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RESEARCH ARTICLE

The Impact of FinTech Adoption on Operational Performance: The Mediating Role of Digital Innovation Capability: An Empirical Study

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ABSTRACT

Financial technology has evolved from a tool used to increase the efficiency of a service organisation to a central force shaping its operating procedures, but the process by which FinTech investment translates into tangible operational benefits is not well defined. This study is based on Dynamic Capabilities Theory and supported by Resource Based View, to explore whether the influence of implementing the FinTech can be transmitted to operational performance through digital innovation capability. 250 survey participants were included and analysed using partial least squares structural equation modelling (SmartPLS 4) with significant results determined with 5,000 bootstrap subsamples. The adoption of FinTech was made operational using digital payment, cloud financial services and mobile financial services; digital innovation capability through digital process innovation and service innovation; and operational performance through operational efficiency and process quality. All the reliability and validity measures of the measurement model were met, the composite reliability for the measurement items were ranged from 0.909 to 0.938, and the average variance extracted for the measurement items were ranged from 0.622 to 0.673. There were 10 structural relationships, all of which were statistically significant. Cloud financial services was the greatest influencing factor on digital process innovation ($\beta = 0.306$, $p < 0.001$), while digital process innovation ($\beta = 0.377$, $p < 0.001$) and service innovation ($\beta = 0.374$, $p < 0.001$) turned out to be the strongest antecedents of operational efficiency. The model explained 42.2 per cent of the variation in operational efficiency and 33.1 per cent of the variation in process quality. All of the 12 specific indirect effects were statistically significant, making digital innovation capability the pathway for FinTech adoption to impact operational outcomes. The results relegate FinTech from being just a technology asset to an enabler with an operational value that only becomes realised when organisations re-configure it as an innovation capability.

INTRODUCTION

Over the last ten years a set of technologies has transformed the financial services landscape, transcended the fringes of organisation activity, and changed the way financial transactions are conducted. Digital payment rails are now the operating backbone of banks, insurers, payment companies and other companies that rely on financial processes to power their businesses, while financial functions are now being delivered via mobile-first service channels, and financial infrastructure are being delivered in the cloud (Muthukannan et al., 2021; Sharma et al., 2024). A limited replacement of paper-based transactions by electronic transactions has evolved to a reshaping of the way work is programmed, how exceptions are managed and how quality is maintained throughout the transaction's life cycle. As a result, industry spending has risen in tandem and along the way, executives have assumed that, similarly, FinTech spending will be factored into the operational ledger in terms of quicker cycle times and reduced error rates, as well as more reliable throughput.

That, however, is an expectation which is not sufficiently justified by the empirical literature. Some significant work has already been done that captures in good detail the antecedents of FinTech adoption, which include perceived value, trust, security, regulatory attitude and digital literacy (Amnas et al., 2023; Bommer et al., 2023; Jafri et al., 2024; Xie et al., 2021). One other stream has looked at consequences, generally in the form of financial or competitive consequences (Campanella et al., 2026; Dwivedi et al., 2021; Rizvi et al., 2024). Theoretically and managerially, there is a space between these two streams, namely "how is adoption related to performance?" Technologies are in themselves inactive. It does not yet have an operational consequence as long as an organisation does not organise around it, and research on digital transformation has consistently warned that companies that implement similar technologies will get significantly different results (Kraus et al., 2022; Plekhanov et al., 2023; Verhoef et al., 2021). It is important to be careful of linking adoption and performance together since adopting the technology would belong to the organisational processes of absorption.

Dynamic Capabilities Theory provides the conceptual guidance to solve the problem. For Teece the competitive results are not based on the possession of the resources but on how well an organisation can sense the opportunities, invest and commit to them and reconfigure their asset base as the conditions change. In the context of the current setting, FinTech is the sensed and seized opportunity, the reconfiguring act is the development of digital innovation capability (the organisational capability of redesigning processes within the organisation and creating new services with digital means (Kroh et al., 2024)). In this view, FinTech should have an impact on performance of operations because it provides them with innovation capability, not alongside it. While it is an intuitive proposition, it echoes Lu et al. (2023) who showed that digital transformation has to go through innovation ambidexterity to deliver performance, it has been very little examined in an empirical test (testing) where the dimensions of digital adoption, capability, and performance are decomposed and examined separately.

This study does just that! This approach does not combine everything related to the adoption of FinTech into a single latent construct, but rather breaks it down into three technology families (digital payment systems, cloud financial services and mobile financial services), whose logics of organization are quite different from one another. Digital innovation capability is also broken down into digital process innovation and service innovation; and operational performance into operational efficiency and process quality. This decomposition allows questions which an aggregated design wouldn't be able to answer. Are there variations across the FinTech families in the contribution to innovation capability – is it just the same or are there some families that are heavier than others? Is there a difference between process and service innovation as to their importance to efficiency and quality? In what ways do technology to performance work well or poorly? Answers to such questions have implications for allocations of wise management of competing technology portfolios to which managers must allocate limited investment.

The study aims to achieve four objectives; to identify the impact of each dimension of FinTech on digital innovation capability; to identify the impact of digital innovation capability on operational performance; to quantify the pathways from adoption to performance that are indirect from digital innovation capability and; to identify pathways that have the most practical significance. The respondents were 250 people, and the data were analysed using partial least squares structural equation modelling (PLS-SEM) according to the SmartPLS 4 program, which was appropriate for this study because it was a complex model with multiple mediating relationships and a prediction goal in conducting research (Cheah et al., 2024; Hair et al., 2019; Ringle et al., 2024).

There are three contributions: In theory, the study is also a new extension of Dynamic Capabilities Theory, with the specification and testing of the reconfiguration mechanism (not assuming), as well as the proof that the mechanism works by identifiable and separable channels, which is specific to the FinTech field. What it does in practice is to give a decompose description, in which every relationship between the different structures is estimated, and every indirect path quantified, thus providing a detailed diagram of the location of the operating revenue generated by the technological investment. In practice it provides managers with a ranking comparison of pathways which can be used to sequence pathways within digital investment programmes.

The rest of the article will be along these lines. The literature in Section 2 summarizes the key studies on FinTech adoption and digital innovation capability and performance. In Section 3, the hypotheses will be developed. The conceptual framework is presented in section 4. A methodology is explained in Section 5. Data analysis and results for sections 6 & 7. The findings of the study in light of the previous evidence is discussed in Section 8 while the last sections outline the contributions, implications, limitations and suggestions for further investigation.

LITERATURE REVIEW

Theoretical foundation

Dynamic Capabilities Theory. The concept of sustained advantage was put forward by Teece et al. (1997) and developed further by Teece (2007), which claims that the ability to integrate, build and reconfigure competences are higher order capacities that are necessary for sustained advantage in changing environments. Eisenhardt and Martin (2000) refined the construct by defining dynamic capabilities as an identifiable organisation routine, rather than an abstract property of the organisation, making them empirically tractable. In the last few years, their microfoundations have been further specified, for example, in how their attention control and problem-solving abilities modify everyday requirements (Schulze & Brusoni, 2022), in how governance conditions their financial returns (Heaton et al., 2023), and in how managerial cognition shapes their use in business model innovation (Hock-Doepgen et al., 2025). The theory is well suited for the current investigation for one reason: it emphasizes that performing does not depend directly on the assets, but on the way they are reconfigured into capabilities. On this score, FinTech is an acquired value that operates through its reconfiguration value.

Resource-Based View. Barney's (1991) idea about the intrinsic value, scarcity, inimitable and non-substitutable nature of the resources completes the necessary complement. In most markets, FinTech applications are easily available for purchase, and are neither scarce nor unCopyable. What is hard to copy is the organisational structure that enables a firm to do so – a linkage that has been made explicit in the digital services literature, linking RBV to innovation outcomes (Cuthbertson & Furseth, 2022; Madhala et al., 2024; Marchiori et al., 2022). The RBV, then, provides insight into the expected weak link between adoption and performance, and the lens of dynamic capabilities provides insight into the gap.

Technology–organization–environment and Diffusion of Innovation. Theoretically, adoption is not inert and two frameworks explain the variability of adoption. The TOE approach places adoption decisions in the context of the relationship between technological readiness, organisational capacity and environmental pressure, which has been shown to be sustainable in several studies such as cloud and FinTech uptake studies (Subramaniam & Teh, 2026). The attribute-based account of differential adoption rates found in much of the literature on barriers to FinTech, as discussed by Griffiths et al. (2025), Nalluri & Chen (2024) and Soluk et al. (2023), is a feature of Diffusion of Innovation. Both frameworks are used here to describe what led to the adoption of the technology, and not the result of the adoption, which is why they are used as a supporting theory instead of a main theory.

Technology Acceptance Model. At the individual level, perceived usefulness and ease of use still dominate in the explanation of use intention, and the extensions of TAM still dominate in the research of users of the FinTech product (Amnas et al., 2025; Choi et al., 2024; Xie et al., 2021). As this study does not measure individual outcomes, but organisational outcomes, the TAM is invoked to explain the measurement of adoption as realised adoption rather than intention.

FinTech adoption and its dimensions

FinTech has evolved into a stage where systematic reviews are able to classify it into technology families (Kajol et al., 2022; Sharma et al., 2024), which are the individual groups of technologies that make up FinTech. There are three families that are highlighted in this model and operate separately in organisational processes. Digital payment systems are systems which automate the process of initiating, clearing and reconciling payments. Their value are during the manual elimination, which results in structured transaction information as a by-product of typical operations (Ha et al., 2024; Ramtiyal et al., 2024). Payment infrastructure is very uniform and dependent on interoperability requirements, meaning that adoption is likely to be external payment protocol driven and not internal discretion a factor in how much reconfiguration it can stimulate. Cloud financial services move computational and storage resources to elastic, external resources. The key difference is not that of cost displacement, rather it is the reduction in capacity constraints on experimentation that occur when the cloud provides access to process-related capacity: This ability to provide cloud-based capacity collapses the lead time between a process change being conceived and being tested (Subramaniam & Teh, 2026; Zheng et al., 2023). The fact that this property puts cloud adoption into the spotlight as an internal redesign enabler, rather than transaction-processing technologies, is significant. Mobile financial services bring financial services to an easily carried and always available interface. The operational impact is that they introduce flexibility in the provision of the service, which changes the nature of demand, and requires the re-design of service processes (Shaikh et al., 2023; Tetteh & Kwateng, 2026; Yuan et al., 2025). A reconfiguring pressure that is primarily customer facing is being applied to service design through the mobile channels.

