
Received 6 November 2024; Received in revised form 18 November 2025; Accepted 29 December 2025
Available online 29 December 2025

advancements and enhances product, service, and process design, control, and improvement. Ultimately, the outcome of the process, service, product design, control, and improvement is reflected in performance outcomes. For an organisation to pursue digital innovation, it must develop new managerial skills. Previous studies suggest that DMC is a key predictor of strategic change [6,7]. However, the existing literature provides limited insight into how DMC influences DI [8,9], especially in the banking industry, where digital technology has been widely adopted over the years.

Moreover, digital banking represents a strategic change that cannot be overlooked due to its significant effects on banks' non-financial and financial performance [10,11]. This study focuses on digital banking in the banking industry, aiming to transition conventional banking and its related services into the digital era by utilising disruptive digital technology. The objective of the inspection is premised on key areas:

(i) Assess the impact of DMC on DI.
(ii) Examine the impact of DMC on perceived financial performance (PFP).
(iii) Evaluating the mediating role of managerial cognition (MC) in the nexus between MHC, MSC, and DI.
(iv) Assessing the mediating role of DI in the nexus between MHC, MSC, MC and PFP.

The resource-based view led to the development of the dynamic capability view theory [12,13], which relates to how businesses can maintain and enhance their competitive advantage, particularly in an environment that is constantly changing. It refers to the company's ability to create, assemble, and reorganise internal and external skills in response to rapidly evolving conditions. Al-Dmour et al. [14] investigated bank efficiency in the context of big data techniques in Jordan. The results indicated that top management support accounts for sixty per cent of the bank's performance. In the banking sector, the dynamic capability hypothesis suggests that banks must develop the ability to perceive and adapt to changing digital trends, technologies, and customer preferences [15,16]. The patterned elements of management intentionality, contemplation, decision-making, and action are based on these resources [17]. Therefore, this study focuses on MHC, MSC, and MC, emphasising the components of the extensive research on social capital and human capital, as well as the dynamic attributes that enable managers to implement strategic [18] and enhance firm performance [19]. In the context of Vietnam, Nguyen et al. [20] evaluated bank performance by employing intellectual capital as a construct of management capability. The findings revealed that the efficiency of banks was influenced by value-added intellectual capital. Likewise, Aslam et al. [21] examined the role of human capital as a mediator between governance and enterprise performance. The empirical findings indicated that the twenty-six enterprises experienced positive effects due to structural and relational capital.

Recent research has linked managerial cognition to sustainable innovation. The qualitative study on Xiaomi revealed that management can adapt to technological developments due to their available managerial qualities. Transformational leaders are also regarded as crucial when an organisation encounters ongoing changes [22]. Moreover, organisations with senior technology executives demonstrate greater proficiency in leveraging digital technologies, resulting in improved asset turnover and superior financial outcomes [23]. MSC and DI capabilities are significant components of the dynamic capability model [9,24]. Banks that cultivate robust big data analytics capabilities can enhance their organisational ambidexterity, enabling them to effectively manage the utilisation of current resources while simultaneously exploring new prospects [25]. The dynamic capability approach suggests that enhanced performance in the digital era can be attained through investments in digital assets and networking capabilities. Moreover, the extensive literature on the broader concept of financial performance has progressed significantly; however, disaggregating performance into more specific metrics offers insights into the aspects that managers and firms should prioritise when appropriating DMC. This is because previous studies have emphasised the impact of broader concepts of leadership, entrepreneurship, and social capital on firm performance [19,26,27]. Currently, there is a lack of studies examining the impact of dynamic managerial capacity variables on organisational performance-specific metrics. Hence, this study assesses the effect of MHC, MC, and MSC on perceived financial performance (PFP).

Previous literature calls for future studies to consider the relationship between MC and MSC and how they directly influence organisational strategies and business performance [8,28]. Moreover, commercial banks must develop and utilise technical proficiency and harness emerging technologies such as big data and AI to meet the increasingly individualised and fragmented needs of consumers. This study focuses on PFP. The research seeks to elucidate the intricate relationships among DMC, DI, and FP, aiming to substantially influence both academic and professional domains. Furthermore, we aim to deliver a thorough comprehension of the efficiency and effectiveness of banks' performance in relation to the changing demands of consumers and technology by clarifying the mediating roles of MC and DI. Our research may aid business executives in addressing the challenges of providing and maintaining digital banking services, as well as consumers looking to discover innovative and more convenient digital banking alternatives amidst rapid digital transformation. By observing the mediation of MC and DI, companies can cultivate effective management capabilities and strategies to enhance DI and PFP. The next part of the investigation considers the theories and their affiliation with the variables. We follow up with the empirical reviews and the development of the model. The method employed in the analysis was next. The final part of the inspection covers the conclusion and the policy recommendations.

Theoretical framework and hypothesis development

Dynamic managerial capability (DMC)

The dynamic capability of a company refers to its ability to integrate, establish, and restructure both internal and external resources in response to an ever-changing environment [13]. In today's complex and unpredictable economic landscape, dynamic capability

serves as a powerful tool for enhancing organisational competitiveness. A company's competitive edge derives from its operational performance and organisational strategy, both of which are shaped by management methods and the organisational assets, including personnel, capital, physical infrastructure, and software. Dynamic capability involves learning, scanning, and interpreting activities, such as recognising latent demands and shifting customer needs, while also assessing the firm's environment and technological advancements (sensing capability). It further includes making business models and strategic choices to create value for the organisation and its customers (seizing capability), as well as reshaping organisational competencies to support strategic renewal and ensure that resources and capabilities continue to meet the evolving environmental expectations (transforming potential) [29]. The dynamic capability theory posits three key pillars that contribute to an organisation's dynamic capabilities: MHC, MC, and MSC.

In parallel with these theoretical developments, digital technology has increasingly become essential for achieving business objectives. Its wide-ranging effects have led to a radical restructuring of entire industries, with studies demonstrating the vast and unpredictable potential of digital technologies for developing novel goods and services. Boudrea et al. [30], for instance, examined the influence of digital innovation on enterprise efficiency through patents and copyrights, finding that digital innovation enhances organisational effectiveness. Similarly, in the process industries, Blichfeldt and Faullant [31] investigated 747 cases involving digital technologies and performance using curated data from the EU manufacturing survey. The outcome indicated that enterprises adopting digital technologies can develop radical and new products for their markets.

This acceleration of digital transformation has raised expectations across all sectors of the economy. To meet new standards of customer experience, traditional business procedures have undergone unprecedented change, driven partly by customers' evolving perspectives on satisfaction [25,32]. The COVID-19 pandemic further exposed the limitations of conventional approaches to product and service innovation, prompting managers to show growing interest in mastering digital innovation. The primary focus of managerial skills relates to managers' responsibility to reinvigorate and enhance the company's resource base to sustain competitive advantage and improve overall performance [6,8]. Achieving this requires managers to engage in entrepreneurship, strengthen their leadership capabilities, and expand their social networks. From the dynamic capability perspective, this study examines the influence of MHC, MSC, and MC on digital innovation (DI). Additionally, we assessed the mediating role of MC in achieving the perceived financial performance of banks.

Hypothesis formulation

Hypothesis of DMC on DI

Managerial human capital (MHC), which comprises managers' educational backgrounds, professional experiences, and personal encounters, forms the foundational base for building dynamic managerial capabilities. Ambrosini and Altintas [33] suggest that managerial experience enables the assimilation of new knowledge, the acquisition of additional skills, and the refinement of existing competencies. This form of human capital equips managers to reorganise the firm's resource base and to identify and seize opportunities and risks [34]. Similarly, Maritan [35] found that effective leadership is essential for initiating investments in new capabilities and resources and for maintaining close engagement with business unit managers during strategic transformation. Both managerial training and job experience, therefore, play a central role in driving strategic change.

Building from this foundation, dynamic managerial capability (DMC) theory, as articulated by Adner and Helfat [6], highlights the importance of managerial social capital (MSC) as a driver that reduces friction and enables seamless adaptation and renewal within the firm. Managers differ in the variety and depth of their skill sets; however, the goodwill derived from their formal and informal relationships with others [33,34] provides access to valuable resources and information. Through these external ties, organisations can incorporate new ideas and expand their technical and knowledge base. Such connections enable managers to learn from others, detect emerging opportunities, and enhance environmental scanning efforts [6]. Thus, MSC underscores the importance of sourcing information and ideas from both internal and external actors to support strategic initiatives. Strengthening strategic processes often requires collaboration with suppliers, customers, partners, and even competitors, recognising that valuable knowledge frequently crosses organisational boundaries. Digital innovation (DI), in particular, represents a form of strategic transformation that benefits greatly from MHC and MSC [8,36,6]. For example, prior studies show that organisations engage in more strategic transformation acquisitions when top managers possess a greater number of external connections [34]. Evidence further suggests that social capital compensates for resource deficiencies and catalyses the development of innovative and competitive capabilities [37,38].

