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Adaptive financial resilience, strategic change agility and MSME performance: The moderating role of digital financial sensing capability

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Abstract

Indonesian MSMEs have rapidly adopted digital financial tools, yet it remains unclear whether these tools raise performance directly, amplify other capabilities, or both. Drawing on the resource-based view, dynamic capabilities theory and complementarity logic, we examine how adaptive financial resilience (AFR) and strategic change agility (SCA) relate to MSME performance, and whether digital financial sensing capability (DFSC) moderates these relationships. PLS-SEM results from 136 micro-enterprise owner-managers in East Java show that AFR (β = 0.330), SCA (β = 0.266) and DFSC (β = 0.299) are positively associated with performance ($p < 0.001$). DFSC strengthens the AFR–performance link (β = 0.285, $p < 0.001$), which nearly disappears when DFSC is low. However, DFSC does not moderate the SCA–performance link (β = 0.016, $p = 0.837$). Sensing therefore complements financial reconfiguration, not strategic change. Digitalization pays off when it builds routines for acting on financial signals, not merely wider technology access.

1. Introduction

Micro, small and medium-sized enterprises (MSMEs) carry an outsized share of Indonesia's economy. Roughly 65 million MSMEs make up about 99% of all business units, generate around 61% of gross domestic product and employ some 97% of the workforce (Bisnis.com, 2024). East Java, the setting of this study, illustrates this dependence vividly: its 9.78 million MSMEs accounted for 57.81% of the province's gross regional domestic product in 2021 (Suara Surabaya, 2022). Yet these firms remain financially fragile. When the COVID-19 pandemic struck, more than four in five Indonesian businesses reported falling revenues, and the share was highest among micro and small firms (BPS, 2020). Access to formal finance has not kept pace either; MSME loans accounted for only 17.49% of national bank credit at the end of 2025 (Infobanknews, 2026), and MSME credit grew by only 1.82% year on year in July 2025, far below the growth of digital payments (Bank Indonesia, 2025). Similar fragility has been documented far beyond Indonesia, where many small businesses hold cash buffers sufficient for only a few weeks of operation (Bartik et al., 2020).

At the same time, digital finance has spread through Indonesian MSMEs faster than almost any other managerial innovation. The national QR payment standard (QRIS) reached 57 million users by mid-2025 (Bisnis.com, 2025), and QRIS transaction volume grew by 162.77% year on year in July 2025 (Bank Indonesia, 2025). However, adoption has outpaced understanding. The 2025 national survey of financial literacy and inclusion found that 80.51% of Indonesians had access to financial services, but only 66.46% were financially literate (OJK, 2025). This gap between access and capability makes Indonesia an instructive case for the international reader. Many emerging economies, from India's Unified Payments Interface to Brazil's Pix, are pursuing similar payment-led digitalization strategies. If digital financial tools generate value mainly when firms can interpret and act on the information they provide, then policies that equate digitalization with adoption may be overestimating what small firms will gain.

Research on how MSMEs survive and grow under such conditions has developed along three largely separate lines. The first, rooted in organizational resilience, examines how firms absorb shocks and adapt (Duchek, 2020; Lengnick-Hall & Beck, 2005; Williams et al., 2017), and recent work has begun to apply this thinking to the finances of small firms (Ariana et al., 2024; Legenzova et al., 2025). The second examines strategic agility, the capacity to renew strategy quickly as conditions change (Doz & Kosonen, 2010; Weber & Tarba, 2014), and finds that agility tends to pay off through business model renewal (Clauss et al., 2021) and is contingent on the environment (Ahammad et al., 2021). The third focuses on digital and financial technology, reporting that fintech and e-commerce adoption are associated with better SME outcomes (Gao et al., 2023; Lontchi et al., 2023), although the evidence is far from uniform (Sari et al., 2023).

Three gaps follow from this fragmentation. First, financial resilience, strategic agility and digital capability are usually studied one at a time. Resilience studies tend to treat financial resilience as an outcome of literacy or digital transformation (Ariana et al., 2024; Probojakti et al., 2025), whereas agility studies model agility as an isolated driver of performance (Ahammad et al., 2021; Clauss et al., 2021). Reviews of the resilience field have repeatedly called for frameworks that connect resilience with other strategic capabilities (Conz & Magnani, 2020; Linnenluecke, 2017). Second, most of the evidence comes from large, listed or high-technology firms. Studies of financial flexibility rely largely on publicly traded companies (Fahlenbrach et al., 2021), and agility research has focused on corporations (Doz & Kosonen, 2010), internationalizing firms (Ahammad et al., 2021) or high-tech B2B SMEs (Zahoor et al., 2022). Much less is known about resource-constrained micro enterprises in trade, food processing and services, where a single owner-manager usually decides both financial and strategic matters. Third, digital financial capability is almost always modeled as a direct antecedent of performance (Gao et al., 2023; Lontchi et al., 2023; Sari et al., 2023). Information systems research, by contrast, has long shown that information technology creates value mainly by complementing other organizational capabilities (Aral & Weill, 2007; Chakravarty et al., 2013; Powell & Dent-Micallef, 1997). To our knowledge, this complementary role has not been examined for digital financial sensing in MSMEs, and the direct evidence is itself inconsistent: the only Indonesian study we know of that tested a direct link found that digital financial capability did not improve MSME performance (Sari et al., 2023). Whether digital financial sensing creates value directly, through the capabilities that act on it, or both therefore remains an open question.

This study therefore asks two questions. To what extent are adaptive financial resilience (AFR) and strategic change agility (SCA) associated with MSME business performance? And is digital financial sensing capability (DFSC) associated with performance directly, and does it amplify these associations? To answer them, we integrate the resource-based view (RBV) and dynamic capabilities theory with the logic of complementarity and test the resulting model using survey data from 136 MSMEs in East Java.

The study makes three contributions. First, it specifies how three capabilities that are usually studied separately fit together within Teece's (2007) sensing–seizing–reconfiguring framework. DFSC captures the sensing of internal financial signals, SCA the seizing of strategic opportunities, and AFR the

reconfiguring of financial resources. Our results show that, in small firms, sensing has both a direct performance value and a complementary one, but that its complementarity is domain-specific: it strengthens the capability that reconfigures financial resources, not the one that enacts strategic change. This refines the microfoundations of dynamic capabilities, which were originally developed with large enterprises in mind. Second, the study offers an RBV explanation for why widely available digital financial tools can still differentiate small firms. Although the tools themselves are neither rare nor hard to imitate, the capability to interpret their outputs varies across firms, and its value is greatest when it is bundled with a firm-specific capability to act on financial signals. This qualifies the IT productivity paradox (Brynjolfsson, 1993) in the context of MSME financial management. Third, we clarify AFR and DFSC as firm-level capabilities and distinguish them from neighboring constructs such as financial slack, financial flexibility, digital financial literacy and fintech adoption, thereby responding to concerns about construct proliferation in this literature.

The remainder of the paper is organized as follows. Section 2 sets out the theoretical framework, reviews prior evidence and develops the hypotheses. Section 3 describes the methodology. Section 4 presents and discusses the results. Section 5 discusses theoretical, practical and policy implications, and Section 6 concludes with limitations and directions for future research.

2. Literature review and hypothesis development

2.1. Theoretical framework

The RBV holds that firms achieve superior performance when they control resources and capabilities that are valuable, rare, inimitable and non-substitutable (Barney, 1991). The view is powerful but has been criticized for being static: it explains why some resource bundles are advantageous but says less about how firms renew them as markets shift (Priem & Butler, 2001). Dynamic capabilities theory addresses this limitation by focusing on the firm's ability to integrate, build and reconfigure competences in response to rapid change (Eisenhardt & Martin, 2000; Teece et al., 1997). Teece (2007) breaks this ability down into three clusters of activity: *sensing* opportunities and threats, *seizing* them through timely decisions and commitments, and *reconfiguring* or transforming the resource base so that the firm stays aligned with its environment. Resource orchestration research bridges the two perspectives by showing that the performance value of resources depends on how managers structure, bundle and deploy them (Sirmon et al., 2007).