Digital innovation capability

Digital innovation capability is the ability of an organisation to develop new processes, services and models using digital technologies. For the construct, a validated, multi-dimensional measurement tool was provided by Kroh et al. (2024) and the body of literature for the construct was mapped by Uršič and Čater (2025) from the perspective of levels of analysis. Prior studies have shown that digital technology adoption has a positive impact on innovation performance (Usai et al., 2021), platform capability has a positive impact on SME innovation outcomes (Jiang et al., 2023), and digital innovation has a positive effect on manufacturing performance via affordance mechanisms (Liu et al., 2023). The construct is considered here to consist of two dimensions. Digital process innovation is about the internal reconfiguration of processes using digital tools, the automation of manual processes, the elimination of handovers, the replacement of scheduled controls with continuous monitoring. Chirumalla (2021) showed, using a dynamic capabilities perspective, how this kind of capability is incrementally built up over time in process industries, while Blichfeldt and Faullant (2021) defined its performance implications. Service innovation relates to the creation or restructuring of services offered to an outside audience, which digital platforms can significantly increase (Chowdhury et al., 2021; Li et al., 2022). The connection between the two dimensions is one way, but not the other: one changes the way of doing work, the other changes what to offer, and one does not necessarily affect the other.

Operational Performance

Operational performance accentuates the effectiveness of an organisation's transformation processes and is assessed by efficiency, quality, flexibility and delivery. Here two dimensions are looked at. Operational efficiency is defined as the ratio of output to resource usage, such as cycle time, cost per transaction and throughput (Kim & Swink, 2021; Qin et al., 2026). Process quality is associated with conformance as the degree of process execution without defect or rework (Csiki et al., 2023; Tortorella et al., 2021). The distinction is important as it means that different interventions have different effects on efficiency and quality, and that in some settings, efficiency and quality may have mutually negative effects.

Digitalisation And Operational Outcomes

There is ample evidence to suggest digitalisation has a relationship with outcomes of operations, but it is not consistent. In the case of process digitalisation, Yang and Yee (2022) concluded that it had an indirect impact on the performance of the firms through the process of developing their dynamic capabilities. Sunder and Prashar (2024) proved that digitalisation and lean practices can influence the operational performance by means of organisational learning systems. In adopting digital technology, if combined with innovative management, then the capability of digital technology will have a positive impact on operational performance, as concluded by Bag et al. (2025). Momeni et al. (2023) identified the processes involved in the development of operational capabilities in digital servitisation contexts, while Abou-Foul et al. (2023) demonstrated the influence of absorptive capacity on the returns to technological capability. The link between capability and operational performance has been demonstrated through a large volume of studies (Raj et al., 2025) with the support of meta-analytic evidence. The common theme in these studies is that rather than direct influence, there is a mediation effect, a theme that is explored in the current study in the context of the domain of FinTech specifically. In that sphere the mediating ascription is still relatively undeveloped. While there are studies that have associated FinTech with competitiveness (Dwivedi et al., 2021), sustainability outcomes (Campanella et al., 2026) and innovation at the system level (Rizvi et al., 2024), there are relatively few studies that have broken down the adoption of FinTech in terms of technology families and followed their individual paths to their different dimensions of performance, and even fewer that have paid attention to the impact that these individual paths have on the system's innovation. This is the gap in the empirical literature that is filled with the present study.

HYPOTHESES DEVELOPMENT

The model is defined and identified within the dimensions of the constructs that make up the model. This provides a more stringent test than an aggregated specification, as it allows the relative contribution of each technology family and each capability dimension to be tested separately. The three hypotheses are grouped into three families, based on the three parts of the mediation chain.

Fintech Adoption and Digital Innovation Capability

The concept of dynamic capabilities logic assumes that absorbed technological resources turn into reconfiguration capability. However, each FinTech family has its own affordance profile and there is no theoretical guarantee that the same effects can be seen in all families. Digital payment systems provide high frequency, structured data of transactions, making visible bottlenecks and exception patterns, which were previously hidden. Targeted process redesign (Ha et al., 2024) can only be done when the process is visible. At the same time, the ability to pay expands the space of possible service configurations as it allows new pricing, settlement and bundling options (Khalek et al., 2024). Payment infrastructure on the other hand is externally standardised, limiting its ability to motivate internal redesign to protocols not controlled by the adopting firm. The economics of experimentation change when it's cloud financial services. If provisioning of computational capacity needs to be done up front, the cost of process redesign will prevent trial from happening; however, if the capacity can be provisioned dynamically, the barrier to trial is eliminated and rapid iteration will be enabled (Zheng et al., 2023). In a TOE framing, Subramaniam and Teh (2026) demonstrated that the relationship between cloud adoption and firm performance outcomes is positive. Guo et al. (2023) were able to show that the returns to investing in cloud technology are innovation when complemented with complementary organisational resources. The adoption of cloud should hence have a strong impact on process innovation in the internal processes. The reconfiguring pressure is mainly due to the demand side of mobile financial services. When services are continuously available, the customer-facing part of the process as well as the process itself must be redesigned in order to account for this (Yuan et al., 2025; Shaikh et al., 2023). The impact of mobile channels is most pronounced in service design where new mobile channels are seen as providing direct service opportunities for services (Tetteh & Kwateng, 2026). Accordingly:

H1a. Digital payment systems positively influence digital process innovation.

H1b. Digital payment systems positively influence service innovation.

H1c. Cloud financial services positively influence digital process innovation.

H1d. Cloud financial services positively influence service innovation.

H1e. Mobile financial services positively influence digital process innovation.

H1f. Mobile financial services positively influence service innovation.

3.2 Digital Innovation Capability and Operational Performance

Digital process innovation operates on top of the operating system. The compression of cycle time, and reductions in resources used per unit of output, the definitional content of efficiency (Sunder & Prashar, 2024; Yang & Yee, 2022), is what automation of manual steps and elimination of handoffs accomplishes. Similarly, the same interventions impact quality in other ways: Manual handoffs are the primary site of transcription and omission errors, and the elimination of manual handoffs leads to fewer defects, whereas periodic inspection detects errors later than continuous digital monitoring (Yin et al., 2024). There is a more subtle but no less powerful way in which service innovation affects operational outcomes: by altering the nature of the inputs themselves.There is another, less obvious but no less powerful way in which service innovation affects operational outcomes: by changing the nature of the inputs themselves. Newly developed digital services are created with modern process logic from the beginning, instead of extracting accumulated workarounds from previous development processes, and they are usually developed as self-service architectures, which shift effort from organisations to customers (Li et al. 2022; Sklyar et al. 2025). Higher conformance in comparison to legacy services, with novel services explicitly specified against explicit quality criteria and instrumented for measurement at launch (Münch et al., 2022).

H2a. Digital process innovation positively influences operational efficiency.

H2b. Digital process innovation positively influences process quality.

H2c. Service innovation positively influences operational efficiency.

H2d. Service innovation positively influences process quality.

The Mediating Role Of Digital Innovation Capability

The main theoretical thesis comes from the two families above. If Innovation Capability leads to FinTech adoption, and Innovation Capability leads to operational performance, then the path to operational performance is through Innovation Capability. Dynamic Capabilities Theory suggests this reconfiguration process and the RBV predicts it will dominate the direct route as there are a number of FinTech applications readily available, and thus not creating a differentiated advantage themselves (Barney, 1991; Teece, 2007). There is empirical evidence in the adjacent literature to support the presence of analogous mediated structures, including: business model innovation as a mediator between digital transformation and firm performance (Merín-Rodrigáñez et al., 2024); innovation as a mediator between digital capability and performance (Ferreira et al., 2024); open innovation as a mediator between platform capability and sustainable innovation performance (Wang et al., 2023); and data-driven culture as a mediator between AI-enabled capability and environmental performance (Fosso Wamba et al., 2024). There are 3 adoption dimensions, 2 capability dimensions and 2 performance dimensions, giving rise to 12 different indirect pathways. Each is hypothesised individually

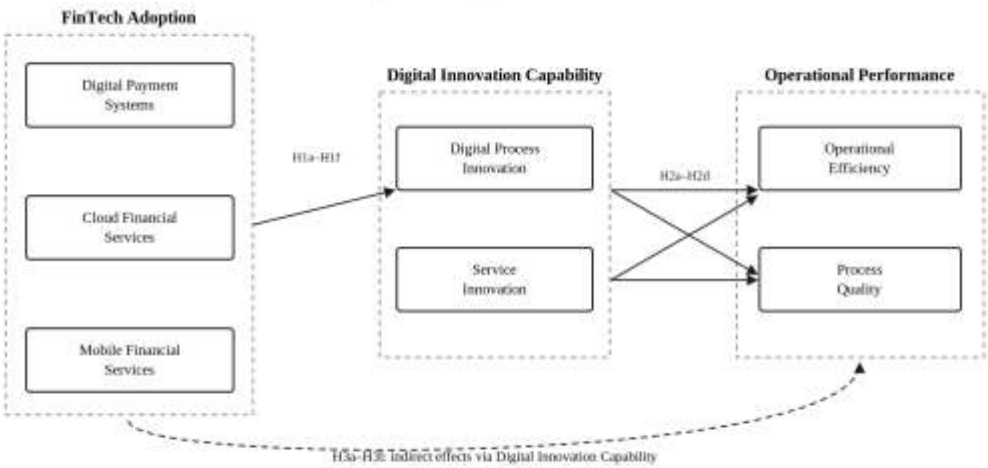
H3a–H3l. Digital innovation capability mediates the relationship between each FinTech adoption dimension and each operational performance dimension. Specifically, each of the twelve indirect pathways from digital payment systems, cloud financial services and mobile financial services, through digital process innovation and service innovation, to operational efficiency and process quality is positive and statistically significant.

A note on the specification of direct effects. Direct paths between the FinTech dimensions and the performance dimensions are not included in the estimated model. It is a planned specification that aligns with the theoretical content of the impact of FinTech on operations by reconfiguration and not by affecting them. One methodological implication is clearly expressed: since no direct effects were estimated, the present design does not allow for differentiating between types of mediation, namely complementary mediation and mediation that is either indirect or absent. The evidence below shows that indirect pathways are positive and significant, but does not prove that there is a direct pathway. This restriction applies again in Section 11.