Complementing MHC and MSC, managerial cognition (MC) encompasses the cognitive processes and abilities that enable managers to observe, interpret, and respond to their internal and external environments [39]. MC has increasingly been recognised as a cutting-edge approach that leverages technologies to strengthen cognitive capacity, thereby enhancing organisational knowledge management and decision-making. Within digital innovation contexts, managers require a distinct set of transformation-oriented cognitive capabilities to orchestrate successful digital initiatives [40]. These capabilities include developing long-term strategic visions, fostering a digitally oriented culture, managing organisational change processes, and maximising value creation from data and digital technologies. Research indicates that proficient digital leaders—capable of navigating digital disruption, designing innovative business models, and leveraging digitalisation benefits—are essential for organisational success in digital transformation efforts [41]. Li and Fei [10] using hierarchical econometric techniques on 239 managers, found that cognitive embeddedness positively affects enterprise performance. Using the dynamic capability model, Yao et al. [42] demonstrated through a mixed-method approach that Chinese managers relied on digital innovations to strengthen engagement with external partners. Additional studies in Industry 4.0 contexts show that managerial human and social capital are closely linked to the development of digital innovation capabilities [39]. This stream of work acknowledges the limitations of human cognition and the increasing complexity of decision-making environments.

The digital revolution has particularly reshaped the banking sector, transforming traditional business models and intensifying

competitive pressures [32,25]. To remain relevant and competitive, banks must cultivate strong digital innovation capabilities. However, the specific role of managerial cognition in shaping digital innovation and its subsequent impact on bank performance remains insufficiently understood. Addressing this gap is essential for advancing both theory and managerial practice in digitally intensive industries. Consequently, the following hypotheses were developed:

H1: MHC positively impacts DI.
H2: MSC positively impacts DI.
H3: MC positively impacts DI.

Hypothesis of DMC on PFP

DMC theory posits that managerial human capital, managerial social capital, and managerial cognition shape managers' abilities to develop, extend, and reconfigure organisational resource bases and revenue streams. This perspective provides insight into how variations in managerial capabilities contribute to differences in strategic change outcomes and organisational performance [6]. As Helfat and Martin [34] argue, changes in business performance during periods of transformation can be traced to variation in managerial capabilities. Empirical evidence supports this view: in six large U.S. software companies, Martin [17] identified strong manifestations of DMC, showing that multibusiness teams composed of senior executives influenced financial performance, new product introduction, business unit creation, and resource reconfiguration. Additionally, variations in top executives' strategic orientations explained performance differences across firms [43]. These findings underscore the relevance of DMC in contexts of strategic change. Despite this, earlier work drawing on DCM theory hypothesised no direct effect of MHC on firm performance, and empirical findings confirmed that entrepreneurial skills—one dimension of MHC—did not directly influence firm performance [8]. This highlights ongoing debate regarding whether MHC exerts a direct or indirect effect on performance outcomes.

Broadening the scope to the entrepreneurship literature, MHC has been consistently linked to firm performance and survival [44,45]. Leadership and entrepreneurial skills, viewed as dimensions of MHC, have been shown to positively influence firm performance. For example, Zehir et al. [46] reported a positive association between leadership and operational performance, and several studies indicate that entrepreneurial leadership capabilities enhance business success [19,26]. Parallel evidence supports a positive and significant relationship between social capital and firm performance [27,47]. MC contributes to performance by shaping managers' abilities to rapidly interpret information, make high-quality strategic decisions, and behave in strategically appropriate ways [6]. Managers construct cognitive frames based on prior experiences and education, and these structures guide information processing and subsequent strategic decisions [9,48]. By developing more sophisticated cognitive schemas, firms can enhance decision-making quality and improve performance outcomes.

In addition, prior studies have demonstrated that organisational digital capabilities and the effective deployment of digital innovation can significantly enhance financial performance [8,22]. These findings reinforce the notion that cognitive, social, and human capital elements of DMC have the potential to shape firm performance, particularly in digitally intensive environments. Taken together, these streams of research suggest that the subcomponents of DMC may directly influence firm performance, as they closely align with broader constructs shown to affect organisational outcomes. However, to the best of our knowledge, no existing study has empirically examined the effects of DMC dimensions on perceived financial performance (PFP). This gap provides the foundation for the present investigation. Consequently, the following hypotheses were developed:

H4: MHC positively impacts PFP.
H5: MSC positively impacts PFP.
H6: MC positively impacts PFP.

Mediating role of MC

Using technology to enhance cognitive abilities and support the cognitive assessment of information is a relatively recent approach that strengthens organisational knowledge management and decision-making. This cognitive assessment is significantly shaped by managerial skills, particularly managerial social capital (MSC) and managerial human capital (MHC) [40]. MHC provides managers with the depth of expertise acquired through exposure to new information, accumulated experience, and the continuous development of skills [33]. These capabilities enable managers to proactively identify external trends and assess them more realistically [49]. Through MHC, managers can also modify the firm's asset portfolio over time to ensure the ongoing availability of essential resources and competencies necessary for competitive adaptation.

MSC complements these capabilities through the trust, solidarity, and strong ties embedded in managers' networks, which facilitate the exchange of opportunities and information [50]. The interaction between MHC and MSC supports managers in the deliberate and systematic evaluation of strategic options, including opportunities for business model innovation [9]. As managers continuously assess the existing business model and intentionally consider its redesign, strategic changes are implemented that ultimately enhance firm performance. For example, in the banking industry, the emergence of digital technologies has driven the development of new business models, illustrating how cognitive evaluation and managerial capabilities translate into organisation-wide strategic transformation. Based on the inference above, the following hypotheses were set:

H7: MHC positively impacts MC.
H8: MSC positively impacts MC.
H9: MC is a channel through which MHC impacts DI.

H10: MC is a channel through which MSC impacts DI.
H11: MC is a channel through which MC impact PFP.
H12: MC is a channel through which MC impact PFP.

Mediating role of DI

Initial research indicates that digital innovation enhances various aspects of a company's performance, including profitability, sales growth, customer satisfaction, net profit margin, and overall performance [2,3,51]. Contemporary literature also acknowledges the impact of digital innovation on society [52–54]. For instance, these studies demonstrate the role of DI in promoting entrepreneurship within societies, impacting economic growth and market accessibility, and addressing societal issues. Moreover, its ability to foster a cashless economy is one of its significant effects, especially in the financial sector. Additionally, it has improved accessibility, client services, engagement, and experience. Guo et al. [1] employed quantitative techniques and data gathered via surveys from 285 digital start-up companies. The findings demonstrated that the favourable link between value proposition innovation and digital start-up performance is mediated by value creation and value capture innovation. To offer a unified model incorporating knowledge management processes (KMP), innovation capability (IC), and organisational performance (OP), as well as to test the effects of KMP on IC, IC's effect on OP, and KMP's impact on OP through the mediator, IC, 261 data samples from Jordanian manufacturing companies were collected for the study [55]. The results indicate that the activities of KMP impact on the capacity for innovation in product, process, marketing, and organisational domains. Additionally, organisational performance - financial, operational, and product quality - is impacted by innovation capabilities. Finally, innovation capacity influences organisational performance and works as a mediator in knowledge management procedures. These studies essentially support the idea that organisational performance is impacted by digital innovation.

Digital innovation is currently a strategic tool to enhance the competitiveness and survival of firms [51,56,57]. The decision-making towards its acceptance and adoption lies on managers driving forces through the MHC, MSC as well as their MC. Considering the phenomenon under study, prior studies suggest digital business model transformation mediates the relationship between MHC and firm performance [8]. Hence, the study suggest digital innovation is more likely to mediate the relationship between MHC, MSC, MC, and PFP. Therefore, the following hypotheses emerged:

H13: DI is positively associated with PFP.
H14: DI is a channel through which MHC impact PFP.
H15: DI is a channel through which MSC impact PFP.
H16: DI is a channel through which MC impact PFP.