We use this combined lens to position the three focal capabilities. DFSC is a sensing capability because it allows an MSME to detect changes in its cash flows, costs and revenues through digitally generated data. SCA is a seizing capability because it concerns the speed and quality with which the firm commits to strategic change once an opportunity or threat has been identified. AFR is a reconfiguring capability because it concerns the firm's ability to absorb financial shocks and redeploy financial resources to support new configurations. The framework implies that the three are interdependent: sensing without

seizing or reconfiguring yields information but no action, while seizing and reconfiguring without good sensing amount to acting blind.

Two further theories explain why the capabilities should interact rather than simply add up. The theory of complementarities states that two activities are complements when doing more of one increases the returns to doing more of the other (Milgrom & Roberts, 1990, 1995). In a regression framework, complementarity appears as a positive interaction term, which is exactly what our moderation hypotheses test. Organizational information processing theory adds a mechanism. Uncertainty raises the amount of information an organization must process to make good decisions, and performance depends on the fit between information-processing requirements and information-processing capacity (Galbraith, 1974; Tushman & Nadler, 1978). For MSMEs facing volatile demand and thin buffers, the requirement is high. DFSC raises information-processing capacity, but this capacity has value only when there is a decision-making capability that can use it, namely AFR for financial adjustments and SCA for strategic ones.

2.2. Conceptualizing the focal capabilities

Because AFR, SCA and DFSC carry labels that are not yet standard in the literature, we define each one precisely, specify its level of analysis and explain how it differs from established constructs (Table 1).

Adaptive financial resilience. We define AFR as an MSME's capability to absorb financial disturbances while actively adjusting its financial resources to changing conditions. Building on capability-based views of organizational resilience (Duchek, 2020; Lengnick-Hall et al., 2011), we see AFR as having four interrelated facets: *buffering capacity* (holding reserves or credit lines that cushion shocks), *financial flexibility* (adjusting cost and funding structures without disrupting operations), *adaptive reallocation* (redirecting cash toward emerging priorities) and *recovery* (restoring liquidity after a disturbance). AFR differs from financial slack, which is a stock of excess resources rather than the ability to use them (Bourgeois, 1981; George, 2005). It also differs from financial flexibility in the corporate finance sense, which concerns a firm's capacity to raise or access capital at low cost (Gamba & Triantis, 2008). And it goes beyond financial resilience as typically defined, which emphasizes the absorption of and recovery from shocks (Ariana et al., 2024; Legenzova et al., 2025), by adding the forward-looking adaptation that Lengnick-Hall and Beck (2005) call adaptive fit.

Strategic change agility. Strategic agility is commonly described as the combination of strategic sensitivity, leadership unity and resource fluidity (Doz & Kosonen, 2010; Shams et al., 2021; Weber & Tarba, 2014), while organizational agility refers more broadly to a firm's ability to detect and respond to change across its operations (Lu & Ramamurthy, 2011; Sambamurthy et al., 2003). We use the term strategic change agility to denote a narrower component of strategic agility, namely the speed and appropriateness with which an MSME actually alters its business model, offerings, channels and resource priorities once a change is needed. The narrower focus is deliberate. In owner-managed firms, leadership unity is largely given because one person holds strategic authority, so what distinguishes agile from less agile MSMEs is the enactment of change rather than its anticipation. SCA is therefore not

a new construct but a focused operationalization of the seizing component of strategic agility, and we retain the label to signal this scope.

Digital financial sensing capability. We define DFSC as an MSME's capability to capture, monitor and interpret digitally generated financial information, such as transaction records from QR payments, mobile banking, point-of-sale systems and bookkeeping applications, in order to detect changes in its financial condition early. DFSC differs from digital financial literacy, which is an individual's knowledge of digital financial products (Kumar et al., 2023), and from fintech adoption, which describes use rather than interpretation (Lontchi et al., 2023). It is narrower than accounting information system alignment (Ismail & King, 2005), data analytics capability, which presumes data infrastructure at scale (Gupta & George, 2016), and the sensing capability described by Teece (2007), which spans the whole external environment. DFSC focuses specifically on internal financial signals made available through low-cost digital tools.

A word on the level of analysis is in order. Kumar et al. (2023) and Sari et al. (2023) measured digital financial capability at the level of the individual, whereas we treat DFSC, like AFR and SCA, as a firm-level capability. We justify this shift on two grounds. First, in MSMEs, decision-making is concentrated in the owner-manager, so the owner's routines for gathering and using information effectively constitute the firm's routines (Hambrick & Mason, 1984). Second, the microfoundations view holds that organizational capabilities are rooted in the skills and interactions of key individuals (Felin et al., 2012). Consistent with this reasoning, all items were worded at the level of the business ("Usaha saya ...", i.e., "My business ...") rather than the individual.

Table 1
Construct definitions and distinctions from established constructs.

Construct	Definition in this study	Role in dynamic capabilities	Closest established constructs and key difference
Adaptive financial resilience (AFR)	Firm-level capability to absorb financial disturbances while adjusting financial resources to changing conditions (buffering, flexibility, reallocation, recovery)	Reconfiguring/transforming	Financial slack (a stock, not a capability); financial flexibility (access to capital); financial resilience (absorption and recovery, without forward-looking adaptation)
Strategic change agility (SCA)	Speed and appropriateness with which an MSME enacts changes to its business model, offerings, channels and resource priorities	Seizing	Strategic agility (broader; includes strategic sensitivity and leadership unity); organizational agility (operational as well as strategic)
Digital financial sensing capability (DFSC)	Firm-level capability to capture, monitor and interpret digitally generated financial information in order to detect changes in financial condition early	Sensing	Digital financial literacy (individual knowledge); fintech adoption (use, not interpretation); AIS use and data analytics capability (broader infrastructure); Teece's sensing (external environment as a whole)

Note: Developed by the authors based on Teece (2007), Doz and Kosonen (2010), Duchek (2020) and the sources cited in Section 2.2.

2.3. Prior empirical evidence

Table 2 summarizes the empirical studies most relevant to our model. Three patterns stand out. First, financial buffers and flexibility clearly help firms withstand shocks (Bartik et al., 2020; Fahlenbrach et al., 2021), but the evidence comes mostly from listed firms or from descriptive surveys and says little about how small firms use their finances adaptively. Second, agility is generally associated with better performance, but the effect often runs through other mechanisms, such as business model innovation (Clauss et al., 2021), and depends on environmental conditions (Ahammad et al., 2021; Chakravarty et al., 2013). Third, the evidence on digital finance and SME performance is mixed. Some studies find strong positive effects (Gao et al., 2023; Lontchi et al., 2023), while others, including a large East Java sample, find none (Sari et al., 2023). Information systems research suggests that such inconsistencies arise when technology is modeled as a stand-alone driver rather than as a complement to organizational capabilities (Chakravarty et al., 2013; Tippins & Sohi, 2003). Taken together, the evidence points to the need for a model that examines the three capabilities jointly and tests whether digital financial sensing creates value directly, through the capabilities that act on it, or both.

Table 2
Summary of selected prior empirical studies.