CONCEPTUAL FRAMEWORK

The conceptual model is shown in Figure 1. Three exogenous constructs are lined up in succession for the adoption of FinTech: digital innovation capability as two constructs; operational performance as two endogenous constructs. The structural relationships between the concepts are specified in 10 ways: six from adoption to capability, and four from capability to performance; the result is 12 specific indirect effects.

Figure 1. Conceptual research model



The framework builds on the literature in two ways. First, it makes explicit the reconfiguration mechanism that dynamic capabilities theory suggests but which has been unstated in FinTech research until now. Second, its decomposed structure allows us to identify asymmetries technology families that develop capability in an uneven manner, capability dimensions that contribute to the efficiency and quality in an unequal manner, which would be hidden by an aggregated model.

RESEARCH METHODOLOGY

Research Philosophy and Design

The study is based on a positivist philosophy, which is compatible with the purpose of the research which is to test the theoretical proposition in the form of measurable quantities and statistical inferences. The research was conducted using a deductive, quantitative and cross sectional research design. The data were collected in a single wave and analysed with variance-based structural equation modelling.

Analytical Approach

PLS-SEM was chosen for three reasons following the recommendations outlined in the literature (Becker et al., 2023; Hair et al., 2019, 2021, 2022; Hair et al., 2011). The first step is that the research goal is not to confirm a contrast hypothesis about a competing covariance structure but instead is explanatory-predictive as it concerns the data. Second, the model is complex, containing seven constructs of the latent variables, forty-eight indicators, and ten structural relationships, in two-stage mediation chain. Third, PLS-SEM does not make any distributional assumptions, which is beneficial in the case of Likert-scaled data (Chin, 1998). The reporting procedures used here are in line with the recent recommendations for PLS-SEM that advocate for transparent reporting (Guenther et al., 2023, 2025; Magno et al., 2024; Ringle et al., 2020). The path weighting scheme was used for estimation in the software SmartPLS 4 (Ringle et al., 2024) with a maximum of 3,000 iterations and stop criterion of 10-7. Bootstrapping (5,000 subsamples, two-tailed test, $\alpha = 0.05$, percentile confidence interval, fixed seed) was used to assess significance.

Instrument Development and Measurement Scales

It consists of 48 items organized around seven constructs: digital payment systems (DPS_1–DPS_8); cloud financial services (CFS_1–CFS_7); mobile financial services (MFS_1–MFS_6); digital process innovation (DPI_1–DPI_7); service innovation (SI__1–SI__7 and SI_8); operational efficiency (OE_1–OE_6); and process quality (PQ_1–PQ_6). Each item was rated on a 5-point Likert scale, and the actual data show that scores range from 1 to 5.

Table 1: Constructs, Dimensions and Measurement Items

Higher-order construct	Dimension	Code	No. of items	Item codes	Source scale
FinTech Adoption	Digital Payment Systems	DPS	8	DPS_1–DPS_8	[AUTHOR TO SUPPLY]
	Cloud Financial Services	CFS	7	CFS_1–CFS_7	[AUTHOR TO SUPPLY]
	Mobile Financial Services	MFS	6	MFS_1–MFS_6	[AUTHOR TO SUPPLY]
Digital Innovation Capability	Digital Process Innovation	DPI	7	DPI_1–DPI_7	[AUTHOR TO SUPPLY]
	Service Innovation	SI	8	SI_8–SI__7	[AUTHOR TO SUPPLY]
Operational Performance	Operational Efficiency	OE	6	OE_1–OE_6	[AUTHOR TO SUPPLY]
	Process Quality	PQ	6	PQ_1–PQ_6	[AUTHOR TO SUPPLY]

Note. All items measured on a five-point Likert scale. Full item wording is required for the questionnaire appendix.

DATA ANALYSIS

Similarly, the analysis was conducted in two steps, as is the typical procedure in PLS-SEM: the first step was to assess the measurement model for reliability and validity, and the second step was to interpret the results of the structural model once the measurement model was found to be reliable and valid (Becker et al., 2023; Hair et al., 2019; Hair & Alamer, 2022). All constructs are expressed in a reflective manner and evaluation criteria are applied in that way.

Descriptive statistics

Table 2 presents the mean and standard deviation for each indicator as calculated from the 250 cases that had complete data on the indicator matrix. Item means range from 2.380 (PQ_3) to 3.484 (MFS_4), and standard deviations from 0.638 (DPS_4) to 0.948 (DPS_1). Two aspects of this distribution are worthy of note. First, the concentration of scores at the middle of the scale reflects moderate – rather than extreme – evaluations for all constructs, which is beneficial to variance-based estimation as it avoids ceiling effects that reduce covariance. Second, the process quality has the lowest mean at the construct level, four out of its six items fall below 2.8 and PQ_3 is the lowest rated item in the instrument. An observation with substantive implications taken up in the discussion was thus rated by the respondents as being rated more critically by respondents than the conformance performance of their organisations.

Table 2. Descriptive statistics of the measurement items (N = 250)

Construct	Item	Mean	SD	Construct	Item	Mean	SD
DPS	DPS_1	3.068	0.948	DPI	DPI_4	3.304	0.804
DPS	DPS_2	2.864	0.805	DPI	DPI_5	3.160	0.801
DPS	DPS_3	2.688	0.699	DPI	DPI_6	3.148	0.754
DPS	DPS_4	2.896	0.638	DPI	DPI_7	3.064	0.867
DPS	DPS_5	3.200	0.841	SI	SI_8	2.848	0.802
DPS	DPS_6	3.116	0.743	SI	SI__1	2.988	0.804
DPS	DPS_7	3.272	0.759	SI	SI__2	2.832	0.763
DPS	DPS_8	3.156	0.725	SI	SI__3	2.876	0.769
CFS	CFS_1	3.240	0.895	SI	SI__4	3.072	0.713
CFS	CFS_2	3.304	0.725	SI	SI__5	2.912	0.826
CFS	CFS_3	3.200	0.816	SI	SI__6	3.224	0.805
CFS	CFS_4	3.048	0.913	SI	SI__7	3.028	0.741
CFS	CFS_5	2.996	0.731	OE	OE_1	2.996	0.747
CFS	CFS_6	3.156	0.720	OE	OE_2	3.124	0.862
CFS	CFS_7	3.100	0.788	OE	OE_3	3.064	0.794
MFS	MFS_1	2.956	0.696	OE	OE_4	2.972	0.730
MFS	MFS_2	3.268	0.720	OE	OE_5	2.936	0.758
MFS	MFS_3	2.812	0.792	OE	OE_6	2.840	0.738
MFS	MFS_4	3.484	0.751	PQ	PQ_1	2.824	0.677
MFS	MFS_5	2.932	0.733	PQ	PQ_2	2.780	0.784
MFS	MFS_6	2.864	0.657	PQ	PQ_3	2.380	0.679
DPI	DPI_1	3.072	0.803	PQ	PQ_4	3.068	0.711
DPI	DPI_2	3.100	0.813	PQ	PQ_5	2.796	0.793
DPI	DPI_3	2.872	0.806	PQ	PQ_6	2.556	0.652

Note. All items measured on a five-point Likert scale; observed range 1–5; no missing values.

Measurement Model: Indicator Reliability And Convergent Validity

Outer loadings and their bootstrap standard errors, t-statistics and corresponding significance levels are presented along with indicator reliability and outer variance inflation factors in Table 3. Each of the forty-eight loadings is higher than the 0.708 threshold for an indicator to account for more than 50% of the variance in its construct (Hair et al., 2019). The distribution runs from 0.7265 (DPS_3) to 0.8658 (OE_3), with a mean in the low 0.80s. The reliability of the indicators, that is, the squared loading of each item, ranges from 0.528 to 0.750 as well, which is an indication that all indicators contribute significantly to the variance of their construct. The t-statistics for all loadings are above 22.521 (for DPS_3) and up to 58.048 (for SI__6), meaning that the measurement structure is estimated with high precision, and all loadings are significant at the $p < 0.001$ level. There was no indicator to be deleted. Outer VIF values range from 1.759 (DPS_3) to 3.045 (SI__6). All values are below the conservative value of 3.3, and thus well below the more liberal value of 5.0 that is used in many reflective-model reports. The collinearity of reflective indicators of a common construct is not an issue since it is expected and not problematic.

Table 3. Measurement Model: Outer Loadings, Indicator Reliability, Significance And Collinearity

Construct	Item	Loading (O)	Indicator reliability (λ^2)	SD	t	p	95% CI [2.5%, 97.5%]	VIF
Digital Payment Systems	DPS_1	0.765	0.586	0.0250	30.671	<0.001	[0.714, 0.811]	1.977
	DPS_2	0.770	0.593	0.0271	28.459	<0.001	[0.712, 0.819]	1.990
	DPS_3	0.727	0.528	0.0323	22.521	<0.001	[0.657, 0.783]	1.759
	DPS_4	0.809	0.655	0.0216	37.398	<0.001	[0.764, 0.848]	2.189