Literary gaps

There is limited empirical investigation on the role that various DMCs play in improving the deployment of DI in emerging economies. Consequently, this research evaluates the significant effects of MHC, MSC, and MC separately on DI in the banking sector. Additionally, we address the gaps in evaluating the mediating role of MC on the relationship between MHC and DI, and MSC and DI. The DMC of managers is often underestimated; however, it is crucial to an organisation's PFP. Experience, competence, and interpersonal relationships are essential for effective decision-making. Cognitive ability significantly influences organisational effectiveness and strategic change. We utilised the emerging region to explore the relationship between DMC, DI and PFP owing to the rapid increase in their banks' digital products and services. Ghana has recently launched various digital initiative programs for employees in the banking sector. The findings from this research will serve as a comprehensive guide for other emerging regions with similar banking

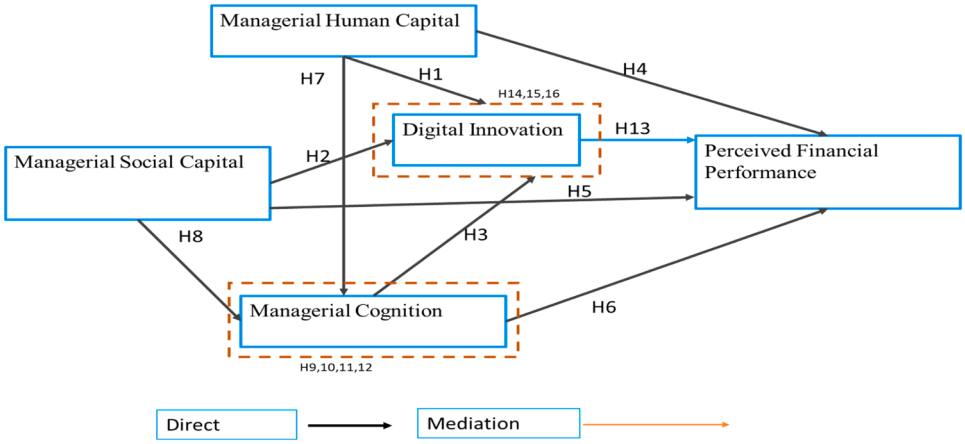

Fig. 1. Conceptual framework.

systems.

Conceptual model

Fig. 1.

Research methodology

Sampling, and data collection

This cross-sectional research of bank performance uses a quantitative methodology with an explanatory-predictive focus. Considering predictive validity assessment, we employed advanced PLS-SEM procedures [58]. This study focuses on gathering information from bankers across several regions of Ghana. All 23 commercial banks in Ghana were included in this study, as they all offer digital banking services. To obtain a representative sample of the targeted population, a sample size of 386 was assumed since the total number of bankers in Ghana is unknown [59]. Following Hair et al. [60], the researchers also utilised the sample's power to establish the required sample size, aiming to achieve 95 per cent power. Thus, a statistical power analysis and inverse square root method were employed to ensure sufficient data for a comprehensive study. Using G* power software version 3.1.9.7, the results indicated that a sample size of 785 or greater is necessary to achieve 0.95 statistical power and a 0.03 medium effect size [61]. Moreover, 618 data points were adequate to achieve the smallest path coefficient of 0.10 and 0.80 statistical power for a 0.05 significant effect [62]. A total of 728 data points were available for the final analysis.

The study utilised the purposive technique coupled with the convenience techniques for sampling to aid in obtaining suitable respondents and the appropriate responses. Participants, guaranteeing their privacy and safety, gave their informed consent. Every piece of information was kept confidential and utilised only for academic purposes. We collected quantitative data employing participant surveys. A questionnaire instrument was developed on a scale of 1 (Strongly Disagree) to 5 (Strongly Agree) to collect the data for the study. Data were mainly collected via a self-administered online questionnaire, which has been used as an applicable means by prior studies [63].

Measurement development, construct and items

All the questionnaire items were adapted from prior studies. The measurement items for the constructs' MHC, MSC, and MC were adapted from Heubeck and Meckl [9]. Likewise, the study utilised the scale of Sanders Jones et al. [59] to measure DI. Lastly, performance scales were adapted from Cazacu et al. [64]. The research questionnaire used to gather data consisted of two sections. The first section of the questionnaire emphasised demographic details such as gender, age, education and working experience. In the second phase of the survey, participants rated their agreement or disagreement with statements on each construct of the study model on a 7-point Likert scale, with 1 connoting strongly disagree and 7, strongly agree. The measures of the study are outlined in Appendix 1.

Data analysis method

When implementing structural equation modelling (SEM), Hair et al. [65] suggest that partial least squares (PLS)-SEM valuation is the most flexible technique, based on the iteration of PLS regressions, compared to covariance-based strategies. Numerous studies [66] confirm the recognition of the PLS-SEM in management research and its suitability for both basic and complex models. Additionally, PLS-SEM provides multiple options for evaluating a scale's validity and reliability [60]. Moreover, due to its suitability for analysing reflective constructs and predictive validity, analysis was necessary; we utilised PLS-SEM. The model was evaluated in two stages based on Hair et al.'s (2022) suggestion. First, we assessed the measurement model, where the validity and reliability of the scales were evaluated. Both convergent and discriminant validity, along with reliability tests, were conducted to ascertain the acceptability of each item, as demonstrated in Table 2. Furthermore, the robustness of the model was verified by carrying out an endogeneity assessment [67] to ensure its consistency and reliability. We also performed a predictive validity assessment to confirm the relevance of the model, following the approach of Sharma et al. [68]. Secondly, we performed a structural model assessment. To determine the importance of indices, we used a bootstrap approach. Bootstrapping involves resampling data to evaluate the path coefficients, weights, and loadings of the indicators (i.e., latent variables) in each composite. The study's significance level was established using a 95 percent confidence interval. All these analyses were carried out applying the SmartPLS software version 4.1.0.9.

Results and analysis

Descriptive analysis

The demographic profile comprised variables such as age, gender, education level, years of working experience, and department, as presented in Table 1. The analysis began with summarising respondents' demographic characteristics using frequencies and percentages. The results indicate that men constituted 441 of the total participants, with the remainder being women. More than half of the respondents were approximately 29 years old. Similarly, over half of the participants possessed a bachelor's degree. While 309 respondents had master's degrees, 61 respondents, representing 8.38 per cent, had a PhD. Additionally, 68 respondents had between 11 and 15 years of job experience, while the remaining had 16+ years. Approximately 88 % of the respondents had <10 years of work

experience.

Measurement model assessment

Reliability and validity test

Evaluating the measurement model, including validity and reliability, before moving on to the structural model analysis is necessary. Hence, the study assessed indicator reliability, internal consistency, discriminant validity, and convergent validity [60]. The achievement of reliability and convergent validity [69] models are confirmed by Table 2, which shows that all composite reliability and average variance extracted values exceeded the thresholds of 0.709 and 0.508, respectively. Since the heterotrait-monotrait ratio of correlations (HTMT) is a popular and experimentally established method, we used it to evaluate discriminant validity [70]. Table 3 shows that all the reported values were less than 0.85, showing excellent discriminant validity.

Common method bias

Initially, common method variance was evaluated due to the intrinsic bias associated with survey-based research. Podsakoff et al. [71] assert that various factors, including social desirability and survey assessment methodologies, influence common method bias. This study employed the entire collinearity evaluation method [72]. This method posits that an inner variance inflation factor (VIF) below 5.0 implies a reduced probability of common procedure bias influencing the study. The collinearity assessment indicates that the VIF of the variables ranged from 1.45 to 3.74, suggesting the absence of common technique bias in the study.

Robustness check - endogeneity

We employed the techniques recommended by Hult et al. [73] to evaluate endogeneity in our model. We initially assessed the Cramer-Von Mises to ensure the latent variables did not exhibit a non-normal distribution, following the methodology of Becker et al. [74]. To assess endogeneity in this model, we used the Gaussian Copula technique, as recommended by Becker et al. [74], as the findings showed that all of the independent latent variables were significant DI ($p = 0.000$), MHC ($p = 0.000$), MSC ($p = 0.000$), and MC ($p = 0.000$). The results of our analysis indicated that the three independent variables – MHC ($\beta = -0.316$, $p = 0.166$), MSC ($\beta = 0.124$, $p = 0.502$), and MC ($\beta = -0.053$, $p = 0.366$) – did not demonstrate significance. However, DI ($\beta = -0.347$, $p = 0.028$) exhibited a significance to indicate that our model is affected by fewer endogeneity issues since endogeneity occurs when important factors are inadvertently left out, and in this case, the affiliation between DI and PFP is missing a crucial variable [75,76].

Structural model evaluation

We assessed the collinearity of the composites in the structural model after confirming that our model complied with all measurement model requirements, and we were able to acquire VIF - acceptable values below 3. By evaluating the magnitude, significance of the parameters and path coefficients, we carried out the structural assessment. The three constructs, MHC ($\beta = 0.056$, $p = 0.017$), MSC ($\beta = 0.217$, $p = 0.000$), and MC ($\beta = 0.659$, $p = 0.000$), all had a significant impact on DI, according to our findings. Therefore, H1, H2 and H3 were all accepted. Further, the direct link between MHC and PFP (H4) was rejected, while H5 and H6 were accepted.

Also, the study outcome proved that MHC ($\beta = 0.177$, $p = 0.000$) enhances MC, while MSC $\beta = 0.595$, $p = 0.001$ enhances MC. These results led to the support for H7 and H8. Moreover, we found MC to be a significant mediator between MHC and DI ($\beta = 0.117$, $p = 0.000$, MHC and PFP ($\beta = 0.060$, $p = 0.000$), MSC and DI ($\beta = 0.92$, $p = 0.000$, and MSC and PFP ($\beta = 0.203$, $p = 0.000$). In all stages, there was a strong direct effect of MHC on DI, MSC on DI and MSC on PFP, indicating that MC partially mediated this interaction in a complementary way [65]. We determined the ratio of the indirect effect to the total effect (VAF) to evaluate the strength of the

Table 1
Demographic characteristics of respondents.