Study	Context and sample	Focal variables	Key findings	Relevance and limitation
Bartik et al. (2020)	More than 5,800 US small businesses; survey	Cash buffers, closures, expectations	Many small firms held cash for only a few weeks; thin buffers were linked to closures	Shows financial fragility, but descriptive and without capability constructs
Fahlenbrach et al. (2021)	US listed firms; COVID-19 shock	Financial flexibility (cash holdings), stock returns	Firms with more financial flexibility suffered smaller value losses	Supports AFR logic, but evidence is from large listed firms
Ariana et al. (2024)	385 MSMEs, Bali, Indonesia; SEM	Financial and digital literacy, inclusion, decisions, financial resilience	Both literacies strengthen financial resilience via inclusion and decisions	Treats resilience as an outcome, not as a driver of performance
Probojakti et al. (2025)	Indonesian banking sector	Transformational leadership, digital transformation, organizational agility, corporate resilience	Digital transformation supports agility and resilience	Large-firm, banking context; not MSMEs
Clauss et al. (2021)	432 German electronics firms	Strategic agility, business model innovation (BMI), performance	Agility improves performance through BMI; turbulence strengthens agility–BMI link	Agility effect is indirect and context dependent; not MSMEs
Ahammad et al. (2021)	Internationalizing Indian firms	Explorative and exploitative agility, environmental uncertainty, international performance	Performance benefits of agility depend on competitive intensity and dynamism	Supports contingency view; larger firms
Zahoor et al. (2022)	Finnish B2B high-tech SMEs; case studies	Dynamic capabilities, strategic agility	Agility and dynamic capabilities helped SMEs adapt during COVID-19	Qualitative; high-tech context
Rozak et al. (2023)	Indonesian SMEs; survey	Social media engagement, organizational agility, digitalization	Agility and digital strategy are associated with better performance	Digital capability modeled as direct driver

Note: Compiled by the authors.

Study	Context and sample	Focal variables	Key findings	Relevance and limitation
		strategic plan, performance		
Chakravarty et al. (2013)	US firms; survey	IT competencies, entrepreneurial and adaptive agility, performance	IT competencies enable agility and facilitate its translation into performance; effects vary with dynamism	Provides the closest template for a complementary (moderating) role of digital capability
Tippins and Sohi (2003)	US manufacturing firms	IT competency, organizational learning, performance	IT competency improves performance largely through organizational learning	Digital capability creates value through organizational processes
Gao et al. (2023)	212 MSMEs, Bangladesh; PLS-SEM	E-commerce and digital marketing adoption, financial and sustainability performance	E-commerce adoption linked to both performance types; digital marketing only to financial performance	Adoption-level measure; direct effects only
Lontchi et al. (2023)	381 SMEs, Cameroon	Fintech, financial literacy, SME performance	Fintech is positively related to performance, partly through financial literacy	Direct and mediated effects only
Sari et al. (2023)	395 MSMEs, East Java, Indonesia	Financial knowledge, behavior, digital financial capability, inclusion, performance	Digital financial capability had no significant effect on MSME performance	Individual-level measure; no test of complementary role

Note: Compiled by the authors.

2.4. Hypothesis development

2.4.1. Adaptive financial resilience and business performance

For MSMEs, financial disturbances are rarely a distant risk. A delayed customer payment, a spike in input prices or a slow month can threaten the ability to pay suppliers and staff. From an RBV perspective, the capacity to absorb such disturbances and redeploy financial resources is a valuable and firm-specific capability, because it rests on accumulated relationships with lenders and suppliers, on the owner's knowledge of the business's cost structure and on routines that are difficult for competitors to observe

or copy (Barney, 1991; Sirmon et al., 2007). Firms with this capability can keep operating through shocks, avoid distress sales of assets and continue investing in customers when competitors are cutting back.

Empirical evidence is broadly consistent with this reasoning. Slack and flexible financial resources are associated with better performance, particularly in privately held and smaller firms (Daniel et al., 2004; George, 2005). During the COVID-19 shock, firms with greater financial flexibility lost considerably less value (Fahlenbrach et al., 2021), while small businesses with thin buffers were the most likely to close (Bartik et al., 2020). Studies of SMEs also suggest that resilient firms use disruptions as opportunities for strategic renewal rather than mere survival (Herbane, 2019). Among Indonesian MSMEs, Ariana et al. (2024) showed that financial resilience grows with better financial decisions, which suggests that resilience reflects adaptive financial management rather than luck. We therefore propose the following:

H1. Adaptive financial resilience is positively associated with MSME business performance.

2.4.2. Strategic change agility and business performance

Small firms in trade, food processing and services compete in markets where customer preferences, platforms and prices change quickly. The theoretical mechanism linking agility to performance runs through timing and fit. Firms that enact strategic change quickly can capture new demand before competitors do, while firms that change appropriately avoid committing resources to responses that no longer fit the market (Teece et al., 2016; Weber & Tarba, 2014). In dynamic capabilities terms, agility is the seizing capacity that converts perceived opportunities into commitments (Teece, 2007). For MSMEs, whose small scale allows rapid decisions but whose limited resources leave little room for error, this capacity may be especially consequential.

The empirical evidence is supportive but nuanced. Agility has been linked to superior performance among European manufacturing and electronics firms (Clauss et al., 2021; Felipe et al., 2016), to better international performance among Indian firms (Ahammad et al., 2021) and to adaptation among high-tech SMEs during the pandemic (Zahoor et al., 2022). In Indonesia, Rozak et al. (2023) found that organizational agility contributes to SME performance. At the same time, several studies suggest that agility does not always translate directly into performance. Clauss et al. (2021) found that its effect runs largely through business model innovation, and Ahammad et al. (2021) showed that the payoff depends on the type of environmental uncertainty. Such contingencies indicate that the agility–performance link should be examined alongside the conditions that enable it, which we do in H5. As a baseline, we expect the following:

H2. Strategic change agility is positively associated with MSME business performance.

2.4.3. Digital financial sensing capability and business performance

There are good reasons to expect DFSC to improve performance directly. Timely financial information allows owner-managers to spot loss-making products, chase overdue receivables and manage working

capital more tightly. Digital finance has also been shown to widen access to credit and payment networks for small firms (Bollaert et al., 2021; Ozili, 2018), and fintech use has been associated with greater SME efficiency and performance (Abbasi et al., 2021; Lontchi et al., 2023). On these grounds, the conventional expectation is a positive direct effect.

There are also reasons for caution. The IT productivity paradox reminds us that investment in information technology often fails to show up in performance measures unless it is accompanied by complementary organizational change (Brynjolfsson, 1993; Brynjolfsson & Hitt, 2000). For MSMEs, the problem may be sharper, because the digital tools that generate financial data are now cheap and widespread and therefore offer little basis for differentiation. Indeed, Sari et al. (2023) found no significant direct effect of digital financial capability among East Java MSMEs. We nevertheless state H3 as a direct positive effect for two reasons: it reflects the dominant expectation in prior studies, and it is the main effect that must be estimated before the interaction effects can be interpreted. The competing explanation, that DFSC creates value mainly by strengthening other capabilities, is captured by H4 and H5.

H3. Digital financial sensing capability is positively associated with MSME business performance.

2.4.4. The moderating role of DFSC in the AFR–performance relationship

AFR gives an MSME the means to adjust its finances, but adjustments are only as good as the information on which they are based. Organizational information processing theory suggests that, under uncertainty, a capability to act yields better outcomes when it is matched by a capacity to process the relevant information (Galbraith, 1974; Tushman & Nadler, 1978). DFSC supplies this capacity. An MSME that monitors its digital transaction data can see a cash shortfall coming weeks before it arrives, identify which costs to cut first and decide when a short-term loan is worth taking. Without such information, even a financially flexible firm may reallocate too late or in the wrong direction.

This complementarity is supported by evidence on information technology and organizational capabilities. Aral and Weill (2007) showed that IT investments raise performance only in firms with matching organizational practices, and Powell and Dent-Micallef (1997) found that technology produces advantage when it is embedded in complementary human and business resources. Research on resilience similarly highlights the role of anticipation, which depends on the timely detection of weak signals, in turning coping capacity into effective adaptation (Duchek, 2020). Following the logic of complementarities (Milgrom & Roberts, 1995), we expect the returns to AFR to rise with the quality of financial sensing:

H4. Digital financial sensing capability strengthens the positive association between adaptive financial resilience and MSME business performance.