Construct	Item	Loading (O)	Indicator reliability (λ^2)	SD	t	p	95% CI [2.5%, 97.5%]	VIF
	DPS_5	0.812	0.659	0.0225	36.136	<0.001	[0.765, 0.851]	2.264
	DPS_6	0.813	0.661	0.0242	33.548	<0.001	[0.759, 0.853]	2.339
	DPS_7	0.806	0.650	0.0216	37.391	<0.001	[0.760, 0.845]	2.250
	DPS_8	0.803	0.645	0.0226	35.534	<0.001	[0.754, 0.843]	2.155
Cloud Financial Services	CFS_1	0.843	0.711	0.0199	42.396	<0.001	[0.801, 0.878]	2.555
	CFS_2	0.779	0.606	0.0248	31.439	<0.001	[0.725, 0.823]	2.019
	CFS_3	0.785	0.617	0.0258	30.420	<0.001	[0.731, 0.831]	2.003
	CFS_4	0.858	0.737	0.0166	51.705	<0.001	[0.824, 0.888]	2.712
	CFS_5	0.786	0.617	0.0261	30.096	<0.001	[0.730, 0.833]	1.972
	CFS_6	0.797	0.635	0.0227	35.072	<0.001	[0.749, 0.837]	2.087
	CFS_7	0.772	0.596	0.0287	26.918	<0.001	[0.710, 0.821]	1.965
Mobile Financial Services	MFS_1	0.785	0.616	0.0270	29.041	<0.001	[0.725, 0.831]	2.005
	MFS_2	0.803	0.644	0.0244	32.842	<0.001	[0.751, 0.845]	2.080
	MFS_3	0.819	0.670	0.0208	39.420	<0.001	[0.774, 0.856]	2.165
	MFS_4	0.861	0.742	0.0176	48.914	<0.001	[0.823, 0.892]	2.629
	MFS_5	0.853	0.727	0.0181	47.169	<0.001	[0.812, 0.884]	2.541
	MFS_6	0.799	0.638	0.0245	32.567	<0.001	[0.745, 0.841]	2.005
Digital Process Innovation	DPI_1	0.826	0.683	0.0205	40.284	<0.001	[0.781, 0.863]	2.337
	DPI_2	0.799	0.639	0.0264	30.236	<0.001	[0.741, 0.845]	2.137
	DPI_3	0.763	0.582	0.0272	28.022	<0.001	[0.704, 0.811]	1.858
	DPI_4	0.858	0.736	0.0175	48.963	<0.001	[0.819, 0.888]	2.771
	DPI_5	0.794	0.631	0.0255	31.147	<0.001	[0.740, 0.840]	2.075
	DPI_6	0.794	0.630	0.0240	33.120	<0.001	[0.742, 0.836]	2.067
	DPI_7	0.842	0.710	0.0176	47.859	<0.001	[0.805, 0.874]	2.535
Service Innovation	SI_8	0.783	0.614	0.0246	31.872	<0.001	[0.732, 0.828]	2.070
	SI__1	0.844	0.712	0.0185	45.620	<0.001	[0.803, 0.876]	2.676
	SI__2	0.817	0.667	0.0209	39.014	<0.001	[0.772, 0.853]	2.366
	SI__3	0.821	0.674	0.0202	40.587	<0.001	[0.777, 0.856]	2.410
	SI__4	0.770	0.593	0.0258	29.864	<0.001	[0.716, 0.815]	2.047
	SI__5	0.794	0.631	0.0262	30.346	<0.001	[0.736, 0.839]	2.212

Construct	Item	Loading (O)	Indicator reliability (λ^2)	SD	t	p	95% CI [2.5%, 97.5%]	VIF
	SI_6	0.861	0.742	0.0148	58.048	<0.001	[0.830, 0.888]	3.045
	SI_7	0.769	0.591	0.0257	29.941	<0.001	[0.713, 0.813]	1.998
Operational Efficiency	OE_1	0.843	0.711	0.0197	42.694	<0.001	[0.799, 0.877]	2.382
	OE_2	0.761	0.578	0.0281	27.046	<0.001	[0.701, 0.810]	1.818
	OE_3	0.866	0.750	0.0163	53.140	<0.001	[0.831, 0.895]	2.639
	OE_4	0.804	0.646	0.0230	34.949	<0.001	[0.754, 0.844]	2.093
	OE_5	0.836	0.698	0.0198	42.273	<0.001	[0.792, 0.870]	2.340
	OE_6	0.786	0.619	0.0247	31.876	<0.001	[0.735, 0.831]	1.983
Process Quality	PQ_1	0.834	0.695	0.0207	40.292	<0.001	[0.789, 0.870]	2.240
	PQ_2	0.781	0.609	0.0288	27.078	<0.001	[0.718, 0.830]	1.969
	PQ_3	0.784	0.614	0.0280	27.963	<0.001	[0.724, 0.833]	1.904
	PQ_4	0.768	0.590	0.0284	27.069	<0.001	[0.706, 0.819]	1.767
	PQ_5	0.823	0.677	0.0194	42.361	<0.001	[0.782, 0.858]	2.125
	PQ_6	0.755	0.570	0.0331	22.821	<0.001	[0.681, 0.814]	1.773

Table 4. Construct Reliability and Convergent Validity

Construct	Items	Cronbach's α	rho_A	Composite reliability (rho_c)	AVE
Digital Payment Systems (DPS)	8	0.913	0.917	0.929	0.622
Cloud Financial Services (CFS)	7	0.908	0.913	0.927	0.646
Mobile Financial Services (MFS)	6	0.903	0.906	0.925	0.673
Digital Process Innovation (DPI)	7	0.913	0.915	0.931	0.659
Service Innovation (SI)	8	0.924	0.925	0.938	0.653
Operational Efficiency (OE)	6	0.900	0.904	0.923	0.667
Process Quality (PQ)	6	0.880	0.886	0.909	0.626

Note. Thresholds: α and rho_c ≥ 0.70; rho_A ≥ 0.70; AVE ≥ 0.50 (Hair et al., 2019).

Discriminant validity

Two criteria were used for the evaluation of discriminant validity. The heterotrait–monotrait ratio of correlations is known as the more sensitive test (Henseler et al., 2015) and is reported on Table 5. All twenty-one HTMT values are within the 90% range, and the majority of them are more than twice the conservative 85% limit, which is also a very conservative value. Considering the hypothesised relationship between digital process innovation and operational efficiency, the highest value obtained (0.6209) is still far from the boundary of concern.

Table 5. Discriminant validity: heterotrait–monotrait ratio (HTMT)

Construct	DPS	CFS	MFS	DPI	SI	OE	PQ
DPS							
CFS	0.544						
MFS	0.462	0.577					

Construct	DPS	CFS	MFS	DPI	SI	OE	PQ
DPI	0.444	0.543	0.474				
SI	0.524	0.544	0.554	0.538			
OE	0.358	0.403	0.455	0.621	0.611		
PQ	0.376	0.409	0.426	0.532	0.561	0.542	

Note. All values below the conservative 0.85 threshold (Henseler et al., 2015).

Table 6 displays the Fornell–Larcker criterion (Fornell & Larcker, 1981). The square root of the AVE for each construct is higher than the correlation of each construct with the other constructs in the model for the constructs of digital payment systems and mobile financial services, ranging from 0.7887 to 0.8204. The smallest diagonal entry is 0.5627, which is the inter construct correlation between digital process innovation and operational efficiency, and is comfortably below the largest inter construct correlation. The criterion is met everywhere.

Table 6. Discriminant validity: Fornell–Larcker criterion

Construct	CFS	DPS	DPI	MFS	OE	PQ	SI
CFS	0.804						
DPS	0.499	0.789					
DPI	0.498	0.411	0.812				
MFS	0.525	0.422	0.433	0.820			
OE	0.368	0.327	0.563	0.415	0.817		
PQ	0.371	0.339	0.481	0.382	0.486	0.791	
SI	0.503	0.486	0.497	0.510	0.561	0.513	0.808

The entire cross-loadings matrix is reported in table 7 as a third line of evidence. All indicators load most heavily on their given construct(s) and in each case, the margin of overloading is significant. Combined these three evaluations confirm that the seven constructs are empirically separate, and that the measurement model can be interpreted structurally.

Table 7. Cross-Loadings

Item	CFS	DPS	DPI	MFS	OE	PQ	SI
DPS_1	0.358	0.765	0.269	0.318	0.289	0.272	0.363
DPS_2	0.381	0.770	0.258	0.270	0.221	0.220	0.371
DPS_3	0.368	0.727	0.308	0.301	0.225	0.234	0.320
DPS_4	0.412	0.809	0.398	0.367	0.252	0.318	0.417
DPS_5	0.412	0.812	0.357	0.403	0.260	0.324	0.414
DPS_6	0.386	0.813	0.292	0.314	0.225	0.252	0.353
DPS_7	0.395	0.806	0.359	0.356	0.285	0.275	0.389
DPS_8	0.424	0.803	0.327	0.317	0.299	0.226	0.424
CFS_1	0.843	0.429	0.413	0.390	0.313	0.338	0.455
CFS_2	0.779	0.342	0.368	0.414	0.212	0.221	0.318
CFS_3	0.785	0.384	0.346	0.443	0.313	0.353	0.432
CFS_4	0.858	0.462	0.474	0.473	0.322	0.339	0.442
CFS_5	0.786	0.364	0.414	0.437	0.328	0.295	0.418
CFS_6	0.797	0.394	0.407	0.393	0.285	0.272	0.366
CFS_7	0.772	0.417	0.362	0.404	0.280	0.250	0.381
MFS_1	0.352	0.352	0.314	0.785	0.232	0.276	0.330
MFS_2	0.415	0.313	0.306	0.803	0.312	0.243	0.422
MFS_3	0.467	0.335	0.400	0.819	0.400	0.317	0.411
MFS_4	0.466	0.345	0.361	0.861	0.343	0.338	0.465
MFS_5	0.465	0.356	0.384	0.853	0.386	0.346	0.418
MFS_6	0.408	0.379	0.356	0.799	0.348	0.350	0.447
DPI_1	0.433	0.376	0.826	0.351	0.489	0.388	0.400
DPI_2	0.387	0.307	0.799	0.354	0.413	0.363	0.414
DPI_3	0.411	0.325	0.763	0.297	0.466	0.342	0.347

Item	CFS	DPS	DPI	MFS	OE	PQ	SI
DPI_4	0.417	0.391	0.858	0.378	0.447	0.413	0.402
DPI_5	0.368	0.232	0.794	0.334	0.478	0.375	0.418
DPI_6	0.379	0.319	0.794	0.330	0.469	0.403	0.419
DPI_7	0.428	0.376	0.842	0.410	0.435	0.444	0.424
SI_8	0.349	0.409	0.387	0.413	0.439	0.431	0.783
SI__1	0.413	0.418	0.434	0.443	0.482	0.415	0.844
SI__2	0.445	0.435	0.488	0.396	0.503	0.464	0.817
SI__3	0.437	0.436	0.378	0.469	0.460	0.427	0.821
SI__4	0.380	0.356	0.362	0.385	0.404	0.389	0.770
SI__5	0.341	0.315	0.304	0.393	0.448	0.326	0.794
SI__6	0.433	0.365	0.396	0.391	0.436	0.439	0.861
SI__7	0.442	0.391	0.443	0.398	0.444	0.408	0.769
OE_1	0.319	0.267	0.461	0.320	0.843	0.415	0.515
OE_2	0.295	0.236	0.480	0.329	0.761	0.366	0.362
OE_3	0.338	0.309	0.505	0.398	0.866	0.463	0.528
OE_4	0.307	0.278	0.455	0.322	0.804	0.389	0.404
OE_5	0.299	0.280	0.467	0.351	0.836	0.383	0.446
OE_6	0.236	0.224	0.385	0.308	0.786	0.354	0.477
PQ_1	0.278	0.243	0.441	0.318	0.383	0.834	0.423
PQ_2	0.292	0.279	0.313	0.290	0.359	0.781	0.356
PQ_3	0.261	0.229	0.369	0.308	0.358	0.784	0.378
PQ_4	0.308	0.303	0.363	0.304	0.405	0.768	0.428
PQ_5	0.357	0.277	0.413	0.305	0.432	0.823	0.479
PQ_6	0.256	0.282	0.370	0.290	0.359	0.755	0.350

Structural Model Collinearity

A check for lateral collinearity was conducted on the inner model prior to interpreting the path coefficients because this may affect the magnitude of the path coefficient if the predictors of a common endogenous construct are highly correlated. The inner VIF values shown in Table 8 are 1.328-1.585, which is well below the value of 3.3 and approach the minimum possible value with correlated predictors. Thus, the path coefficients presented below can be considered as “pure” contributions of each predictor.