Demographic indicators	characters	Frequency (728)	Percent (100 %)
Gender	Male	441	60.58
	Female	287	39.42
Age of participants	< 29	375	51.51
	30 - 49	241	33.10
	50 - 60	112	15.39
Education	Bachelors	358	49.18
	Masters	309	42.44
	PhD	61	8.38
Working experience	< 5	421	57.83
	5 –10	222	30.49
	11 – 15	68	9.34
	16 - 20	11	1.51
	> 20	6	0.82

Table 2
Measurement of convergent validity and reliability.

	Composite reliability	AVE
MC	0.994	0.944
DI	0.921	0.566
PFP	0.976	0.890
MHC	0.943	0.893
MSC	0.849	0.652

Table 3
HTMT results.

	DI	PPP	MHC	MSC	MC
DI					
PFP	0.478				
MHC	0.545	0.328			
MSC	0.805	0.514	0.688		
MC	0.838	0.519	0.541	0.786	

mediated component based on these findings. As a result, the VAF values for MHC -> MC -> DI, MSC -> MC -> DI and MSC -> MC -> PFP were 67.6 per cent, 64.3 per cent and 55 per cent, respectively, indicating partial mediation of the association (Nitzl et al., 2016). But since there is no direct influence of MHC on PFP, the VAF value of 93.6 per cent suggests that MC emerged as a full mediator (Hair et al., 2020). Thus H9, H10, H11 and H12 were accepted.

Concerning H13, we proposed a direct and significant relationship between DI and PFP. However, we did not obtain support for that statement. Hence, H13 is rejected. Furthermore, Table 4 illustrates that there is no substantial specific indirect effect of MHC ($\beta = 0.004,\ p = 0.004$), MSC ($\beta = 0.016,\ p = 0.142$) and MC ($\beta = 0.050,\ p = 0.135$) on PFP through DI. In this regard, H14, H15 and H16 were rejected.

R-square, F-square and SRMR analysis

The coefficient of determination (R2 value) analyses how predictive the model is. From the perspective of Sarstedt et al. [77], the coefficient of determination calculates the in-sample extrapolative power of the model. However, the adjusted R2 is a more effective criterion for mitigating bias towards complex models. The number of exogenous constructs to the sample size modifies this criterion. Hair et al. [65] assert that values of 0.25, 0.50, and 0.75 denote weak, moderate, and substantial coefficients of determination, respectively. MC: $R^2 = 0.503$, The model explains 50.3 % of the variance in the dependent variable. This is a moderate level of explanatory power. Also, DI: $R^2 = 0.733$, The model explains 73.3 % of the variance. This is a strong explanatory level. PPP: $R^2 = 0.289$, The model explains 28.9 % of the variance. This is relatively weak, indicating that the predictors do not account for much of the variability in PPP.

The adjusted R^2 results presented in Table 5 indicate that the model explains substantial variance in DI. Specifically, the adjusted R^2

Table 4
Hypothesis Evaluation.

	Hyp.	Path	β	CI	P value	Support
Direct effect	H1	MHC -> DI	0.056	[0.014, 0.100]	0.017***	Yes
	H2	MSC -> DI	0.217	[0.163, 0.270]	0.000*	Yes
	H3	MC -> DI	0.659	[0.614, 0.703]	0.000*	Yes
	H4	MHC -> PFP	0.004	[−0.066, 0.078]	0.462	No
	H5	MSC -> PFP	0.163	[0.071, 0.252]	0.001**	Yes
	H6	MC -> PFP	0.341	[0.235, 0.443]	0.000*	Yes
	H7	MHC -> MC	0.177	[0.127, 0.228]	0.000*	Yes
	H8	MSC -> MC	0.595	[0.547, 0.640]	0.000*	Yes
	H13	DI -> PFP	0.076	[−0.037, 0.189]	0.134	No
Specific Indirect effect	H9	MHC -> MC -> DI	0.117	[0.083, 0.152]	0.000*	Yes
	H10	MSC -> MC -> DI	0.192	[0.348, 0.437]	0.000*	Yes
	H11	MHC -> MC -> PFP	0.060	[0.039, 0.088]	0.000*	Yes
	H12	MSC -> MC -> PFP	0.203	[0.140, 0.271]	0.000*	Yes
	H14	MHC -> DI -> PFP	0.004	[−0.001, 0.015]	0.173	No
	H15	MSC -> DI -> PFP	0.016	[−0.007, 0.044]	0.142	No
	H16	MC -> DI -> PFP	0.050	[−0.024, 0.125]	0.135	No

Notes: β = beta coefficient; CI = 95 % bias-corrected confidence interval based on percentile bootstrapping ($n = 10{,}000$; one-tailed test); *$p < 0.001$, **$p < 0.01$, ***$p < 0.05$.

value of 0.732 shows that MSC, MHC, and MC collectively account for 73.2 % of the variation in DI. In contrast, MHC and MSC provide only moderate explanatory power for MC. The explanatory power for perceived firm performance (PFP) is relatively weak, suggesting that MSC, MHC, MC, and DI contribute minimally to variations in PFP within the present model. The effect size f^2 displays how the model's R^2 changes when a particular construct is omitted [78]. Cohen's [78] standards state that small, medium, and high impacts are represented by values of 0.02, 0.15, and 0.35, respectively. Moreover, the fit indices of the SRMR value of 0.063 indicate the model is fit [78].

Predictive power analysis

Q-square is the first step of assessing the predictive accuracy of a model. Based on prior studies' recommendation [79], our study evaluates the overall model's ability to forecast new observations with accuracy. Using hold-out samples and cross-validation, the predictive validity was assessed employing the methodology described by Sharma et al. [68]. As suggested by Liengaard et al. [80], the cross-validated predictive ability test (CVPAT) is more stringent and can improve out-of-sample prediction by lowering generalisation inaccuracy. We began by examining the predictive performance of PFP, DI, and MC using a 10-fold PLS-prediction procedure. As shown in Table 6, all Q^2 values exceeded 0.0, confirming that the model's endogenous constructs exhibit predictive relevance. To further assess predictive accuracy, we applied the CVPAT by statistically comparing the model with a naïve benchmark based on mean-value prediction. The results show that the proposed model achieved a significantly lower average loss than the indicator-average (IA) prediction benchmark (PLS-IA $= -0.408$; $p = 0.000$), demonstrating that the model accurately predicts PFP.

Discussion and implications

Discussion

The path coefficient estimates, variance explanations, and model hypotheses presented in Table 6 and Fig. 2 indicate that MHC, MSC, and MC have a direct positive impact on DI. These findings provide initial evidence that these DMC components enhance bankers' ability to engage in DI. Although past studies have emphasised the broader perspective of leadership skills [35], entrepreneurial skills, and social capital [34,38], our results are consistent with Heubeck [39], who found that MHC and MSC influence digital business model transformation. This suggests that DMC theory applies to understanding DI adoption processes in the banking industry. It is important to acknowledge that most participants in our study are employees without formal managerial experience; nonetheless, they demonstrate clear awareness of the role managerial skills play in strategic decision-making.

The findings further show that MHC does not exert a direct and significant effect on perceived financial performance (PFP). This result aligns with Heubeck [8], who reported that entrepreneurial and leadership qualities derived from MHC do not directly influence firm performance. However, MSC and MC exhibit a strong and significant association with PFP. Since MSC emerges from managers' social connections [27,26], and MC reflects the cognitive structures used to process information, these results suggest that both social networks and cognitive schemas play critical roles in predicting financial performance. Effective managerial networks provide access to essential organisational resources such as capital, talent, and strategic partnerships, directly influencing operational efficiency and growth [81]. Well-developed networks also enable managers to acquire timely information on technological advancements, market trends, and regulatory shifts [9,50], enabling faster and more informed strategic responses. These findings align with Martin [17], who demonstrated that managers' social ties significantly influence firm-level outcomes.

Beyond their direct effects, the results indicate that MHC and MSC function as antecedents of MC. Managers with strong human capital accumulate the knowledge base required to analyse information, engage in complex strategic processes, and forecast long-term organisational outcomes [9]. This foundation enhances their ability to interpret situations, assess risks, engage teams, and respond to strategic challenges. Similarly, MSC strengthens MC by expanding access to diverse perspectives, data, and knowledge sources. Networks enhance collaborative capacity, improve information sharing, and enable managers to leverage collective expertise. Consequently, managers with strong social capital are better positioned to anticipate difficulties, react to environmental shifts, and make higher-quality strategic decisions. These findings reinforce the argument of Heubeck and Meckl [9] that higher levels of MHC and MSC enhance MC.

The structural model results also demonstrate that MC mediates the relationship between MHC and DI, as well as between MSC and DI. Additionally, MC mediates the relationship between MHC and PFP, and between MSC and PFP. This highlights MC as a crucial intervening mechanism through which leadership skills, entrepreneurial skills, and social connections shape strategic choices and firm performance. These results emphasise the importance for banks to continuously strengthen the cognitive structures and processes of

Table 5
R2, Adj. R2 and F2.