2.4.5. The moderating role of DFSC in the SCA–performance relationship

Strategic change has financial consequences. Launching a new product line, moving onto an online marketplace or shifting to a different customer segment requires money and changes cash flows, often before any benefits are visible. An agile MSME that cannot see the financial implications of its moves risks changing quickly but unprofitably. DFSC addresses this risk by allowing the owner-manager to compare the costs and returns of alternatives, track the early financial results of a change and reverse course before losses mount.

The information systems literature provides direct support for this argument. Chakravarty et al. (2013) found that IT competencies play a facilitating role by helping firms implement entrepreneurial and adaptive actions, so that agility is more strongly reflected in performance. Related work shows that IT-enabled capabilities shape performance largely through their effect on agility (Lu & Ramamurthy, 2011; Mikalef & Pateli, 2017) and that digital options make strategic responses faster and better informed (Sambamurthy et al., 2003). Translating these insights to MSME financial management, we expect sensing and seizing to work as complements:

H5. Digital financial sensing capability strengthens the positive association between strategic change agility and MSME business performance.

2.5. Conceptual model

Figure 1 summarizes the hypothesized relationships. AFR and SCA are expected to be positively associated with business performance (H1 and H2). DFSC enters the model as a main effect (H3) and as a moderator of both relationships (H4 and H5).

3. Methodology

3.1. Research design

We used a cross-sectional, explanatory survey design to test the hypotheses. Because the data were collected at a single point in time, we interpret the structural paths as associations consistent with the theorized model rather than as evidence of causality, and we use the language of association throughout. Partial least squares structural equation modeling (PLS-SEM) was chosen because the study aims to explain and predict business performance, includes interaction terms and relies on a moderate sample size, conditions under which PLS-SEM is well suited (Hair et al., 2019, 2022).

3.2. Population, sampling and data collection

The target population consisted of MSMEs in East Java that use digital financial applications. Because no complete register of digitally active MSMEs exists, we recruited respondents through MSME communities and the researchers' professional and personal networks across East Java. Purposive

sampling was used to select firms that met four criteria: (1) the business was an active MSME in East Java, from any sector; (2) it had operated for at least three years; (3) it used at least one digital financial technology (e.g., QRIS, mobile banking, a bookkeeping application or another digital platform for financial transactions and management); and (4) its owner or main manager, who is responsible for financial and strategic decisions, was willing and able to complete the questionnaire in full. The third criterion follows from the study's focus on how firms use digital financial information, not whether they have access to it. We return to its implications for the interpretation of H3 in Section 4.4.

Data were collected in June 2026 using paper questionnaires delivered and collected in person by the researcher in twelve regencies and cities of East Java, most of them in Lumajang, Madiun, Nganjuk, Banyuwangi, Jember and Tuban. Of the 250 questionnaires distributed, 200 were returned (a return rate of 80.0%). After screening, 64 questionnaires were excluded because the respondents did not meet the eligibility criteria, leaving 136 valid responses for analysis (54.4% of the questionnaires distributed). All responses were entered from the paper questionnaires and verified against the originals before analysis, there were no missing values in the measurement items, and no respondent gave identical answers to all items (straight-lining). Because the survey did not record the date on which each questionnaire was returned, a comparison of early and late respondents to assess non-response bias was not possible; we acknowledge this in Section 6. Table 3 reports the profile of the responding businesses. All are micro enterprises with an annual turnover of no more than Rp2 billion, and they operate mainly in food processing and manufacturing (39.0%) and trade (30.9%), followed by agriculture and fisheries, culinary services, crafts and other services.

Table 3
Profile of respondents and businesses (n = 136).

Characteristic	Category	Frequency	Percentage
Sector	Food processing and manufacturing	53	39.0
	Trade (retail and wholesale)	42	30.9
	Agriculture, livestock and fisheries	16	11.8
	Culinary (food service)	13	9.6
	Crafts and furniture	7	5.1
	Other services	5	3.7
Firm age	3–5 years	37	27.2
	6–10 years	58	42.6
	> 10 years	41	30.1
Monthly turnover	< Rp5 million	23	16.9
	Rp5–10 million	84	61.8
	> Rp10–25 million	24	17.6
	> Rp25 million	5	3.7
Firm size (Government Regulation No. 7/2021)	Micro (annual turnover ≤ Rp2 billion)	136	100.0
Location (regency/city)	Lumajang	50	36.8
	Madiun	34	25.0
	Nganjuk	14	10.3
	Banyuwangi	10	7.4
	Jember	9	6.6
	Tuban	9	6.6
	Magetan	4	2.9
	Other (Jombang, Probolinggo, Gresik, Sidoarjo, Surabaya)	6	4.4

Note: Sector was coded by the authors from the business activity reported by respondents. Percentages may not sum to 100 because of rounding.

We determined the required sample size in two ways. A G*Power analysis (Faul et al., 2009) for a model with five predictors, a medium effect size ($f^2 = 0.15$) and $\alpha = 0.05$ indicated a minimum of 92 observations for a statistical power of 0.80; the achieved sample of 136 provides a power of about 0.95.

The inverse square root method (Kock & Hadaya, 2018) indicates that 136 observations are sufficient to detect path coefficients of about 0.21 or larger at the 5% level with 80% power. All significant paths in our model exceed this threshold, but the study has limited power to detect smaller effects, which matters for the interpretation of the non-significant DFSC × SCA interaction. We discuss this point as a limitation.

3.3. Measurement

All constructs were measured with multi-item reflective scales on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). AFR, SCA and DFSC were each measured with four items and business performance with three items. Appendix A lists all items in English and in the original Indonesian, together with their sources, loadings and indicator VIFs.

Because the sources that informed the items are largely conceptual articles or qualitative studies that do not provide ready-made scales (Legenzova et al., 2025; Lengnick-Hall & Beck, 2005; Teece, 2007; Teece et al., 2016; Zahoor et al., 2022), all items were developed by the authors from the construct definitions in these works (Appendix A) rather than taken from existing validated scales. The items were written and administered in Indonesian; the English versions reported in Appendix A were translated by the authors for reporting purposes. The items were not reviewed by a formal expert panel, and no separate pilot test was conducted. Instead, the reliability and validity of all scales were assessed on the main sample (Section 4.1), and we note these points as limitations in Section 6.

Business performance was measured subjectively with three items based on the balanced scorecard (Kaplan & Norton, 1992), each capturing one perspective: the development of the firm's financial performance, customer satisfaction with its products or services, and the effectiveness and efficiency of its internal operational processes. Respondents rated the general condition of their business; the items did not specify an explicit time frame or comparison referent, which we acknowledge as a limitation. Subjective measures are widely used when objective financial data for privately held small firms are unavailable or unreliable, and they correlate well with objective indicators (Dess & Robinson, 1984; Wall et al., 2004).

To reduce the risk of omitted variable bias, we re-estimated the model with three control variables: firm age (years in operation), firm size (the natural logarithm of monthly turnover, because the number of employees was not recorded) and sector (dummy variables for food processing and manufacturing and for trade, with the remaining sectors as the reference group). All 136 respondents reported these characteristics.

3.4. Common method bias and endogeneity

Because all constructs were reported by a single respondent at one point in time, we addressed common method bias (CMB) through both procedural and statistical remedies (Podsakoff et al., 2003, 2012). Procedurally, respondents were told in the cover letter that there were no right or wrong answers and that their responses would be used for academic purposes only, the items for each construct were placed in separate sections of the questionnaire with the outcome measured last, and item wording was

kept short and simple to reduce ambiguity. Statistically, we conducted a full collinearity assessment (Kock, 2015). All variance inflation factors (VIFs) obtained by regressing each latent variable on all others were below the threshold of 3.3 (range 1.188–1.457), suggesting that the model is not contaminated by CMB. As an additional check, Harman's single-factor test showed that the first unrotated factor explained 33.36% of the variance in the 15 indicators, below the 50% threshold, and four factors had eigenvalues above 1. We also note that CMB tends to deflate rather than inflate interaction effects, so it is an unlikely explanation for the significant moderation results (Siemsen et al., 2010).