Table 8. Structural Model Collinearity (Inner VIF)

Structural relationship	VIF
CFS → DPI	1.585
CFS → SI	1.585
DPS → DPI	1.397
DPS → SI	1.397
DPI → OE	1.328
DPI → PQ	1.328
MFS → DPI	1.450
MFS → SI	1.450
SI → OE	1.328
SI → PQ	1.328

Note. All values well below the 3.3 threshold, indicating no lateral collinearity.

Explanatory Power

Table 9 shows the R2 for each endogenous construct. The model accounts for 42.18 per cent of the variance in operational efficiency, 38.21 per cent in service innovation, 33.10 per cent in process quality and 31.01 per cent in the digital process innovation. In all cases, adjusted values are found to be slightly lower than the original, and it is not possible to distinguish between greater or lesser reduction in explanatory power—since it is a slightly adjusted, the reduction is at most 0.0084, it is not an artefact of the complexity of the model. These values are in the "moderate" range according to the Hair et al. (2019) proposed values for behaviour research. This is a sensible result – no other factor is captured, such as the capability of the workforce, the intensity of capital, regulatory constraint or competitive position – in the operational performance of any organisation. The fact that the three FinTech dimensions, translated into the two capability dimensions are responsible for over two-fifths of the variance in operational efficiency is quite an important discovery per se. The difference between the two aspects of the performance is an analytical one. The difference between the percent of the variance accounted for in operational efficiency and process quality is around nine percentage points, with operational efficiency explaining the variance well, at 0.4218. Digital innovation capability seems therefore to translate more easily to resource consumption gains, than conformance gains, which is picked up on in the discussion.

Table 9. Coefficient Of Determination (R^2) And BIC

Endogenous construct	R^2	R^2 adjusted	BIC
Digital Process Innovation	0.310	0.302	-71.718
Service Innovation	0.382	0.375	-99.278
Operational Efficiency	0.422	0.417	-121.388
Process Quality	0.331	0.326	-84.923

Note. Q^2 predictive relevance was not available in the uploaded output; see Section 6.6.

Predictive Relevance

SmartPLS does not include the result of predictive relevance of Q^2 in the uploaded output. The procedure of blindfolding and the PLSpredict routine (Shmueli et al., 2019) do not seem to be part of either of the report files and no cross-validated redundancy values are provided. Where there are gaps in the data, they are not filled and no Q^2 statistics are reported. It can be applied to the already existing model without new data being gathered, and is suggested before submission, because reviewers of prediction-oriented PLS-SEM studies are increasingly expecting the out-of-sample predictive assessment.A more indirect measure of predictive adequacy is available, however. The four endogenous constructs are strongly negatively valued with BIC values ranging from −71.718 (digital process innovation) to −121.388 (operational efficiency), as shown in Table 9. In the model selection context these values represent desirable fit-to-parsimony balances, with the operational efficiency equation being the best.

Effect sizes

For each predictor, the f^2 effect size is reported in Table 10, indicating the percentage of the variance in each predictor's dependent construct that is accounted for by the other predictor(s). In relation to Cohen's benchmarks (1988), two relationships reach the medium effect size: 1st the relationship between digital process innovation and operational efficiency (f^2 = 0.185) and 2nd the relationship between service innovation and operational efficiency (f^2 = 0.182). Service innovation on process quality (f^2 = 0.148) is immediately below the 0.15 boundary, while digital process innovation on process quality (f^2 = 0.102) is in the small range, and all six relationships between adoption and capability are in the range of 0.032 to 0.089. The two sets of effect sizes, however, do not overlap: the smallest effect size for capability-to-performance (0.102) is larger than the largest effect size for adoption-to-capability (0.089). This is not necessarily an artefact of the data, but a theoretical meaning. It suggests that technology-to-capability segment has less explanatory power than capability-to-performance segment of the chain. In other words, the impact of an organisation's actions on FinTech is more significant than the effect of FinTech on the organisation. This is the ordering that Dynamic Capabilities Theory would foresee, and it is hard to see how this could be understood as simply a direct productivity of technology adoption.

Table 10. Effect Sizes (F^2)

Structural relationship	f^2	Interpretation
CFS → DPI	0.086	Small

Structural relationship	f²	Interpretation
CFS → SI	0.053	Small
DPS → DPI	0.032	Small
DPS → SI	0.074	Small
DPI → OE	0.185	Medium
DPI → PQ	0.102	Small
MFS → DPI	0.039	Small
MFS → SI	0.089	Small
SI → OE	0.182	Medium
SI → PQ	0.148	Small

Note. Thresholds per Cohen (1988): 0.02 small, 0.15 medium, 0.35 large.

Model Fit

Table 11 describes approximately which conditions are met when applying PLS-SEM. Standardised root mean square residual for the saturated model is 0.0447, compared with the threshold of 0.08, which is regarded as a good fit, while for the estimated model, it is 0.0549, which is also below 0.08. The estimated model has the normed fit of 0.8530. This is lower than the 0.90 target value typical and is reported here as is. There are two considerations in interpreting it: (1) NFI is sensitive to model complexity and (2) the use of NFI as a key criterion is not supported by all the methodological researchers of PLS-SEM (Hair et al., 2019). In this context it has been broadly agreed upon that SRMR is a more appropriate measure of approximate fit than other measures, and the fit of the model is considered acceptable. Nevertheless, the value is reported openly because it is common for reviewers to be concerned about selective reporting.

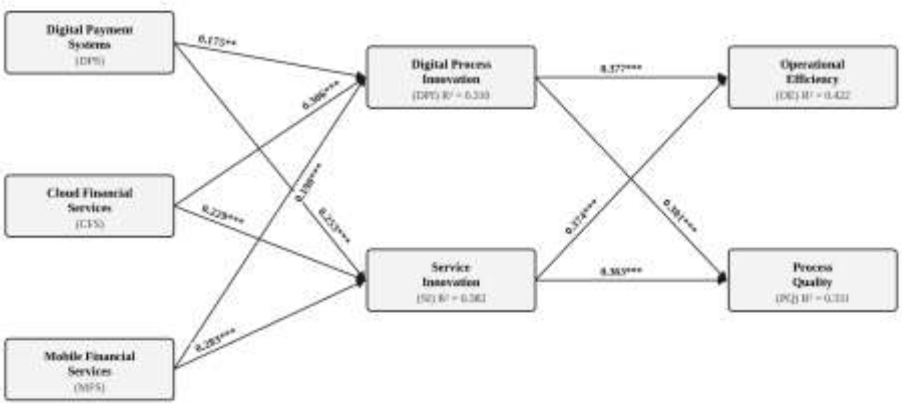
Table 11. Model Fit Indices

Index	Saturated model	Estimated model
SRMR	0.0447	0.0549
d_ULS	2.3449	3.5464
d_G	0.9002	0.9214
Chi-square	1223.7370	1220.3241
NFI	0.8526	0.8530

RESULTS

Figure 2 presents the estimated structural model with standardised path coefficients.

Figure 2. Estimated structural model (N = 250; 5,000 bootstrap subsamples)



Direct Effects

The ten structural path coefficients, along with bootstrapped standard errors, t statistics, and p values and percentile intervals are reported in Table 12. All paths are positive and significant at the .05 level and none of the confidence intervals contain the value of zero. The correlation between the adoption of FinTech and digital innovation capability (H1a – H1f). All six relationships are fostered. Cloud financial services exerts the strongest influence on digital process innovation (β = 0.3061, t = 4.821, $p < 0.001$, CI [0.1787, 0.4331]), followed by mobile financial services (β = 0.1982, t = 3.403, $p < 0.001$) and digital payment systems (β = 0.1750, t = 2.859, p = 0.004). The ordering reverses for service innovation, where mobile financial services leads (β = 0.2828, t = 4.961, $p < 0.001$), followed by digital payment systems (β = 0.2528, t = 4.093, $p < 0.001$) and cloud financial services (β = 0.2287, t = 3.955, $p < 0.001$).This crossover is one of the more significant of the study. The contribution of cloud adoption to process innovation is 34 per cent higher than in service innovation and the contribution of mobile in service innovation is 43 per cent higher than in process innovation. The two technologies are not two generalised inputs to innovation capacity; they rather drive innovation capability development in a particular direction. Digital payment systems lie between the extremes, being more service innovative than process innovative, and the weakest of the entire model (β = 0.1750). Innovation capability in the digital world to operational performance (H2a–H2d). All four relationships are fostered. Three of the four have values that are greater than all other paths measured by adoption-to-capability; digital process innovation on process quality (β = 0.3011) is marginally lower than only the strongest path of adoption, cloud financial services on digital process innovation (β = 0.3061). In terms of effect size, the separation is maximal (see Section 6.7 for details). Process innovation is the strongest predictor of operational efficiency with digital process innovation (β = 0.3770, t = 7.574, $p < 0.001$) and service innovation (β = 0.3737, t = 6.255, $p < 0.001$) both being virtually indistinguishable. For process quality the ordering reverses: service innovation leads (β = 0.3629, t = 7.283, $p < 0.001$) ahead of digital process innovation (β = 0.3011, t = 5.699, $p < 0.001$). That innovation of the service should be more effective than innovation of the process as a determinant of the process's quality is counter-intuitive and needs to be emphasized. It implies that conformance gains result not so much from optimizing current processes as designing new services where quality requirements are built-in from the start, which, again, is in line with the design-for-quality principle, and where the defect burden that the current processes typically include is reduced.