	R^2	Adj R^2	MC	DI	PFP
MHC	-	-	0.044	0.008	0.000
MSC	-	-	0.491	0.081	0.016
MC	0.503	0.502		0.808	0.045
DI	0.733	0.732			0.002
PPP	0.289	0.285			

Table 6
PLS $_{predict}$ result report.

	Q^2 predict		
Managerial cognition	0.499		
Digital innovation	0.514		
Perceived financial performance	0.206		
	Average loss difference	t-value	p-value
Digital innovation	−0.515	8.148	0.000
Managerial cognition	−0.501	8.206	0.000
Perceived financial performance	−0.207	6.117	0.000
Overall CVPAT (PLS-IA)	−0.408	8.323	0.000

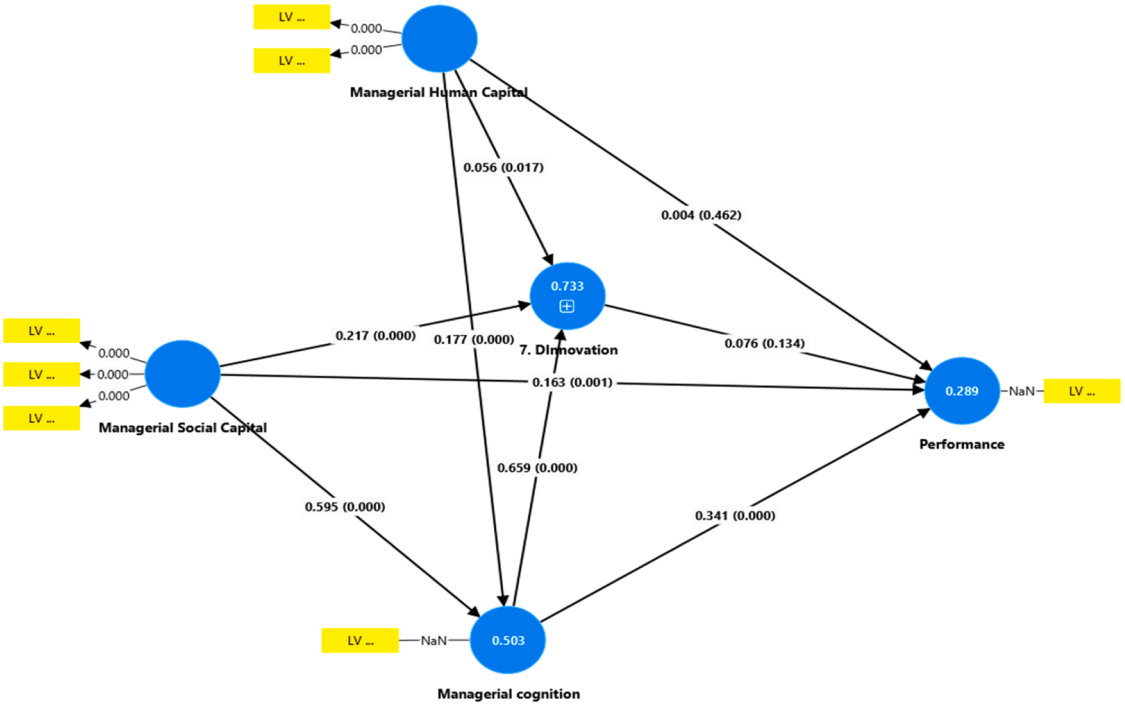

Fig. 2. Structural model: direct and indirect paths.

managers to improve decision-making speed, enhance strategic alignment, and reinforce competitive advantage, growth, and survival [82].

In contrast to expectations, the study did not support a direct effect of DI on PFP. Thus, the hypothesised positive link between DI and performance is not empirically supported in this context, diverging from earlier findings showing that DI enhances firm performance [51,2,3]. For example, Migdadi [55] found DI to be positively associated with operational, financial, and product-quality performance, and prior studies have shown significant and positive effects of DI on financial outcomes [3]. In our study, although the coefficient for DI → PFP is positive, it is not significant, indicating that while DI may provide performance potential, it is not a central driver of PFP in this model.

Furthermore, DI does not serve as a mediating mechanism linking MHC, MSC, and MC to PFP. The absence of mediation is theoretically noteworthy because MHC, MSC, and MC are frequently described as essential drivers of firm performance through strategic change of which DI is a key component [6,34]. Our findings, therefore, suggest that DI is not the pathway through which DMC influences financial performance in the banking sector.

Theoretical implications

This study offers significant theoretical contributions to the dynamic managerial capabilities (DMC) literature, the digital innovation (DI) discourse, and the broader discussion on organisational performance in emerging economies. First, the study extends the DMC framework by providing empirical evidence that managerial human capital (MHC), managerial social capital (MSC), and managerial cognition (MC) operate as distinct yet interrelated micro foundations that shape the development of digital innovation capabilities within the banking sector. Prior studies have primarily conceptualised DMC as a holistic or composite construct [18];

however, by disaggregating MHC, MSC, and MC, this study advances theoretical understanding of how each dimension individually influences strategic actions, particularly within digital transformation contexts. The findings demonstrate that both MHC and MSC significantly enhance MC, highlighting cognition's central role as a mechanism that links managerial resources to organisational adaptability and innovation. Second, this study enriches the theoretical discourse on MC as a significant component of dynamic managerial capabilities. The results show that MC serves as a critical mediating mechanism in the affiliation between MHC, MSC, and both DI and PFP. This reinforces the argument that cognitive structures and evaluative routines are essential for sensing, seizing, and transforming opportunities in digitally intensive environments [8]. This empirically validates MC as a key conduit between managerial capabilities and organisational outcomes. Hence, the study adds nuance to the dynamic capability theory, which acknowledges cognition but rarely examines it empirically at this level of detail [36]. Third, the findings challenge widely held assumptions regarding the direct effect of digital innovation on performance outcomes. Contrary to expectations from prior digital transformation and innovation literature, DI did not significantly influence PFP and did not mediate the relationship between DMC components and organisational performance. This theoretical deviation suggests that in emerging economy contexts, where digital infrastructure, regulatory conditions, and customer digital readiness vary widely, the benefits of digital innovation may not immediately translate into financial gains. This insight signals the need for refined theoretical models that account for contextual moderators that shape the DI-performance affiliation, particularly in banking systems undergoing early or uneven stages of digital maturity. Conclusively, the study contributes to the growing literature on dynamic capabilities in emerging markets. Much of the existing DMC literature is situated in developed economies, where managerial competencies and technological infrastructures differ substantially. Focusing on Ghana's banking sector, the study contextualises DMC theory within an emerging digital ecosystem, establishing how cognitive, human, and social resources interact to shape strategic decisions in resource-constrained or institutionally evolving environments. This contextual extension highlights that dynamic managerial capability processes may function differently across economic settings, prompting scholars to revisit assumptions about the universality of DMC-performance pathways.

Managerial implications

This study addresses gaps in prior research concerning the relationships among MHC, MSC, MC, DI, and PFP. The empirical findings demonstrate that MHC, MSC, and MC enable financial institutions to enhance their DI practices, which, in turn, contribute to improved PFP. The results suggest that organisations seeking to expand the adoption of digital technologies and increase financial performance should prioritise the development of managers' abilities to deliberately and effectively evaluate strategic options. This includes assessing customer needs, value propositions, and the alignment between value propositions and customer requirements. Additionally, careful consideration of the organisation's resource requirements, potential financial gains, and project-related costs can improve both PFP and strategic change decisions.

Fostering social connections among managers further facilitates the effective assessment of information, supports strategic change, and strengthens organisational strategy and firm performance. The study also highlights the substantial explanatory power of managerial capabilities: MHC and MSC together account for over 50 percent of the variance in MC, while the three constructs collectively explain >70 percent of the variance in DI. These findings underline the importance of the foundational dimensions of managerial capabilities—including relational, cognitive, structural, entrepreneurial, and leadership aspects—when recruiting, selecting, and designing training programs for prospective managers. Organisations are encouraged to continuously enhance managers' cognitive processes and structures to support strategic decision-making. Although MHC alone did not directly impact PFP, the introduction of MC strengthened this relationship. MC consistently served as a mediating mechanism through which both MHC and MSC influenced DI and PFP, highlighting its critical role in translating managerial skills and networks into improved digital innovation and financial outcomes.

Conclusion, limitations and further research

The urgency of deploying digital innovation is particularly high for enhancing perceived financial performance (PFP) within the Ghanaian banking sector. This aligns with the broader adoption of managerial practices such as managerial human capital (MHC), managerial social capital (MSC), and managerial cognition (MC) to achieve effective digital innovation. This study aimed to investigate the relationships between MHC, MSC, and PFP, with MC and digital innovation (DI) acting as mediating mechanisms. The dynamic managerial capability (DMC) framework was employed to examine both the direct and mediating effects of MHC, MSC, and MC on DI and PFP. To achieve these objectives, 728 questionnaires were distributed to employees within the Ghanaian banking industry, and Smart PLS-SEM was used to analyse the proposed relationships.