Endogeneity could also bias the estimates if unobserved factors such as managerial ability influenced both the capabilities and performance. Following Hult et al. (2018), we applied the Gaussian copula approach to the paths from AFR, SCA and DFSC to business performance. The approach requires non-normally distributed predictors. The Shapiro–Wilk test rejected normality for the AFR scores ($p = 0.021$) but not for the SCA and DFSC scores ($p = 0.177$ and 0.178), so the copula results for the latter two should be interpreted with caution. We added the copula terms to the structural model one at a time and jointly, and assessed their significance with 5,000 bootstrap subsamples. None of the copula terms was significant (individual models: AFR $p = 0.119$, SCA $p = 0.606$, DFSC $p = 0.108$; joint model: $p = 0.206$, 0.886 and 0.219, respectively), which provides no evidence that endogeneity biases these paths.

3.5. Data analysis

The model was estimated using the PLS-SEM algorithm with the path weighting scheme and Mode A estimation for all reflective constructs, following a two-step procedure (Hair et al., 2019). The initial estimation was carried out in SmartPLS 4 (version 4.1.1.9; Ringle et al., 2024). To obtain bias-corrected and accelerated confidence intervals, the controlled and copula models, PLSpredict, CVPAT and the simple slope tests in a single consistent framework, we replicated the PLS-SEM algorithm in Python; the replication reproduced the SmartPLS 4 measurement model and main-effect estimates to within 0.002, although interaction-term estimates can differ slightly between implementations, and all structural estimates reported below come from this replication. The measurement model was assessed by examining indicator loadings, internal consistency reliability (Cronbach's α, ρ_A and composite reliability ρ_c), convergent validity (average variance extracted, AVE) and discriminant validity using the heterotrait–monotrait ratio (HTMT) with bootstrapped confidence intervals (Henseler et al., 2015). The structural model was assessed by checking collinearity among predictors (inner VIF), path coefficients and their significance, the coefficient of determination (R^2), effect sizes (f^2) and out-of-sample predictive power using PLSpredict (Shmueli et al., 2019) and the cross-validated predictive ability test (CVPAT) (Liengaard et al., 2021).

The interaction terms were created using the two-stage approach, which is recommended when the aim is to test the significance of moderation and is robust across conditions (Becker et al., 2018). In the first stage, the main-effects model was estimated to obtain latent variable scores; in the second stage, the standardized scores of AFR and SCA were each multiplied by the standardized score of DFSC to form the interaction terms. Significance was assessed by bootstrapping with 10,000 subsamples and bias-

corrected and accelerated (BCa) 95% confidence intervals. In each subsample, the signs of the outer weights were aligned so that every construct score correlated positively with its indicators, which prevents arbitrary sign reversals of construct scores from contaminating the bootstrap distribution of the interaction terms. All p-values are two-tailed. Although the hypotheses are directional, two-tailed tests offer a more conservative standard and allow effects in the unexpected direction to be detected. Effect sizes for the interaction terms were evaluated against the thresholds proposed by Kenny (2018), namely 0.005, 0.01 and 0.025 for small, medium and large effects, respectively. Finally, simple slope analysis was used to interpret the nature of the significant interactions (Aiken & West, 1991).

4. Results and discussion

4.1. Measurement model

Table 4 reports the reliability and convergent validity results. All indicator loadings exceed the 0.708 threshold, ranging from 0.808 to 0.850 for AFR, 0.800 to 0.849 for SCA, 0.812 to 0.864 for DFSC and 0.824 to 0.845 for business performance (see Appendix A). Cronbach's α ranges from 0.787 to 0.861, ρ_A from 0.787 to 0.884 and composite reliability from 0.876 to 0.904, and all AVE values exceed 0.50 (0.675–0.703), which indicates good internal consistency and convergent validity (Hair et al., 2022).

Table 4
Construct reliability and convergent validity.

Construct	Items	Loading range	Cronbach's α	ρ_A	ρ_c (CR)	AVE
Adaptive financial resilience (AFR)	4	0.808–0.850	0.854	0.860	0.901	0.696
Strategic change agility (SCA)	4	0.800–0.849	0.842	0.876	0.893	0.675
Digital financial sensing capability (DFSC)	4	0.812–0.864	0.861	0.884	0.904	0.703
Business performance (BP)	3	0.824–0.845	0.787	0.787	0.876	0.701

Note: ρ_A = Dijkstra–Henseler's reliability coefficient; ρ_c = composite reliability; AVE = average variance extracted.

Two features of these results deserve comment. First, ρ_A lies between Cronbach's α and ρ_c for every construct and is below 1, as expected for a consistent reliability estimator (Dijkstra & Henseler, 2015). Second, indicator-level VIFs range from 1.579 to 2.145 (Appendix A), well below the conservative threshold of 3.3, and loadings are high but not uniform, which suggests that the items capture related but non-redundant facets of each construct. Together with the CMB tests reported in Section 3.4, these checks indicate that the measurement model is reliable and valid.

Discriminant validity was assessed using HTMT (Table 5). All values are well below the conservative threshold of 0.85, the highest being 0.515 (AFR–BP), and the upper bounds of all bootstrapped 95% confidence intervals are below 0.85 (Henseler et al., 2015). Following current guidelines, interaction terms are not included in the HTMT assessment because they do not represent conceptually distinct constructs.

Table 5
Discriminant validity (HTMT ratios).

Construct	AFR	SCA	DFSC	BP
AFR				
SCA	0.360 [0.204, 0.529]			
DFSC	0.276 [0.124, 0.459]	0.205 [0.109, 0.338]		
BP	0.515 [0.331, 0.663]	0.416 [0.244, 0.567]	0.460 [0.263, 0.621]	

Note: Figures in brackets are bias-corrected and accelerated 95% bootstrap confidence intervals (10,000 subsamples). AFR = adaptive financial resilience; SCA = strategic change agility; DFSC = digital financial sensing capability; BP = business performance.

4.2. Structural model

Inner VIF values ranged from 1.083 to 1.280, well below 3, so collinearity among the predictors does not bias the path estimates (Hair et al., 2022). The model explains 39.3% of the variance in business performance ($R^2 = 0.393$; adjusted $R^2 = 0.370$), which represents weak-to-moderate explanatory power, typical for a construct as multifaceted as small-firm performance. The SRMR of the saturated model is 0.063, below the 0.08 threshold. Table 6 reports the path coefficients, and Fig. 2 presents the estimated model.

Table 6
Results of hypothesis testing.

Hypothesis	Path	β	SE	t	p	95% CI	f^2	Inner VIF	Decision
H1	AFR → BP	0.330	0.084	3.948	< 0.001	[0.162, 0.487]	0.150	1.187	Supported
H2	SCA → BP	0.266	0.068	3.937	< 0.001	[0.130, 0.391]	0.101	1.156	Supported
H3	DFSC → BP	0.299	0.075	3.962	< 0.001	[0.141, 0.436]	0.132	1.083	Supported
H4	DFSC × AFR → BP	0.285	0.079	3.615	< 0.001	[0.133, 0.439]	0.105	1.270	Supported
H5	DFSC × SCA → BP	0.016	0.077	0.206	0.837	[− 0.137, 0.161]	0.000	1.280	Not supported

Note: β = standardized path coefficient; SE = bootstrap standard error; 95% CI = bias-corrected and accelerated confidence interval (10,000 subsamples); p-values are two-tailed. f^2 for the interaction terms is evaluated against Kenny's (2018) thresholds. R^2 = 0.393; adjusted R^2 = 0.370; SRMR = 0.063.