Table 12. Structural Model Path Coefficients (5,000 Bootstrap Subsamples)

Path	β (O)	Sample mean (M)	SD	T	p	2.5%	97.5%	Decision
CFS → DPI	0.306	0.306	0.0635	4.821	<0.001	0.179	0.433	Supported
CFS → SI	0.229	0.229	0.0578	3.955	<0.001	0.113	0.339	Supported
DPS → DPI	0.175	0.177	0.0612	2.859	0.004	0.053	0.295	Supported
DPS → SI	0.253	0.256	0.0618	4.093	<0.001	0.134	0.377	Supported
DPI → OE	0.377	0.381	0.0498	7.574	<0.001	0.283	0.477	Supported
DPI → PQ	0.301	0.303	0.0528	5.699	<0.001	0.201	0.405	Supported
MFS → DPI	0.198	0.200	0.0582	3.403	<0.001	0.082	0.313	Supported
MFS → SI	0.283	0.283	0.0570	4.961	<0.001	0.167	0.392	Supported
SI → OE	0.374	0.371	0.0597	6.255	<0.001	0.248	0.483	Supported
SI → PQ	0.363	0.365	0.0498	7.283	<0.001	0.263	0.460	Supported

Specific Indirect Effects

All twelve specific indirect effects are listed in table 13. All of them have positive values and are statistically significant and therefore uphold H3a-H3l. The effects are between 0.0527 and 0.1154, p values under 0.001 and up to 0.0135, and the results do not include zero in the confidence interval. The strongest pathway is the one linking the constructs of cloud financial services to digital process innovation to operational efficiency (β = 0.1154, t = 4.042, $p < 0.001$, CI [0.0627, 0.1750]). The second is the mobile financial services via service innovation to operational efficiency (β = 0.1057, t = 3.720, p < 0.001), and the third is mobile financial services via service innovation to process quality (β = 0.1026, t = 4.213, p < 0.001). The weakest pathway is from digital payment systems to digital process innovation to process quality (β = 0.0527, t = 2.470, p = 0.0135) which is less than one-half as strong as the dominant pathway. It is followed by digital payment systems with digital process innovation to operational efficiency (β = 0.0660) and the mobile financial services with digital process innovation to process quality (β = 0.0597). This ranking has a direct application to the real world. All the top three pathways start in cloud and/or mobile revolution and all three of the poorest start in digital process innovation, two of these in digital payment systems. Cloud infrastructure routed through process redesign provides an organization with the most leverage in returning operational value from FinTech investments while payment systems routed through process redesign provides least leverage. This is not necessarily a reason to be against payment infrastructure because it's often a necessity for regulatory or interoperability reasons and not a choice of investment, but it does mean that we can't assume that payment adoption will be enough to get operational transformation.

Table 13. Specific Indirect Effects

Indirect path	β	Sample mean	SD	T	p	2.5%	97.5%	Decision
MFS → SI → OE	0.106	0.105	0.0284	3.720	<0.001	0.054	0.165	Supported
CFS → DPI → OE	0.115	0.116	0.0285	4.042	<0.001	0.063	0.175	Supported
MFS → SI → PQ	0.103	0.103	0.0244	4.213	<0.001	0.057	0.152	Supported
CFS → DPI → PQ	0.092	0.093	0.0271	3.399	<0.001	0.045	0.152	Supported
DPS → DPI → OE	0.066	0.068	0.0257	2.563	0.010	0.019	0.121	Supported
DPS → DPI → PQ	0.053	0.054	0.0213	2.470	0.014	0.015	0.099	Supported
MFS → DPI → OE	0.075	0.076	0.0246	3.033	0.002	0.030	0.127	Supported
MFS → DPI → PQ	0.060	0.060	0.0202	2.952	0.003	0.024	0.104	Supported
CFS → SI → OE	0.085	0.085	0.0261	3.275	0.001	0.038	0.141	Supported
CFS → SI → PQ	0.083	0.083	0.0238	3.490	<0.001	0.038	0.132	Supported
DPS → SI → OE	0.094	0.095	0.0275	3.440	<0.001	0.045	0.152	Supported
DPS → SI → PQ	0.092	0.094	0.0283	3.238	0.001	0.043	0.153	Supported

Total Indirect and Total Effects

Total indirect effects are reported in Table 14, which includes the 2 capability paths for each adoption–performance combination. All six are important at p < 0.001. Cloud financial services has the highest total indirect effect on operational efficiency, with a value of β = 0.2008, t = 5.498; mobile financial services has β = 0.1804, t = 4.957; and digital payment systems has a β = 0.1604, t = 4.397. Process quality is ordered, but at successively lower levels: 0.1752, 0.1623 and 0.1444. Note that throughout the total effects are numerically equal to the total indirect effects, since no direct effects between the adoption and the performance constructs were indicated. This identity is a characteristic of that model (specified) and is explicitly asserted so as to avoid misinterpretation. It is clear from the present results that the indirect pathways are important and of great magnitude, but that does not prove that there is a direct pathway as well.

Table 14. Total Indirect Effects And Total Effects

Relationship	Total indirect β	SD	T	p	2.5%	97.5%
CFS → OE	0.201	0.0365	5.498	<0.001	0.130	0.274
CFS → PQ	0.175	0.0355	4.938	<0.001	0.108	0.248
DPS → OE	0.160	0.0365	4.397	<0.001	0.090	0.235
DPS → PQ	0.144	0.0350	4.130	<0.001	0.080	0.220
MFS → OE	0.180	0.0364	4.957	<0.001	0.110	0.254
MFS → PQ	0.162	0.0318	5.107	<0.001	0.100	0.227

Statistical Power

The minimum sample size requirements for each structural path are presented in Table 15. Requirements range from 44 observations (for the strongest path) to 202 observations (for the weakest path) at $\alpha = 0.05$ with 80 per cent power. Achieved sample sizes for all ten paths are adequate: 250. When the requirement is the more difficult 90 per cent power level, the range of required observations is from 61 to 280, with the sample only failing to meet the requirement for digital payment systems to digital process innovation, which requires 280 observations. Although this path is also important at $p = 0.004$, achieved in the sample, its value in practice is limited, and the constraint is noted.

Table 15. Post-Hoc Minimum Sample Size Requirements

Path	β	α 1%, power 80%	α 5%, power 80%	α 1%, power 90%	α 5%, power 90%
CFS → DPI	0.306	108	66	139	92
CFS → SI	0.229	192	119	249	164
DPS → DPI	0.175	328	202	425	280
DPS → SI	0.253	158	97	204	135
DPI → OE	0.377	71	44	92	61
DPI → PQ	0.301	111	69	144	95
MFS → DPI	0.198	256	158	332	219
MFS → SI	0.283	126	78	163	108
SI → OE	0.374	72	45	94	62
SI → PQ	0.363	77	47	99	66

Note. Achieved sample size N = 250.

7.5 Summary of Hypothesis Testing

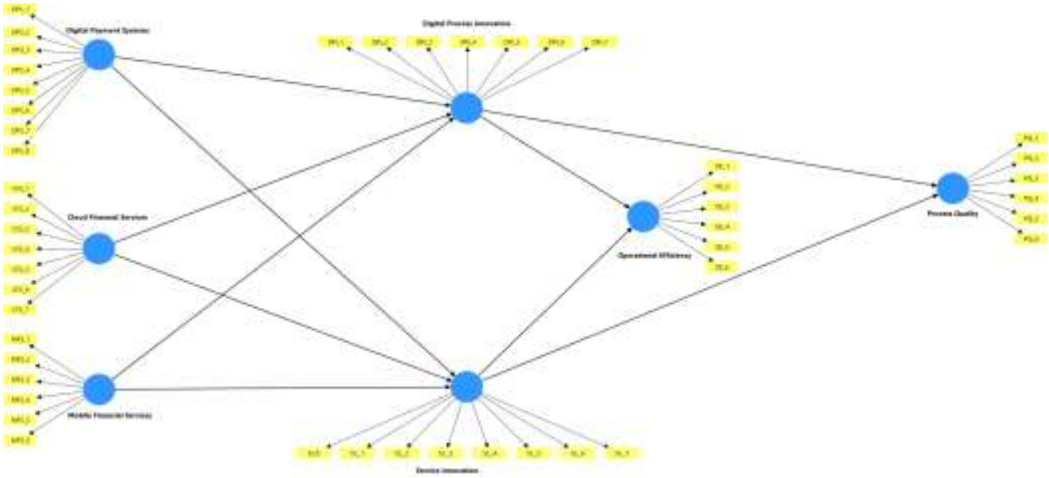
The results of all the hypotheses are presented in Table 16. All twenty-two hypotheses six adoption-to-capability, four capability-to-performance and twelve mediation pathways are supported by the data.