The findings indicate that managerial cognition significantly mediates the interactions among MHC, MSC, DI, and PFP, whereas DI does not serve as a mediating variable. In particular, MC acts as a conduit through which managerial human capital influences PFP. These results underscore the importance for managers and policymakers to implement DMC-focused initiatives to enhance banks' digital innovation capabilities, which are critical in today's dynamic and digital business environment. The study further highlights the influence of DMC on advancing DI within the banking sector.

Despite these contributions, several limitations provide avenues for future research. First, the use of cross-sectional data may constrain the ability to fully examine antecedents and strategies influencing DI and PFP; longitudinal data would enable a more comprehensive assessment. Second, the study did not explore all interactions among the subcomponents of DMC, such as the interplay between MHC and MSC, which prior research suggests may have complex and context-dependent effects [8,34,9]. Third, the study's focus on a single country (Ghana) and reliance on employees' perspectives may limit generalisability and increase the potential for

bias.

Future research should consider including a broader range of respondents across departments and countries to enhance external validity. Additionally, examining which specific attributes of MSC (structural, relational, and cognitive) and MC (e.g., value proposition, value architecture) most strongly influence bank performance could provide actionable insights for personnel selection and managerial training, particularly from the perspective of managers themselves.

Ethical consideration

Not applicable

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1

Construct	Code	Items	Source
DI	DI1	We monitor our processes, services, and products using digital process control.	Sanders Jones et al. [83]
	DI2	We strive to continually improve all aspects of products, services, and processes using digital technologies, rather than taking a static approach.	
	DI3	We believe that the improvement of processes, services and products is never complete; there is always room for more incremental improvement, hence, we upgrade our digital solutions.	
	DI4	Our processes, services, and products are effectively developed and implemented based on digital technologies.	
	DI5	We pay close attention to the digital skill changes needed for new processes, services, and products.	
	DI6	We strive to be highly responsive to our customers' needs, hence we improve our digital solutions.	
	DI7	Management takes all product, service, and process improvement suggestions seriously.	
	DI8	Information on quality performance regarding our processes, products and services is readily available to employees.	
	DI9	Problem-solving teams constantly helped improve processes, products, and services.	
PFP	PFP1	Our net profit, return on assets and turnover saw a substantial increase over the previous year.	Cazacu et al. [64]
	PFP2	Our net profit, return on assets and turnover compared to the previous year increased	
	PFP3	Net profit, return on assets and turnover are the same as last year.	
	PFP4	Net profit, return on assets and turnover decrease compared to the previous year	
	PFP5	Net profit, return on assets, and turnover decreased substantially compared to last year	
MSC	SD1	I always communicate openly and honestly with other company members.	Heubeck and Meckl [9]
	SD2	As a rule, I completely disclose my plans and intentions	
	SD3	I willingly share information with other company members	
	SD4	When exchanging information, I draw on my internal company relationships	
	RD1	I always have the utmost trust in other company members and their actions/ decisions	
	RD2	I always act with integrity in my dealings with other company members	
	RD3	In general, I have a high level of trust in other company members	
	RD4	I am always considerate of the feelings and sensibilities of other company members	
	CD1	I feel committed to the goals of my company	
	CD2	I share a common purpose with other company members	
	CD3	I see myself as a discussion partner in determining the company's direction	
	CD4	My vision for the future of the company is in line with that of other company members	
MHC	LS1	One of my greatest strengths is getting results by organizing and motivating people.	Heubeck and Meckl [9]
	LS2	One of my greatest strengths is organizing and coordinating tasks.	
	LS3	One of my greatest strengths is my ability to delegate effectively.	
	LS4	One of my greatest strengths is my ability to monitor, influence, and lead people.	
	LS5	I make resource allocation decisions that achieve maximum results with limited resources	
	ES1	I like to think about new ways to do business.	
	ES2	I frequently identify opportunities to start new business	
	ES3	I often identify ideas that can be turned into new products and services	
	ES4	I keep my eyes open for previously unnoticed entrepreneurial opportunities	
	ES5	I see myself as a creator of entrepreneurial opportunities	
MC		When designing digital products/services,	Heubeck and Meckl [9]
	VO1	I consciously evaluate alternatives to a very high extent regarding customer problems and needs	
	VO2	I consciously evaluate alternatives to a very high extent concerning value propositions	
	VO3	I consciously evaluate alternatives to a very high extent about the relationship between value propositions and customer problems/needs	
	VA1	I evaluate alternatives about promotion, advertising and communication channels	
	VA2	I assess options for business transactions and the ways of collaborating with partners	
	VA3	I examine alternatives concerning linking business participants together in novel ways	
	VA4	I evaluate alternatives when taking over new value propositions or substituting existing parts of the value chain	
	VA5	I purposefully evaluate alternatives for applying new revenue streams	
	VC1	I consciously evaluate alternatives regarding resource requirements for my company	

(*continued on next page*)

(*continued*)

Construct	Code	Items	Source
	VC2	I consciously evaluate alternatives regarding the financial benefits for our company	
	VC3	I consciously evaluate alternatives concerning all the business-related costs of the project	

SD – structural dimension, RD – relational dimension, CD – cognitive dimension, ES – entrepreneurial skills, LS – leadership skills, VO – value offering, VA – value architecture, VC – value capture, PFP – perceived financial performance, DI – digital innovation.

References

[1] H. Guo, A. Guo, H. Ma, Inside the black box: how business model innovation contributes to digital start-up performance, J. Innov. Knowl. 7 (2) (2022) 100188, https://doi.org/10.1016/j.jik.2022.100188.

[2] T.T. Le, M. Ikram, Do sustainability innovation and firm competitiveness help improve firm performance? Evid. SME sect. Vietnam, Sustain. Prod. Consum. 29 (2022) 588–599, https://doi.org/10.1016/j.spc.2021.11.008.

[3] C. Wang, F. Guo, Q. Zhang, How does disruptive innovation influence firm performance? A moderated mediation model, Eur. J. Innov. Manag. 26 (3) (2023) 798–820, https://doi.org/10.1108/EJIM-07-2021-0369.

[4] G.Y.Q. Al-Subaihi, S.A. Salim, A study on digital service innovation factors influencing organisation performance: ajman Police Department In UAE, Int. J. Sustain. Constr. Eng. Technol. 14 (5) (2023) 426–437.

[5] S. Nambisan, K. Lyytinen, A. Majchrzak, M. Song, Digital Innovation Management: reinventing innovation management research in a digital world, MIS q. 41 (1) (2017).

[6] R. Adner, C.E. Helfat, Corporate effects and dynamic managerial capabilities, Strateg. Manag. J. 24 (10) (2003) 1011–1025, https://doi.org/10.1002/smj.331.

[7] M. Matarazzo, L. Penco, G. Profumo, R. Quaglia, Digital transformation and customer value creation in made in Italy SMEs: a dynamic capabilities perspective, J. Bus. Res. 123 (2021) 642–656, https://doi.org/10.1016/j.jbusres.2020.10.033.

[8] T. Heubeck, Managerial capabilities as facilitators of digital transformation? Dynamic managerial capabilities as antecedents to digital business model transformation and firm performance, Digit. Bus. (2023) 100053, https://doi.org/10.1016/j.digbus.2023.100053.

[9] T. Heubeck, R. Meckl, Antecedents to cognitive business model evaluation: a dynamic managerial capabilities perspective, Rev. Manag. Sci. 16 (8) (2022) 2441–2466, https://doi.org/10.1007/s11846-021-00503-7.

[10] Y. Li, G.Z. Fei, Network embeddedness, digital transformation, and enterprise performance—The moderating effect of top managerial cognition, Front. Psychol. 14 (2023) 1098974, https://doi.org/10.3389/fpsyg.2023.1098974.

[11] P.C. Verhoef, T. Broekhuizen, Y. Bart, A. Bhattacharya, J.Q. Dong, N. Fabian, M. Haenlein, Digital transformation: a multidisciplinary reflection and research agenda, J. Bus. Res. 122 (2021) 889–901, https://doi.org/10.1016/j.jbusres.2019.09.022.

[12] D.J. Teece, Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance, Strateg. manag. j. 28 (13) (2007) 1319–1350, https://doi.org/10.1002/smj.640.

[13] D. Teece, G. Pisano, *The Dynamic Capabilities of Firms: An Introduction* (Working Paper), International Institute for Applied Systems Analysis, Laxenburg, 1994.

[14] H. Al-Dmour, N. Saad, E. Basheer Amin, R. Al-Dmour, A. Al-Dmour, The influence of the practices of big data analytics applications on bank performance: filed study, VINE J. Inf. Knowl. Manag. Syst. 53 (1) (2023) 119–141, https://doi.org/10.1108/VJIKMS-08-2020-0151.