AFR shows a positive association with business performance (β = 0.330, p < 0.001), supporting H1. SCA is also positively associated with performance (β = 0.266, p < 0.001), supporting H2. The direct path from DFSC to performance is positive and significant as well (β = 0.299, p < 0.001), so H3 is supported. The DFSC × AFR interaction is positive and significant (β = 0.285, p < 0.001), supporting H4, whereas the DFSC × SCA interaction is close to zero and not significant (β = 0.016, p = 0.837), so H5 is not supported. The effect size of the DFSC × AFR interaction is 0.105, well above Kenny's (2018) threshold for a large moderating effect, while that of the DFSC × SCA interaction is effectively zero. The results remain substantively unchanged when firm age, firm size and sector are controlled for: in this supplementary estimation, the coefficients are 0.315 for AFR, 0.264 for SCA, 0.305 for DFSC, 0.293 for DFSC × AFR (p = 0.001) and 0.019 for DFSC × SCA (p = 0.800), and none of the control variables is significant (all p > 0.25).

The model also has meaningful predictive power. The $Q^2_{predict}$ value for business performance is 0.329 at the construct level, and all three indicators have $Q^2_{predict}$ values above zero (0.210–0.242). At the indicator level, the PLS-SEM model yields lower RMSE and MAE values than the linear model benchmark for all three indicators (Table 7), which indicates high predictive power (Shmueli et al., 2019). The CVPAT results confirm that the model predicts significantly better than both the indicator average benchmark (average loss difference = − 0.200, p < 0.001) and the linear model benchmark (average loss difference = − 0.091, p = 0.029) (Liengaard et al., 2021).

Table 7
Predictive power assessment (PLSpredict).

Indicator	Q^2_predict	PLS-SEM RMSE	LM RMSE	PLS-SEM MAE	LM MAE
BP1	0.231	0.855	0.919	0.672	0.723
BP2	0.210	0.832	0.889	0.662	0.707
BP3	0.242	0.783	0.823	0.639	0.677
Construct level (BP)	0.329	0.816	–	0.653	–

Note: LM = linear regression model benchmark; RMSE = root mean squared error; MAE = mean absolute error. Indicator-level values are in the original scale units; construct-level values refer to the standardized construct score. Predictions are based on 10-fold cross-validation with 10 repetitions.

4.3. Simple slope analysis

To see what "strengthening" means in practice, we plotted the relationships between AFR and SCA and business performance at low (− 1 SD), average and high (+ 1 SD) levels of DFSC (Fig. 3) and tested each conditional slope with the bootstrap. For AFR, the slope is small and not significant when DFSC is low (0.045, p = 0.642, 95% CI [− 0.169, 0.215]), rises to 0.330 at the mean and reaches 0.616 when DFSC is high (p < 0.001, 95% CI [0.367, 0.871]). In other words, financial resilience appears to pay off only when MSMEs can monitor and interpret their financial condition. The pattern for SCA is different. Its slope is almost identical at low (0.250, 95% CI [0.053, 0.429]) and high (0.282, 95% CI [0.048, 0.473]) levels of DFSC, so agility is associated with better performance regardless of the level of financial sensing.

To test whether the two moderating effects differ, we bootstrapped the difference between the DFSC × SCA and DFSC × AFR coefficients. The difference (− 0.270) is marginally significant: its BCa 95% confidence interval [− 0.545, − 0.006] excludes zero, although the normal-theory p-value is borderline (p = 0.050). The evidence therefore indicates, with appropriate caution, that DFSC strengthens the resilience–performance association more than the agility–performance association.

4.4. Discussion

Adaptive financial resilience. AFR is positively associated with performance, but the simple slope analysis shows that this association depends on financial sensing: it is substantial when DFSC is high and negligible when DFSC is low. The overall finding is consistent with evidence that financial flexibility protects firm value under stress (Fahlenbrach et al., 2021) and that small businesses with thin buffers are the most vulnerable to closure (Bartik et al., 2020). It also extends the work of Ariana et al. (2024), who studied financial resilience as an outcome among Indonesian MSMEs; our results suggest that resilience is not only something MSMEs achieve but also something that helps them perform. The contingency is the more novel part of the finding. In larger firms, slack resources show modest and sometimes curvilinear associations with performance (Daniel et al., 2004; George, 2005), and resource orchestration research stresses that resources create value only when they are deployed well (Sirmon et

al., 2007). Our results suggest a concrete reason for this in micro enterprises: a firm that can absorb and reallocate funds but cannot see where its cash is going is likely to reallocate too late or in the wrong direction. In RBV terms, AFR behaves like a firm-specific capability, built on relationships and routines that competitors cannot easily replicate (Barney, 1991), but its value is realized through the information that guides it.

Strategic change agility. The positive association between SCA and performance is consistent with studies linking strategic agility to performance (Clauss et al., 2021; Felipe et al., 2016) and with Indonesian evidence on organizational agility in SMEs (Rozak et al., 2023). Unlike AFR, however, SCA is associated with better performance at every level of DFSC, and H5 is not supported. This contrasts with Chakravarty et al. (2013), who found that IT competencies facilitate the translation of agility into performance. Two explanations seem plausible. First, the agility items capture the recognition of market changes and the adaptation of strategy to customer needs, activities that in micro enterprises rely mainly on direct contact with customers and competitors rather than on internal financial data. Internal financial sensing is therefore a poor match for the information that strategic change requires. Second, Clauss et al. (2021) and Ahammad et al. (2021) show that the payoff of agility depends on business model innovation and environmental conditions; the relevant contingencies for agility may thus lie outside the firm's financial information system. At the same time, with 136 observations the study has limited power to detect small interaction effects (Kock & Hadaya, 2018), so the absence of moderation should be read as the absence of a substantial effect rather than as proof of no effect.

Digital financial sensing capability. DFSC is positively and directly associated with performance, which supports H3. The finding agrees with studies reporting positive effects of fintech and e-commerce adoption on SME outcomes (Gao et al., 2023; Lontchi et al., 2023) but contrasts with the null finding of Sari et al. (2023) in a larger East Java sample. One reason for the difference may lie in measurement. Sari et al. (2023) measured digital financial capability at the individual level, as the owner's skills, whereas DFSC captures whether the business actually uses digital data to monitor and interpret its financial condition. Our results suggest that it is this organizational use, rather than individual competence or mere adoption, that is associated with performance. The finding also qualifies the IT productivity paradox (Brynjolfsson, 1993; Brynjolfsson & Hitt, 2000). Although QRIS, mobile banking and bookkeeping applications are cheap and widely available, the routines for reading and acting on their outputs evidently are not uniformly distributed, so they can still distinguish better-performing firms. Timely financial information may help owner-managers spot loss-making products, chase overdue receivables and manage working capital more tightly, even before it is combined with other capabilities.

The complementary role of DFSC. The interaction results show that the complementarity of digital financial sensing is selective. DFSC strengthens the association between AFR and performance, consistent with evidence that IT creates value when bundled with matching organizational practices (Aral & Weill, 2007; Powell & Dent-Micallef, 1997) and with organizational information processing theory, which holds that the capacity to process information raises performance when it is matched by a capacity to decide and act on that information (Galbraith, 1974; Tushman & Nadler, 1978). The match is

domain-specific: DFSC supplies information about the firm's own finances, and AFR is the capability that adjusts those finances, so the two fit closely. SCA, by contrast, depends on information about markets and customers that DFSC does not supply, which explains why DFSC neither strengthens nor weakens its payoff. The near-zero slope of AFR at low DFSC suggests that financial buffers and flexibility without financial visibility may yield little performance benefit, an important caution for MSMEs and lenders that focus on access to finance alone.

5. Implications

5.1. Theoretical implications

This study has three implications for theory. First, it refines the dynamic capabilities framework for small firms. Teece's (2007) sensing–seizing–reconfiguring logic was developed largely with large enterprises in mind, where specialized units perform each function. In MSMEs, all three functions are concentrated in the owner-manager, and our results show that they are related in a specific way. Sensing, as captured by DFSC, has a direct association with performance and strengthens reconfiguring (AFR) but not seizing (SCA). This leads to a proposition that future work can test directly: in resource-constrained firms, the complementarity between sensing and other dynamic capabilities is strongest when the information sensed belongs to the same domain as the resources the capability reconfigures.