Table 16. Summary of Hypothesis Testing

Hypothesis	Structural relationship	β	t	p	Decision
H1a	DPS → DPI	0.175	2.859	0.004	Supported
H1b	DPS → SI	0.253	4.093	<0.001	Supported
H1c	CFS → DPI	0.306	4.821	<0.001	Supported
H1d	CFS → SI	0.229	3.955	<0.001	Supported
H1e	MFS → DPI	0.198	3.403	<0.001	Supported
H1f	MFS → SI	0.283	4.961	<0.001	Supported
H2a	DPI → OE	0.377	7.574	<0.001	Supported
H2b	DPI → PQ	0.301	5.699	<0.001	Supported
H2c	SI → OE	0.374	6.255	<0.001	Supported
H2d	SI → PQ	0.363	7.283	<0.001	Supported
H3a	DPS → DPI → OE	0.066	2.563	0.010	Supported
H3b	DPS → DPI → PQ	0.053	2.470	0.014	Supported
H3c	DPS → SI → OE	0.094	3.440	<0.001	Supported
H3d	DPS → SI → PQ	0.092	3.238	0.001	Supported
H3e	CFS → DPI → OE	0.115	4.042	<0.001	Supported
H3f	CFS → DPI → PQ	0.092	3.399	<0.001	Supported
H3g	CFS → SI → OE	0.085	3.275	0.001	Supported
H3h	CFS → SI → PQ	0.083	3.490	<0.001	Supported
H3i	MFS → DPI → OE	0.075	3.033	0.002	Supported
H3j	MFS → DPI → PQ	0.060	2.952	0.003	Supported
H3k	MFS → SI → OE	0.106	3.720	<0.001	Supported

Hypothesis	Structural relationship	β	t	p	Decision
H3l	MFS → SI → PQ	0.103	4.213	<0.001	Supported

Note. H3a–H3l are specific indirect effects. All hypotheses supported at α = 0.05.



DISCUSSION

Fintech Adoption and Digital Innovation Capability

The positive and significant six adoption to capability relationships support the key tenet of the model which is that FinTech investment is successful in developing innovation capability. It is more illustrative, however, to show the pattern of differential magnitudes, which addresses another question the combined literature fails to answer. The strongest of the six paths of adoption, cloud financial services was identified as the main driver for digital process innovation (β = 0.3061). This is in line with and builds on the cloud adoption and firm performance outcome relationship (Subramaniam & Teh, 2026; Zheng et al., 2023), uncovering the mechanism through which this relationship occurs. The unique feature of cloud infrastructure is not its cost, it is elastic provisioning, which means that any experiment with process redesign can be tested out and discarded without any significant cost. The findings match Chirumalla (2021) who qualitatively described the process of process innovation through digital means as built through dynamic capabilities, and provide quantitative confirmation of the relationship found in Chirumalla's (2021) study based on qualitative case evidence. The strongest antecedent of service innovation was mobile financial services (β = 0.2828). This is in keeping with the literature on mobile financial services, which focuses on reconfiguring the services through the channel (Shaikh et al., 2023; Tetteh & Kwateng, 2026; Yuan et al., 2025) and explains why it has been noted that with the deployment of mobile financial services, the shape of what organisations offer is more significant than the shape of how they produce it. The mechanism is demand side – with continuous availability, batch-oriented routines are broken and opportunities are created for offerings that would not have been available in the fixed-location channel. The most theoretically substantive of the adoption-stage findings is the flip-flop between these two technologies, cloud favouring process vs mobile favouring service. Masked in aggregate measures of FinTech effects is the assumption of undifferentiated technology effects, which it falsifies. Kroh et al. (2024) noted that there is no one-to-one relationship between digital innovation capability and digital innovation, with the results of the present study confirming that the antecedents of digital innovation capability are systematically different, if not distinct. Digital payment systems had the lowest path in the model (β = 0.1750 to digital process innovation) and they performed relatively well to service innovation (β = 0.2528). This is asymmetry that can be understood via the standardisation of the payment infrastructure. Payment rails are subject to external interoperability and regulatory mandates and therefore limit the extent of redesigning around payment rails by an adopting organisation. They do not need to change the rails and their input in service innovation is freer, as the payment capability expands the range of feasible pricing, settlement and bundling models. (Ha et al., 2024; Khalek et al., 2024). It is an important discovery and therefore serves as a necessary stepping stone to operational change, though for the moment it is one of the less powerful levers in the practitioner's toolbox for internal process change; as such, the assumption that payment digitisation is the first step to operational change is not necessarily correct, as the present evidence suggests.

Digital Innovation Capability And Operational Performance

All four capability-to-performance relationships were supported and as a group, they outperform the adoption-to-capability paths. Three of the four are larger than any of the adoption paths, and the separation, in the sense of effect-size, is complete: The largest effect size for adoption-capability (0.089) is smaller than the smallest effect size for capability-performance (0.102), meaning their ranges do not overlap. This ordering is the main structure discovered by the present study. It means that the second link in the capability to performance link is more explanatory than the first link. This finding aligns with a growing body of evidence digitalisation has an impact on operational outcomes indirectly via capability. The findings of Yang and Yee (2022) revealed that process digitalisation works through the dynamic capability development of the company; Sunder and Prashar (2024) showed that digitalisation and lean practices work through the organisational learning system; Bag et al. (2025) demonstrated that digital technology capability requires complementary innovative management capability. This trend is continued in the present study which gives the decomposed estimates that allow the relative weight of each segment to be directly compared. Of the two performance results, the latter—that service innovation is a stronger determinant of process quality than digital process innovation ($\beta = 0.3629$ versus 0.3011) is more surprising and warrants special note as intuition and much of the operations literature would suggest the opposite. There are two possible explanations (which do not conflict) for this. The first is a design-for-quality argument: newly designed digital services define their quality requirements in their early stages of design, and instrument them for measurement during launch, while process innovation entails modifying existing processes, which tend to contain exception-handling logic, and workarounds that may not have been documented (Münch et al., 2022; Sklyar et al., 2025). The second is substitution: with digital service innovation, often it deconstructs processes back to the customer, and when customers do it, conformance failures tend to focus on the eliminated handoffs within the internal process. In both readings, emphasising the design of new services instead of optimising existing ones may yield an organisation greater benefits than it would from an optimisation process; a fact that contradicts the more traditional process improvement doctrine, and one that can be tested. The two capability dimensions performed almost identically (β = 0.3770 and 0.3737) in terms of operational efficiency, so that efficiency gains are possible in either direction. This substitutability is managerially useful because it means that if in one instance management is unable to go down a path due to inflexibility in the legacy system, for example, or regulatory restrictions on service redesign, they can achieve efficiency of the other route without any appreciable loss.

The Mediating Role Of Digital Innovation Capability

The findings revealed that all twelve specific indirect effects were positive and significant, with digital innovation capability as the unique pathway connecting FinTech adoption with operational performance for all the combinations explored. From a theoretical perspective, the result is complete since none of the 12 pathways failed, suggesting that the mediating mechanism is general, rather than depending on specific combinations of technology families and performance dimensions. This offers empirical evidence for the reconfiguration logic that lies at the heart of Dynamic Capabilities Theory (Dynamic Capabilities Theory, 2007; Dynamic Capabilities Theory, 1997). The sensed and seized opportunity is the FinTech applications, the reconfiguration is the digital innovation capability, and the outcome is operational performance. The results are similar to analogous mediated structures that have been found in other contexts related to business model innovation and firm performance (Merín-Rodrigáñez et al., 2024), to innovation and digital capability and their relationship with firm performance (Ferreira et al., 2024), and to open innovation and platform capabilities and their relationship with sustainable innovation performance (Wang et al., 2023) and extend it to a context where it has not been broken down. Pathways ranking is of its own interest. The three strongest routes all begin with cloud adoption or mobile adoption, and two of the three weakest routes start with payment systems suggests that the mediating mechanism, although ubiquitous in use, is very unevenly productive. This granularity is not possible in studies with aggregate FinTech measures and is exactly what is needed for investment sequencing. Some sort of limit must be established on these conclusions. The results indicated that the indirect pathways are significant but did not provide information on whether there are direct pathways also. The design does not allow the indirect effects to be identified but not the mediation type in the taxonomy of Zhao et al. (2010). The argument presented here is therefore not that digital innovation capability is the only channel through which FinTech influences operational performance but rather that FinTech does so via this channel.

Interpretation Of The Low Process Quality Ratings

A description of the finding should be discussed with the structure results. Process quality had the lowest mean construct score on the instrument with four of its six items below 2.8 and PQ_3 was the lowest rated on all forty-eight items. This is coherent not anomalous, when seen in the light of the structural results. The model explains the performance dimension of process quality least ($R^2 = 0.3310$) and has lower capability paths (toward process quality). The fact that three independent indicators are all lowered, three paths are all weak and three explanatory variances are all low points indicates that conformance quality is the domain in which the capability of FinTech enabled is least or is perceived to be the least. This is a practical priority and a research opportunity – the quality-related returns come with digital investment seem to systematically be more difficult to achieve than the efficiency-related.

THEORETICAL CONTRIBUTIONS

The study makes four contributions to theory. First, it operationalizes and demonstrates the reconfiguration mechanism that the Dynamic Capabilities Theory is based on, in a domain where this reconfiguration mechanism has been taken for granted but not studied. The study not only shows that all 12 indirect pathways from FinTech adoption to operational performance are significant but also provides direct evidence that acquired technological resources are translated into performance via reconfiguration of capabilities. The ordering of the effect-sizes for all capability-to-performance paths for the theory, which are greater than all the adoption-to-capability paths, offers quantitative support to the core tenet of the theory that value is created through reconfiguration, not acquisition. Secondly, it reveals that technology influence on innovation capability varies. Two crossovers reveal a divergence in FinTech families' capability development efforts between cloud (process innovation) and mobile (service innovation). This contradicts the common practice in the adoption literature which assumes that aggregation results in homogeneous measures of FinTech and demonstrates that theoretically relevant variation in these measures cannot be captured by aggregates. It adds a third dimension to the multi-dimensional perspective of digital innovation capability presented by Kroh et al. (2024), by adding the antecedent of the relation. Third, it makes a significant contribution to operations management literature on digitalisation by uncovering that the same capability inputs have different impacts on efficiency and quality. Contrary to expectation, it is found that service innovation has a stronger predictive power of process quality than process innovation; this indicates a potential service design-for-quality logic over a process optimisation logic for improving process quality in digital contexts. This meets the assumption of a common pathway of digitalisation to performance that is assumed in several recent studies (Sunder & Prashar, 2024; Yin et al., 2024). Fourth, it connects Dynamic Capabilities Theory with the Resource Based View in a way that allows for testable implications but not the kind of rhetorical implications. The RBV suggests that the adoption of FinTech applications should not bring any differentiation to the firm, as there is a lot of adoption in the market, and the dynamic capabilities lens clarifies what creates differentiation. This joint prediction is confirmed by the empirical superiority of capability-to-performance paths over adoption-to-capability paths and shows the value of the analytical combination of the two.