[15] A. Abdurrahman, A. Gustomo, E.A. Prasetio, Impact of dynamic capabilities on digital transformation and innovation to improve banking performance: a TOE framework study, J. Open Innov.: Technol. Mark. Complex. 10 (1) (2024) 100215, https://doi.org/10.1016/j.joitmc.2024.100215.

[16] A.W. AL-Khatib, A. Shuhaiber, I. Mashal, M. Al-Okaily, Antecedents of industry 4.0 capabilities and technological innovation: a dynamic capabilities perspective, Eur. Bus. Rev. 36 (4) (2024) 566–587, https://doi.org/10.1108/EBR-05-2023-0158.

[17] J.A. Martin, Dynamic managerial capabilities and the multibusiness team: the role of episodic teams in executive leadership groups, Organ. sci. 22 (1) (2011) 118–140, https://doi.org/10.1287/orsc.1090.0515.

[18] S.Y. Dwikat, D. Arshad, M.N. Mohd Shariff, Effect of competent human capital, strategic flexibility and turbulent environment on sustainable performance of SMEs in manufacturing industries in palestine, Sustainability. 15 (6) (2023) 4781, https://doi.org/10.3390/su15064781.

[19] A. Razzaque, I. Lee, G. Mangalaraj, The effect of entrepreneurial leadership traits on corporate sustainable development and firm performance: a resource-based view, Eur. Bus. Rev. (2023), https://doi.org/10.1108/EBR-03-2023-0076.

[20] D.T. Nguyen, T.D. Le, S.H. Tran, The moderating role of income diversification on the relationship between intellectual capital and bank performance evidence from Viet Nam, Cogent Bus. Manag. 10 (1) (2023) 2182621, https://doi.org/10.1080/23311975.2023.2182621.

[21] E. Aslam, A. Ur Rehman, A. Iqbal, The mediating role of intellectual capital in corporate governance and financial efficiency of Islamic banks, Corp. Gov.: Int. J. Bus. Soc. 24 (1) (2024) 19–40, https://doi.org/10.1108/CG-06-2022-0276.

[22] Q. Wang, Z. Shao, Linking transformational leadership and digital creativity from the lens of social cognitive theory, Ind. Manag. Data Syst. (2024), https://doi.org/10.1108/IMDS-07-2023-0444.

[23] D. Ye, M.J. Liu, J. Luo, N. Yannopoulou, How to achieve swift resilience: the role of digital innovation enabled mindfulness, Inf. Syst. Front. 26 (2) (2024) 551–573, https://doi.org/10.1007/s10796-021-10225-6.

[24] J.M. Martin-Flores, Is bank misconduct related to social capital? Evidence from US banks, J. Bank. Financ. 167 (2024) 107256, https://doi.org/10.1016/j.jbankfin.2024.107256.

[25] S. Corbet, Y.G. Hou, Y. Hu, L. Oxley, M. Tang, Do financial innovations influence bank performance? Evidence from China, Stud. Econ. Finance 41 (2) (2023) 241–267, https://doi.org/10.1108/SEF-02-2022-0119.

[26] M. Stasa Ouzký, O. Machek, Family firm performance: the effects of organisational culture and organisational social capital, J. Fam. Bus. Manag. (2023), https://doi.org/10.1108/JFBM-06-2023-0089.

[27] A. Schmid, A. Sender, How social capital influences performance in family firms: the moderating role of nepotism, Int. J. Hum. Resour. Manag. 32 (18) (2021) 3973–3993, https://doi.org/10.1080/09585192.2019.1674355.

[28] T. Felin, N.J. Foss, K.H. Heimeriks, T.L. Madsen, Microfoundations of routines and capabilities: individuals, processes, and structure, J. manag. stud. 49 (8) (2012) 1351–1374, https://doi.org/10.1111/j.1467-6486.2012.01052.x.

[29] D.J. Teece, G. Pisano, A. Shuen, Dynamic capabilities and strategic management, Strateg. Manag. J. 18 (7) (1997) 509–533, https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID−SMJ882>3.0.CO;2-Z.

[30] K.J. Boudreau, L.B. Jeppesen, M. Miric, Profiting from digital innovation: patents, copyright and performance, Res. Policy. 51 (5) (2022) 104477, https://doi.org/10.1016/j.respol.2022.104477.

[31] H. Blichfeldt, R. Faullant, Performance effects of digital technology adoption and product & service innovation–A process-industry perspective, Technovation 105 (2021) 102275, https://doi.org/10.1016/j.technovation.2021.102275.

[32] S. Chauhan, A. Verma, C.V. Kumar, Effect of capital structure on the financial and social performance of Indian microfinance institutions, FIIB Bus. Rev. 13 (2) (2024) 243–256, https://doi.org/10.1177/23197145221099677.

[33] V. Ambrosini, G. Altintas, Dynamic managerial capabilities. Oxford Research Encyclopedia of Business and Management, 2019, https://doi.org/10.1093/acrefore/9780190224851.013.20.