Second, the study extends the RBV to the era of commoditized digital tools. When the technologies that generate financial information are cheap and widely available, the tools themselves are neither rare nor inimitable, but the organizational routines for interpreting their outputs remain heterogeneous across firms. Our results show that these routines are associated with performance both directly and through their combination with financial resilience. This offers a capability-based explanation for the mixed evidence on digital finance and SME performance (Gao et al., 2023; Lontchi et al., 2023; Sari et al., 2023): studies that measure adoption or individual literacy may miss the organizational use of digital financial information, and studies that model it only as a direct driver may underestimate its value in financially resilient firms. More broadly, the findings lend support to complementarity theory (Milgrom & Roberts, 1995) while showing that complementarities between digital and organizational capabilities need not be general.

Third, the study clarifies the conceptual boundaries of AFR, SCA and DFSC relative to established constructs (Table 1) and shows that individual-level constructs such as digital financial literacy can be meaningfully elevated to firm-level capabilities in owner-managed MSMEs. Evidence from an emerging economy in which digital payments have spread faster than financial literacy also shows that the conditions under which capabilities translate into performance are context dependent. Theories of digital capability developed in advanced economies may therefore need to account more explicitly for gaps between access and capability.

5.2. Practical and policy implications

For MSME owner-managers, the main message is that installing a digital financial application is the beginning rather than the end of digitalization. The value of these tools comes from routines that turn data into decisions. Concretely, owner-managers can (1) set aside a fixed weekly time to review QRIS and mobile banking transaction reports alongside a simple cash-flow forecast for the coming four to eight weeks; (2) use free bookkeeping applications such as SI APIK (Bank Indonesia) or LAMIKRO (Ministry of Cooperatives and SMEs) to separate business and personal finances and to track margins by product; (3) define a few early-warning triggers, such as a drop in weekly sales or a rise in receivables beyond an agreed number of days, that prompt predefined responses such as cutting discretionary spending or drawing on a credit line; and (4) estimate the cash-flow implications of any major strategic change, such as entering an online marketplace, before committing to it, and track its actual financial results monthly. Building financial buffers, through reserves or pre-arranged access to programs such as the People's Business Credit (KUR), remains important, but our results suggest that buffers pay off mainly when they are managed with good financial information.

For policymakers and MSME support institutions, the findings suggest a shift in emphasis from adoption to capability. Programs run by the Ministry of MSMEs, Bank Indonesia and the Financial Services Authority (OJK), including QRIS expansion and the national financial literacy movement, have been highly successful in expanding access. The next step is to embed training on interpreting digital financial data and using it in decisions. Programs could, for instance, measure success by the share of participating MSMEs that prepare monthly cash-flow reports or use their transaction data to support loan applications, rather than by the number of new QRIS merchants. Because financial resilience appears to pay off only with adequate financial sensing, programs that improve MSMEs' access to credit and financial buffers should be paired with training on monitoring and interpreting digital financial records, whereas programs that build strategic agility may need to focus on market and customer information. Finally, financial institutions could use MSMEs' digital transaction histories as an input for credit assessment, which would reward good financial sensing with better access to the buffers that underpin AFR.

6. Conclusion, limitations and future research

This study set out to examine whether adaptive financial resilience and strategic change agility are associated with the performance of Indonesian MSMEs and whether digital financial sensing capability is associated with performance directly and strengthens these associations. Both capabilities are associated with higher performance, and so is digital financial sensing in its own right. Its moderating role, however, is selective: digital financial sensing strengthens the performance association of financial resilience, without which resilience shows little benefit, but it does not change the performance association of strategic agility. Digital financial sensing therefore matters both for what it does directly and for how it improves what MSMEs do with their financial resources, a conclusion that holds within the limits of a cross-sectional design in which all relationships should be read as associations.

Several limitations qualify these conclusions and point to avenues for further research. First, purposive, non-probability sampling of micro enterprises recruited through community and personal networks in East Java limits the generalizability of the findings to larger firms, other regions and other countries, and the sector composition of the sample was coded from self-reported business activities. Second, a single informant reported both the predictors and the outcome. Although procedural and statistical tests suggest that common method bias is unlikely to drive the results, it cannot be ruled out entirely. Third, business performance was measured subjectively, with one item for each balanced scorecard perspective and without an explicit time frame or comparison referent, and may differ from objective financial results. Fourth, because only MSMEs that already used digital financial applications were sampled, the variance in DFSC is likely restricted, and the findings cannot speak to non-users. In addition, because response dates were not recorded, non-response bias could not be assessed by comparing early and late respondents, and the newly developed items were neither reviewed by a formal expert panel nor pilot-tested before the main survey, although all scales showed high reliability and validity in the main sample. Future studies should subject the scales to formal content validation. Fifth, the sample provides adequate power for the effects observed but limited power to detect small interaction effects, so the non-significant DFSC × SCA interaction should be re-examined in larger samples. Sixth, the cross-sectional design precludes causal inference and cannot rule out reverse causality, for example that better-performing firms invest more in financial sensing.

These limitations suggest concrete directions for future work. Researchers could link survey measures of capability with objective performance data, such as digital transaction records from QRIS or bank statements, which would also reduce single-source bias. Multi-wave or panel designs could test whether strengthening DFSC precedes improvements in performance and in the returns to AFR. Studies could also measure market-related sensing alongside financial sensing to test whether the former, rather than DFSC, conditions the payoff of strategic agility. Comparing users and non-users of digital financial applications would show whether the role of DFSC also applies at earlier stages of digitalization, and larger samples drawn from several Indonesian provinces or other emerging economies would allow multi-group analysis by firm size, sector and digital maturity. Finally, studies could test the proposition developed in Section 5.1 by comparing the relative value of sensing, seizing and reconfiguring capabilities across firms of different sizes.

Ethical approval

and informed consent

The study was conducted with a research permit issued by the Faculty of Economics and Business, Universitas Negeri Surabaya (No. B/83281/UN38.7/TU.00/2026, 12 June 2026). Formal review by a research ethics committee was not obtained for this non-interventional questionnaire survey of business owners and managers, which did not collect sensitive personal information. Participation was voluntary; the cover letter of the questionnaire explained the purpose of the study and stated that responses would

be used for academic purposes only, and completion of the questionnaire was taken as informed consent. The data were analyzed and reported only in aggregate form.

Declarations

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CRediT authorship contribution statement

Yulianto Umar Rofi'i: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. Hariyati: Conceptualization, Supervision, Validation, Writing – review & editing. Ni Nyoman Alit Triani: Methodology, Supervision, Validation, Writing – review & editing.