PRACTICAL CONTRIBUTIONS

The study translates to four things that organisations investing in financial technology need to do. Provides a scientifically produced ranking of investments paths. The path from cloud financial services to digital process innovation to process quality is the strongest ($\beta = 0.1154$) and the path from digital payment services to digital process innovation to process quality is the weakest ($\beta = 0.0527$) of the twelve paths. For organisations with limited investment resources, there are now some empirical data which can justify the sequencing of investments. It points out the capacity development phase is the constraint. Because capability-to-performance paths are more likely to have larger effects on adoption than paths from technology to capability, it pays to strengthen the innovation capability more than to acquire more technology. If they have implemented FinTech without achieving operational benefits, then the question to ask is – how can they restructure their operation? It offers a matchmaking between the objective and the technology. If the goal is to redesign internal processes, the better investment is in cloud infrastructure, if the goal is to expand service portfolio, it's mobile channels. Undifferentiated FinTech investment programmes are not likely to be optimised to either of these. It sets the standards for the results of quality. The ratings of the items measuring process quality are weaker and the paths are weaker, with process quality consistently weaker than overall ratings, overall explained variance was significantly lower, indicating that conformance does not improve automatically with technology adoption and active efforts are needed to improve process quality. If organizations are expecting to automatically get a better quality gain once they have digitalized, they will probably not get it.

MANAGERIAL IMPLICATIONS

There are specific recommendations for practising managers that follow. Get ready to reconfigure in addition to technology. The study shows that innovation is the key factor in the transition of FinTech to performance, rather than the technology. Budget allocations which include funding for process redesign but not for infrastructure and licences are unlikely to deliver. Capability development cross-functional redesign teams, experimentation protocols, and redesign skills should be considered a line item in same breath as the other line items, and not overhead. Take the cloud adoption before process redesign projects. If the redesign programmes are launched before cloud provisioning has been made, then there will be a fixed-cost barrier to experimentation, which is overcome by cloud financial services. The order of things is important – first build infrastructure, only then redesign it. Promote the innovation goals of route services via mobile. The strategic goal of portfolio expansion has the greatest relationship with mobile financial services. Organisations that are looking for new offerings based on back office digitisation are going against the trends that have been observed. Payment digitisation is not an enabler for transformation. Pathways to process innovation, and overall indirect pathway were weakest for digital payment systems. This does not mean that payment infrastructure isn't a necessary prerequisite to the interoperability and regulatory requirements often imposed on it, but it is not enough to bring about operational transformation, and managers should not count on it. Emphasise service design, not just optimisation of the services. The finding that service innovation can have a greater influence on process quality than process innovation can has implications for how conformance gains can be achieved, showing that it's easier to design a new digitally native service that has conformance criteria built in from the start, than to improve a legacy workflow that has embedded exception logic. Set up measurement prior to investment. The moderate R2 values for all four endogenous constructs suggest that there is a significant amount of variation in performance beyond the

FinTech–capability system. It is important for managers to have a baseline operational measurement prior to the investment and be able to attribute the change afterwards.

POLICY IMPLICATIONS

The results have implications for regulators and policymakers who are worried about the productivity gains from financial digitalisation. If incentives for adoption are provided, they must be accompanied by capacity-building assistance. Subsidies such as technology acquisition grants, tax credits and subsidized infrastructure only solve the weak link. Instruments with a focus on capacity-building may lead to uptake without productivity gains, since the relationship between capability and performance is predominant. The binding constraint would be targeted more directly through complementary programmes which would provide support for process redesign skills, managerial capability and experimentation capacity. One policy to be especially discussed in regard to cloud infrastructure is security. Cloud financial services was the most powerful individual predictor of process innovation. Regulatory requirements for data residency, cloud outsourcing for regulated financial institutions, and third-party risk management thus go beyond their compliance theme to impact the capability to innovate. Innovation consequences should be taken into account along with prudential goals in designing such frameworks. There is a trade off with payment standardisation which needs to be recognised. The relatively low levels of process innovation from the digital payment systems can likely be explained by the external standardisation involved with payment interoperability. While there are significant process level benefits of standardisation, the evidence so far indicates that these can have a negative effect on systemic innovation. Awareness of this trade-off will help design an appropriate policy, instead of opposing standardisation. The outcomes of quality must be made explicit targets for policy. As process quality is the least well-explained performance dimension and the lowest rated, digitalisation policy based on efficiency and cost reduction without considering service quality is unlikely to boost service quality. If a financial services quality measures are relevant to consumer protection, this gap is of regulatory concern. Programmes that develop capabilities in certain sectors can be more effective than training programmes for individual firms. However, shared infrastructure for capability development sector-level training, redesign toolkits, benchmarking consortia could provide a higher overall return than acquisition subsidies for firms because the constraint is only on capability and not access.

LIMITATIONS

The results are subject to a number of restrictions that should be taken into account when interpreting the results. Cross-sectional design. Data were gathered only once, so that causal inferences cannot be made. The mediation results are congruent with the hypothesized causal ordering, but it cannot be inferred from cross-sectional results; the conditions for this remain controversial (Baron & Kenny, 1986; Zhao et al., 2010). It is worth noting that reverse and/or reciprocal causation may be ruled out: organisations with a high innovation capability could be more open to FinTech, and high-performing organisations may spend more in both FinTech and high-performing. No specifications of direct effect. There are no direct links in the estimated model between the FinTech dimensions and the performance dimensions. The study is not able to categorise the type of mediation as per the categorisation of Zhao et al. (2010) and cannot establish if there are direct effects in addition to the indirect effects found. This is the most material limitation of the present specification, and re-estimation with the inclusion of the direct paths would greatly support the mediation claim. Estimation at a lower level, ie, instead of higher order. The model was estimated at the level of the 7 first order constructs and not estimated by a higher order model of FinTech adoption, digital innovation capability and operational performance. This results in granularity but without the parsimony of a higher-order model and the construct-level coefficients thereof (Sarstedt et al., 2019). The findings should rather be interpreted as relating to the technology families and the capability dimensions than the constructs as a whole. Absent predictive assessment. No out-of-sample predictive assessment (using PLSpredict; Shmueli et al.,

2019) was conducted and Q^2 predictive relevance was not calculated. Explanatory power is thus provided but predictive power is not. No attempt to control for common method bias. Self-report from one instrument was used to measure all variables. A single factor test was not conducted and the complete collinearity analysis (Kock, 2015) was not conducted. Inner VIF values between 1.328 and 1.585 are considered to be an indirect test and are a sign of reassurance. Model fit. The normed fit index (0.8530) is below the traditional 0.90 cutoff, but well within the limits of acceptability at 0.0447 and 0.0549, respectively, for the SRMR. Sample characteristics undocumented. The data does not include any variables that would allow for a description of the composition of the sample by sector, size, role or region. This limits the analyses on generalisability and does not allow for any analysis of demographic heterogeneity. Unmodelled determinants. The range of explained variance is between 31-42 percent, which means that the model organisational culture, leadership, workforce capability, competitive intensity and regulatory environment explains a large proportion of the variance in the endogenous constructs.

FUTURE RESEARCH DIRECTIONS

The above restrictions are suggestive of a research agenda. Longitudinal and delayed designs. Panel data with separation of the adoption period and the period of measuring ability and performance would enable causal inference and facilitate the estimation of a question of direct managerial interest, the time lag between the investment and the operational return, which is currently unknown. Re-specification using direct and higher order constructs. Adopting-to-performance paths would allow for formal mediation classification in the estimation of the model. Construct-level estimates which add to the dimension-level estimates in this report would be obtained using a parallel higher-order specification based on the disjoint two-stage approach (Sarstedt et al., 2019). Predictive validation. PLSpredict and cross valid blindfolding would determine if the model predicts out of sample as well as explains it in sample (Shmueli et al., 2019). Moderator identification. There is a moderate level of explained variance that requires investigation into boundary conditions. Key factors that might moderate the linkage between capability and performance are the size of the organization, regulatory intensity, digital maturity, absorptive capacity, and leadership commitment. It would be a useful place to begin, to compare multi-group analysis of various sectors or size bands. An investigation of the anomaly in the quality. This is counter-intuitive and consequential as it means that service innovation has a greater impact on process quality than process innovation has on service. A research study would be best suited to determine if the design for quality mechanism proposed here is a cause of this. Expansion of other technology families. The following technologies were not explored: artificial intelligence, distributed ledger technologies, open banking interfaces and embedded finance. Their inclusion would help to assess if the differentiated-effects pattern found here extends to a broader technology set (Fosso Wamba et al., 2024; Gangwar et al., 2025). Objective performance measures. However, using archival operational data cycle times, defect rates, cost per transaction would circumvent the typical method issues, and allow for an evaluation of the relationship between perceived and actual operational performance. Configurational analysis. This complementation of PLS-SEM with fuzzy-set qualitative comparative analysis would allow to determine that alternative sets of adoption and capability would lead to similar performance results, which cannot be revealed by variance-based methods (Yuan et al., 2025).

CONCLUSION

The purpose of this study was to understand the path towards operational performance of the adoption of FinTech. It analysed the survey data of 250 respondents using partial least squares (PLS) structural equation modelling, which identified three technology families, two dimensions of digital innovation capability, and two dimensions of operational performance (efficiency and quality), then estimated the entire set of relationships between these dimensions. No items were deleted from the measurement model and all reliability/criterion were satisfied. All 10 of the structural relationships were found to be positive and significant and all 12 of the indirect pathways from adoption to performance were found to be supported. The model explained 42.2 % of the variability for operational efficiency and 33.1 % for process quality. There are three revelations. Innovation capability is more important than technology for getting to performance than the converse: each capability-to-performance pathway had a higher effect size than did each adoption-to-capability pathway. Cloud infrastructure is for process innovation, mobile channels are for service innovation – these two are not one and the same. And quality is harder won than efficiency: process quality had lowest rating on quality, least explanation on process and was worst in serving process. The overall message is the absence of a performance modification. It's an input of one. Organisations that attempt to acquire financial technology but don't have the capacity to rearchitect around it will likely see a modest gain from the acquisition, as the evidence gathered here suggests that value creation likely comes from the reconfiguration and not the acquisition. The take-away for managers is that the capability budget like the technology budget is subject to scrutiny. To policymakers, it's that policies to promote adoption won't on their own create the productivity boost that they want.

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