[34] C.E. Helfat, J.A. Martin, Dynamic managerial capabilities: review and assessment of managerial impact on strategic change, J. Manage 41 (5) (2015) 1281–1312, https://doi.org/10.1177/0149206314561.
[35] C.A. Maritan, Capital investment as investing in organisational capabilities: an empirically grounded process model, Acad. Manag. J. 44 (3) (2001) 513–531, https://doi.org/10.5465/3069367.
[36] J.B. Beck, M.F. Wiersema, Executive decision making: linking dynamic managerial capabilities to the resource portfolio and strategic outcomes, J. Leadersh. Organ. Stud. 20 (4) (2013) 408–419, https://doi.org/10.1177/1548051812471722.
[37] F. Halim, R.C.S.D. Kusuma, S. Sherly, C. Loist, A. Sudirman, The influence of social capital and innovation capability on creative industry business performance, Int. J. Bus. Law Educ. 4 (2) (2023) 971–978, https://doi.org/10.56442/ijble.v4i2.267.
[38] M. Hughes, R.E. Morgan, R.D. Ireland, P. Hughes, Social capital and learning advantages: a problem of absorptive capacity, Strateg. Entrep. J. 8 (3) (2014) 214–233, https://doi.org/10.1002/sej.1162.
[39] T. Heubeck, R. Meckl, More capable, more innovative? An empirical inquiry into the effects of dynamic managerial capabilities on digital firms' innovativeness, Eur. J. Innov. Manag. 25 (6) (2022) 892–915, https://doi.org/10.1108/EJIM-02-2022-0099.
[40] S. Zang, M. Sun, Q. Wang, H. Wang, S. Tian, Windows of opportunity, strategic cognition and enterprise digital transformation, Chin. Manag. Stud. (2024), https://doi.org/10.1108/CMS-09-2023-0489.
[41] Q. Lu, Y. Zhou, Z. Luan, Y. Deng, Influences of top management team social networks on enterprise digital innovation, J. Knowl. Econ. (2024) 1–34, https://doi.org/10.1007/s13132-023-01716-9.
[42] G. Yao, Z. Dato'Mansor, H.B. Ghazali, Z. Yan, A comprehensive mixed-methods study on cross-border e-commerce SMEs, digital transformation and dynamic managerial capabilities, Environ. Soc. Psychol. 9 (4) (2024), https://doi.org/10.54517/esp.v9i4.2255.
[43] D. Holbrook, W.M. Cohen, D.A. Hounshell, S. Klepper, The nature, sources, and consequences of firm differences in the early history of the semiconductor industry, Strateg. Manag. J. 21 (10–11) (2000) 1017–1041, https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1017::AID−SMJ131>3.0.CO;2-G.
[44] J. Dahlqvist, P. Davidsson, J. Wiklund, Initial conditions as predictors of new venture performance: a replication and extension of the Cooper et al. study, Enterp. innov. manag. stud. 1 (1) (2000) 1–17, https://doi.org/10.1080/146324400363491.
[45] F.J. Gimeno-Gascon, T.B. Folta, A.C. Cooper, C.Y. Woo, Survival of the fittest? Entrepreneurial human capital and the persistence of underperforming firms, Adm. Sci. Q. 42 (4) (1997) 750–783, https://doi.org/10.2307/2393656.
[46] C. Zehir, Ö.G. Ertosun, S. Zehir, B. Müceldili, The effects of leadership styles and organisational culture over firm performance: multi-national companies in İstanbul, Procedia-Soc. Behav. Sci. 24 (2011) 1460–1474, https://doi.org/10.1016/j.sbspro.2011.09.032.
[47] J. Tata, S. Prasad, Immigrant family businesses: social capital, network benefits and business performance, Int. J. Entrep. Behav. Res. 21 (6) (2015) 842–866, https://doi.org/10.1108/IJEBR-06-2014-0111.
[48] J.P. Walsh, Managerial and organisational cognition: notes from a trip down memory lane, Organ. sci. 6 (3) (1995) 280–321, https://doi.org/10.1287/orsc.6.3.280.
[49] A.J. Bock, T. Opsahl, G. George, D.M. Gann, The effects of culture and structure on strategic flexibility during business model innovation, J. Manag. stud. 49 (2) (2012) 279–305, https://doi.org/10.1111/j.1467- 6486.2011.01030.x.
[50] M.I. Mostafiz, M. Sambasivan, S.K. Goh, Impacts of dynamic managerial capability and international opportunity identification on firm performance, Multinatl. Bus. Rev. 27 (4) (2019) 339–363, https://doi.org/10.1108/MBR-09-2018-0061.
[51] A. Hanelt, S. Firk, B. Hildebrandt, L.M. Kolbe, Digital M&A, digital innovation, and firm performance: an empirical investigation, Eur. J. Inf. Syst. 30 (1) (2021) 3–26, https://doi.org/10.1080/0960085X.2020.1747365.
[52] A. Alaassar, A.L. Mention, K. Kryzhanivska, Digital innovation: a bibliometric review and research agenda, Rev. Manag. Sci. (2025) 1–47, https://doi.org/10.1007/s11846-025-00895-w.
[53] C. Buck, L. Heim, K. Körner-Wyrtki, A. Krombacher, M. Röglinger, Making the most of digital social innovation: an exploration into success factors, J. Bus. Res. 190 (2025) 115215, https://doi.org/10.1016/j.jbusres.2025.115215.
[54] C. Kreiterling, Digital innovation and entrepreneurship: a review of challenges in competitive markets, J. Innov. Entrep. 12 (1) (2023) 49, https://doi.org/10.1186/s13731-023-00320-0.
[55] M.M. Migdadi, Knowledge management processes, innovation capability and organisational performance, Int. J. Product. Perform. Manag. 71 (1) (2022) 182–210, https://doi.org/10.1108/IJPPM-04-2020-0154.
[56] S. Khin, T.C. Ho, Digital technology, digital capability and organisational performance: a mediating role of digital innovation, Int. J. Innov. Sci. (2019), https://doi.org/10.1108/IJIS-08-2018-0083.
[57] J.M. Sohu, T. Hongyun, U.S. Akbar, F. Hussain, Digital innovation, digital transformation, and digital platform capability: detrimental impact of big data analytics capability on innovation performance, Int. Res. J. Manag. Soc. Sci. 4 (3) (2023) 265–281, https://doi.org/10.5281/zenodo.10498159.
[58] J.F. Hair, M. Sarstedt, C.M. Ringle, S.P. Gudergan, Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM) (2e), Sage, Thousand Oaks, CA, 2024.
[59] J.K. Janes, J.M. Miller, J.R. Dupuis, R.M. Malenfant, J.C. Gorrell, C.I. Cullingham, R.L. Andrew, The K= 2 conundrum, Mol, Ecol 26 (14) (2017) 3594–3602, https://doi.org/10.1111/mec.14187.
[60] J.F. Hair, G.T.M. Hult, C.M. Ringe, M. Sarstedt, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 3rd ed., SAGE, 2022.
[61] F. Faul, E. Erdfelder, A. Buchner, A.G. Lang, Statistical power analyses using G* Power 3.1: tests for correlation and regression analyses, Behav. Res. Methods 41 (4) (2009) 1149–1160, https://doi.org/10.3758/BRM.41.4.1149.
[62] N. Kock, P. Hadaya, Minimum sample size estimation in PLS-SEM: the inverse square root and gamma-exponential methods, Inf. syst. j. 28 (1) (2018) 227–261, https://doi.org/10.1111/isj.12131.
[63] S.C. Rife, K.L. Cate, M. Kosinski, D. Stillwell, Participant recruitment and data collection through Facebook: the role of personality factors, Int. J. Soc. Res. Methodol. 19 (1) (2016) 69–83, https://doi.org/10.1080/13645579.2014.957069.
[64] M. Cazacu, S. Dumitriu, I. Georgescu, D. Berceanu, D. Simion, A.A. Vărzaru, C.G. Bocean, A perceptual approach to the impact of CSR on organisational financial performance, Behav. Sci. 13 (5) (2023) 359, https://doi.org/10.3390/bs13050359.
[65] J.F. Hair, G.T.M. Hult, C.M. Ringe, M. Sarstedt, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 2nd ed., Thousand Oaks: SAGE, 2017 https://doi.org/10.1017/CBO9781107415324.004.
[66] J.F. Hair, M.C. Howard, C. Nitzl, Assessing measurement model quality in PLS-SEM using confirmatory composite analysis, J. Bus. Res. 109 (2020) 101–110, https://doi.org/10.1016/j.jbusres.2019.11.069.
[67] M. Sarstedt, C.M. Ringle, J.-H. Cheah, H. Ting, O.I. Moisescu, L. Radomir, Structural model robustness checks in PLS-SEM, Tour. Econ. 26 (4) (2020) 531–554, https://doi.org/10.1177/1354816618823921.
[68] P.N. Sharma, B.D. Liengaard, J.F. Hair, M. Sarstedt, C.M. Ringle, Predictive model assessment and selection in composite-based modeling using PLS-SEM: extensions and guidelines for using CVPAT, Eur. J. Mark. 57 (6) (2023) 1662–1677, https://doi.org/10.1108/EJM-08-2020-0636.
[69] C. Fornell, D.F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, J. Mark. Res. 18 (1) (1981) 39, https://doi.org/10.2307/3151312.
[70] J. Henseler, C.M. Ringle, M. Sarstedt, A new criterion for assessing discriminant validity in variance-based structural equation modelling, J. Acad. Mark. Sci. 43 (2015) 115–135, https://doi.org/10.1007/s11747-014-0403-8.
[71] P.M. Podsakoff, S.B. MacKenzie, J.Y. Lee, N.P. Podsakoff, Common method biases in behavioral research: a critical review of the literature and recommended remedies, J. appl. psychol. 88 (5) (2003) 879, https://doi.org/10.1037/0021-9010.88.5.879.
[72] N. Kock, Common method bias in PLS-SEM: a full collinearity assessment approach, Int. J. E-Collab. 11 (4) (2015) 1–10, https://doi.org/10.4018/IJEC.2015100101.
[73] G.T.M. Hult, J.F. Hair, D. Proksch, M. Sarstedt, A. Pinkwart, C.M. Ringle, Addressing endogeneity in international marketing applications of partial least squares structural equation modeling, J. Int. Mark. 26 (3) (2018) 1–21, https://doi.org/10.1509/jim.17.0151.

[74] J.-M. Becker, D. Proksch, C.M. Ringle, Revisiting Gaussian copulas to handle endogenous regressors, J. Acad. Mark. Sci. 50 (1) (2022) 46–66, https://doi.org/10.1007/s11747-021-00805-y.
[75] R.D. Isabel, M.R. David, C.C. Gabriel, The effect of servant leadership on employee outcomes: does endogeneity matter? Qual. Quant. 57 (Suppl 4) (2023) 637–655, https://doi.org/10.1007/s11135-021-01109-7.
[76] M.A. Manzi-Puertas, I. Agirre-Aramburu, S. López-Pérez, Navigating the student entrepreneurial journey: dynamics and interplay of resourceful and innovative behavior, J. Bus. Res. 174 (2024) 114524, https://doi.org/10.1016/j.jbusres.2024.114524.
[77] M. Sarstedt, C.M. Ringle, J. Henseler, J.F. Hair, On the emancipation of PLS-SEM: a commentary on Rigdon (2012), Long. Range Plann. 47 (2014) 154–160, https://doi.org/10.1016/j.lrp.2014.02.007.
[78] J. Cohen, Statistical Power Analysis For the Behavioral Sciences, 2nd ed., 1988, https://doi.org/10.4324/9780203771587.
[79] G. Shmueli, O.R. Koppius, Predictive analytics in information systems research, MIS Q.: Manag. Inf. Syst. 35 (3) (2011) 553–572, https://doi.org/10.2307/23042796.
[80] B.D. Liengaard, P.N. Sharma, G.T.M. Hult, M.B. Jensen, M. Sarstedt, J.F. Hair, C.M. Ringle, Prediction: coveted, yet forsaken? Introducing a cross-validated predictive ability test in partial least squares path modeling, Decis. Sci. 52 (2) (2021) 362–392, https://doi.org/10.1111/deci.12445.
[81] M. Acquaah, Managerial social capital, strategic orientation, and organisational performance in an emerging economy, Strateg. manag. j. 28 (12) (2007) 1235–1255, https://doi.org/10.1002/smj.632.
[82] M. Tripsas, G. Gavetti, Capabilities, cognition, and inertia: evidence from digital imaging, SMS Blackwell Handb. Organ. Capab. (2017) 393–412, https://doi.org/10.1002/9781405164054.ch23.
[83] J.L. Sanders Jones, K. Linderman, Process management, innovation and efficiency performance: the moderating effect of competitive intensity, Bus. Process Manag. J. 20 (2) (2014) 335–358, https://doi.org/10.1108/BPMJ-03-2013-0026.