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.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Claude (Anthropic) to improve the language and structure of the manuscript and to assist in writing the Python code used to replicate the PLS-SEM estimation and the supplementary analyses. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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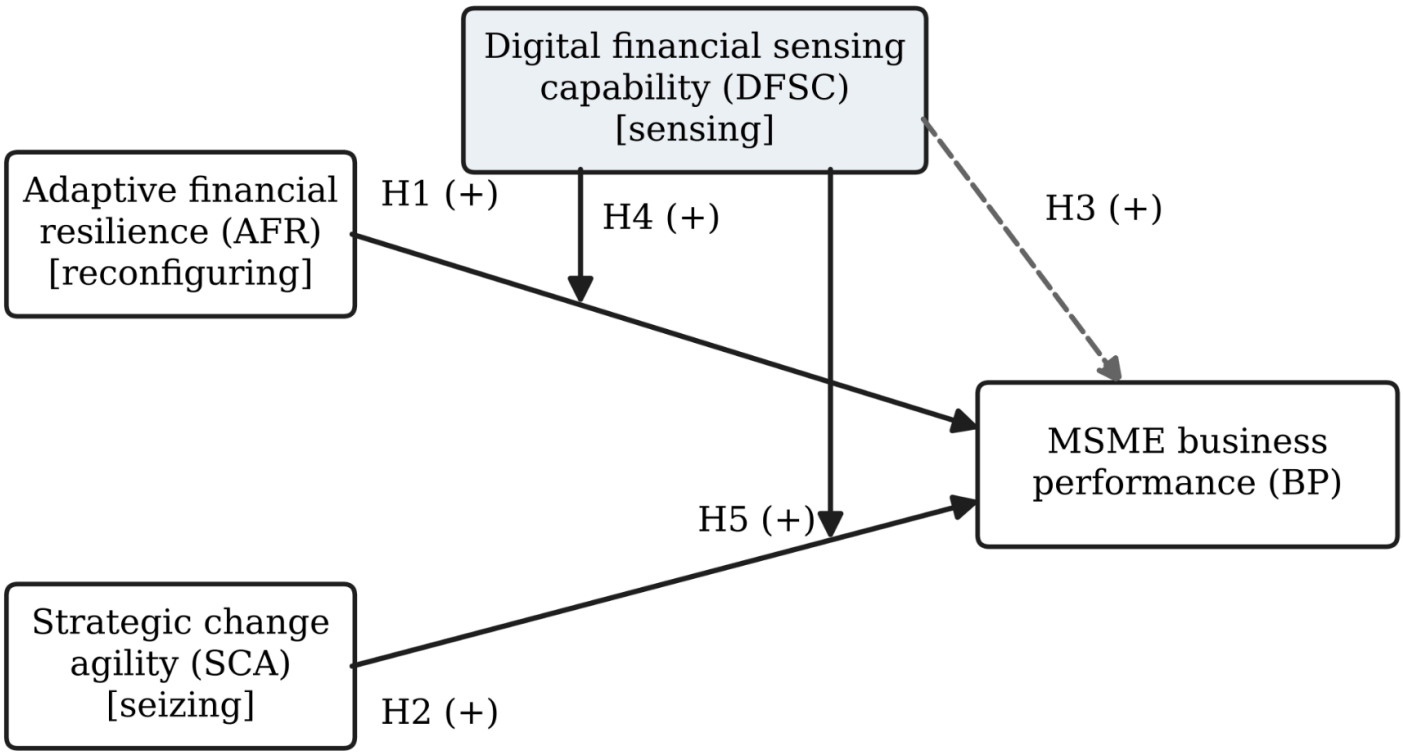
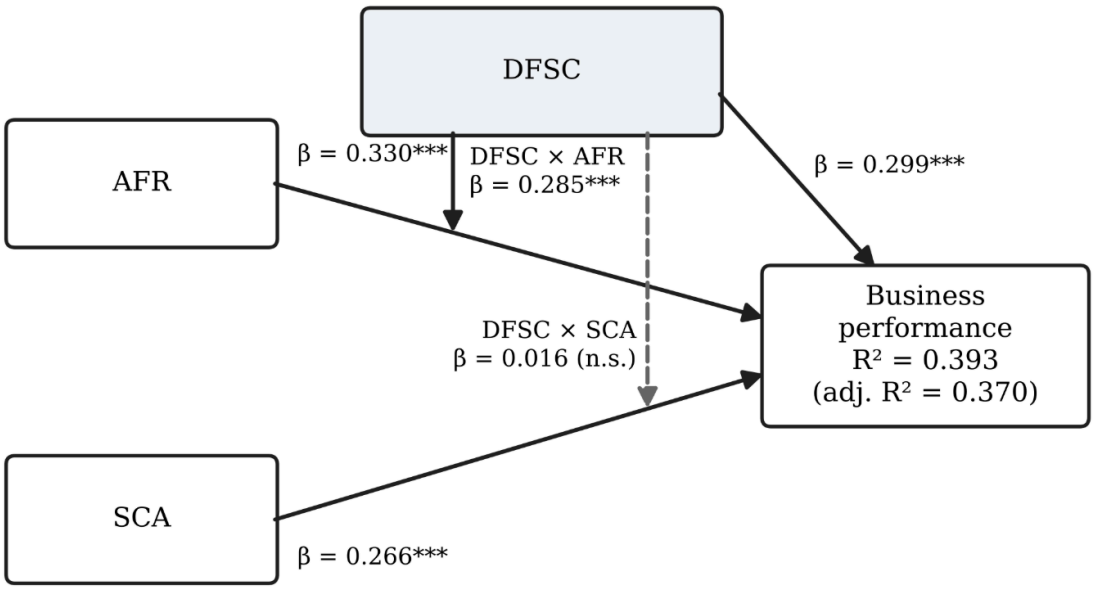
Figures



Dashed arrow: direct effect of DFSC (H3), also the main effect required to test the interactions. Bracketed labels denote each capability's role in the sensing–seizing–reconfiguring logic.

Figure 1

Conceptual model.



Standardized path coefficients; two-tailed bootstrap tests. ***p < 0.001; **p < 0.01; *p < 0.05; n.s. = not significant (dashed arrow).

Figure 2

Estimated structural model.

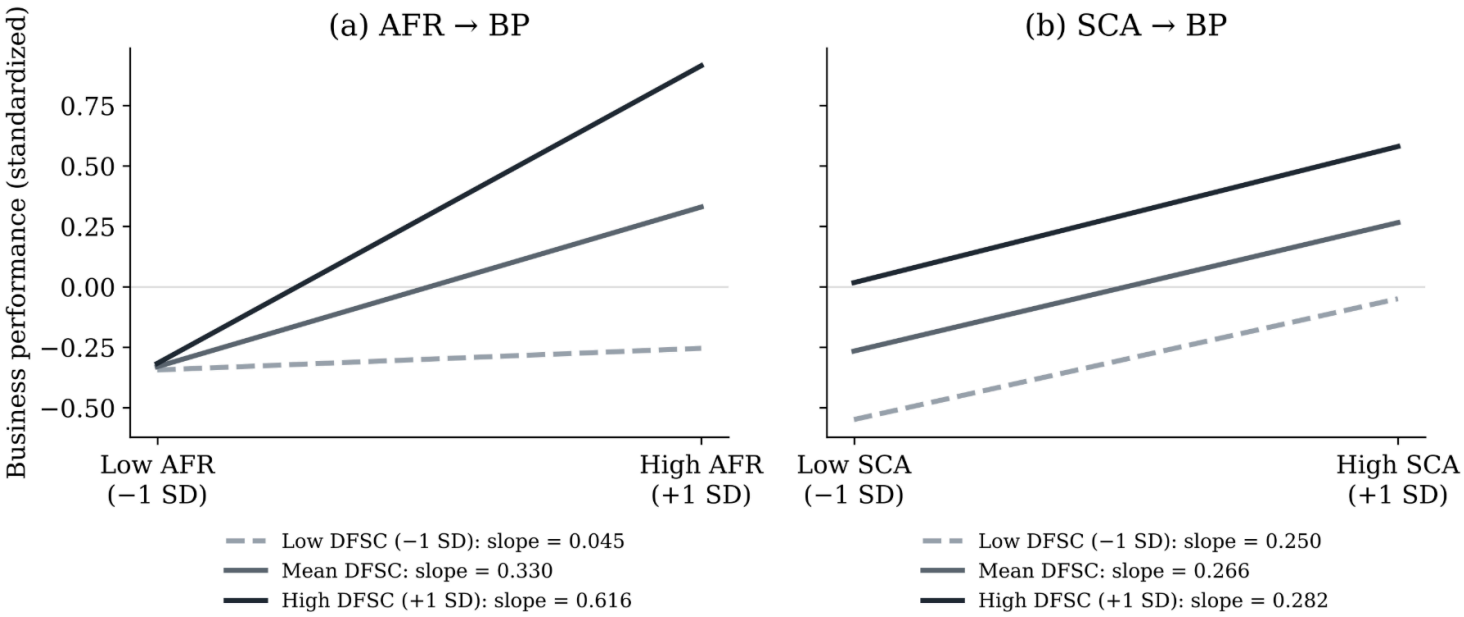


Figure 3

Simple slope analysis of the moderating effects of DFSC.