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Article

Artificial Intelligence Adoption and Business Performance: The Mediating Role of Organizational Agility

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Abstract: While organizations invest in artificial intelligence (AI) as a whole, they have not yet consistently been able to achieve better business outcomes as they have done in the past with other productivity technologies, a trend that mirrors the well-documented productivity paradox in the information-systems literature. In this study, we draw on the insights from the two perspectives, the dynamic capabilities view and the resource-based view, and examine the mediating role of organizational agility in the linkage between AI use and measurable business results. A cross sectional survey design was used. The survey sample consisted of 385 managers and senior executives at manufacturing, financial services, retail/e-commerce and information-technology companies. The measurement model was assessed using partial least squares structural equation modelling (PLS-SEM) which were tested for reliability, convergent validity, and discriminant validity using 5,000 resampling bootstrapping, while the structural model was tested for the degree of mediation (indirect effect). Organizational agility ($\beta = 0.586$, $p < 0.001$) and business performance ($\beta = 0.318$, $p < 0.001$) were both positively and significantly related to the use of AI. Organizational agility, in turn, was positively correlated with business performance ($\beta = 0.402$, $p < 0.001$) and partially mediated the relationship between the AI adoption and business performance, with around 42.6 percent of the total effect (indirect $\beta = 0.236$, 95% CI [0.159, 0.318]). The study takes a step toward applying the concepts of dynamic capabilities to the field of AI and provides evidence of organizational agility as a vital transmission mechanism, not just a key AI performance enabler. It provides evidence-based advice for managers looking to drive performance from AI investments and demonstrates the need for agility building investments in parallel with the deployment of AI.

Keywords: Artificial Intelligence Adoption; Organizational Agility; Business Performance; Dynamic Capabilities; Digital Transformation

1. Introduction

Increasingly, artificial intelligence (AI) has shifted from the experimental lab and into the mainstream as an influential factor in an organization's strategy. In addition to helping simplify business processes, these technologies also increasingly find their place in essential business functions like demand forecasting, customer service, supply-chain management, fraud detection, and product development (Aldossary, M. A., Ayad, T. H., & Moustafa, 2026). While enterprise AI investment is consistently reported to be in double digits annually across the globe, the effectiveness of these investments in terms of better financial and operational outcomes varies significantly across firms and industries. This is similar to the classic paradox in information technology where significant investments in technology does not result in an equally obvious and measurable increase in the performance of individual firms (Khan, 2025).

Many studies are now emerging that the problem is not the technology, but what is missing is the organizational ability to turn the potential offered by AI into value for the business. Organizational agility, in particular, has garnered attention among these capabilities as the ability of a company to detect and react swiftly, efficiently, and at low cost to environmental changes (Tahir, M. A., Yousaf, T., Shahzad, M. F., Zain, F., & Ain, 2024). These capabilities, in theory, should enable a company to react quickly to market changes, re-align resources

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and free manager and employee time for more valuable, judgmental tasks.In principle, these capabilities should improve a company's ability to sense market changes and re-align resources quickly, freeing up managerial and employee time to focus on more valuable, judgmental tasks. Wang, Lin, and Shao (2022) found in practice that the use of AI-powered chatbots, both in a conventional and an innovative way, had a positive impact on both internal and external agility, which in turn boosted the performance in the customer-service function. Likewise, Fosso Wamba (2022) reported that customer agility and organizational agility partially and jointly mediated the link between AI assimilation and the firm performance in a large cross-industry sample (Erlangga, 2026).

However, the causal relationship between the use of AI and the organization's agility and business performance is not consistently captured in models and/or has not been consistently tested in different contexts, and there are several open questions. First, the existing literature has largely regarded the adoption of AI as a binary or attitudinal construct (e.g., perceived benefits, intention to adopt), rather than a capability in business processes, which reduces the general applicability of the results to outcomes of performance (Hameed, 2026). Second, organizational agility has been implemented in an inconsistent fashion; for some studies, it was considered one-dimensional, while other studies split it into three dimensions: customer, operation, and partnering agility. Third, there are few studies that test the direct AI–performance path, the AI–agility path, and the agility–performance path in one structural model that also quantifies the proportion of the total effect mediated, which is needed to determine whether agility is a complementary or a substitute mechanism (Shatila, 2025).

This study aims to fill these gaps by creating and testing an integrated model that links the relationship between the adoption of AI and business performance through the lens of organizational agility (Babatunde, 2025). The study is based on the two theoretical perspectives of the dynamic capabilities view and the resource-based view that hold that AI is a valuable but increasingly imitable technological resource that can only create sustained competitive advantage when integrated into higher-order organizational capabilities, such as agility (Mariani, C., & Mancini, 2025). The research aims are: (1) to investigate the direct impact of AI adoption on business performance; (2) to investigate the influence of AI adoption on organizational agility; (3) to investigate the influence of organizational agility on business performance; and (4) to test the mediation between AI adoption and business performance by organizational agility and quantify the strength of the mediation.

2. Literature Review and Theoretical Background

2.1 Theoretical foundations: the dynamic capabilities view and the resource-based view

The resource-based view (RBV) is the theory that competitive advantage can be achieved through the exploitation of those resources that are valuable, rare, inimitable and non-substitutable. The first wave of RBV application to IT has focused on the potential for advantage in the IT infrastructure itself, but commodity technologies (such as the widely available AI platforms and cloud-based machine-learning services) have been spreading among competitors quickly, putting the emphasis on the complementary organizational capabilities that drive the way the technology is used (Alshamsi, Hussain, 2024).

The dynamic capabilities view (DCV) of the RBV was proposed by Teece, Pisano, and Shuen (1997) and developed by Teece (2007), which is an elaboration of the RBV to explain how organizations leverage the building, integration, and reconfiguration of their resources in an environment of rapid change. Based on the work of Teece (2007), three microfoundational processes were identified: sensing opportunities and threats, seizing opportunities by making timely resource allocations, and transforming the organisation's asset base to ensure competitiveness. Dynamic capabilities have since been explicitly connected to organizational agility (Teece, Peteraf and Leih, 2016), which they view as a calibrated ability, rather than an innate attribute of a company, that can be cost-effectively applied when confronted with deep uncertainty, compared to routine risk where traditional management tools are applicable (Alghamdi, 2023). This is the key difference for this study, and the theory is that the sensing and seizing microfoundations are enabled by the use of AI, whereas the organizational agility is the transforming capability that converts inputs into coordinated organizational responses, that in turn materialize in business performance (Panichayakorn, & Jermsittiparsert, 2019).

2.2 The Technology-Organization-Environment framework and AI adoption

The Technology-Organization-Environment (TOE) framework is a model that helps explain the adoption of technology based on technological factors (e.g., relative advantage, complexity, compatibility), organizational factors (e.g., top management support, employee capability, organizational readiness), and environmental factors (e.g., competitive pressure, government support, customer pressure). The TOE model has been widely used in the field of AI adoption studies. The 305 small and medium sized enterprises (SMEs) included in this hybrid SEM-ANN study were most likely to say that top management support, employee capability and relative advantage were the most important drivers of AI adoption, which had a significant positive impact on economic, social and environmental performance (Ștefan, Olariu, 2024). Using a technology readiness-resource based view perspective, a related study of Pakistani manufacturing SMEs found that technological readiness, leadership vision, and competitive pressure guided the adoption of AI, while the adoption of AI, in turn, influenced firm performance (Syarkani, 2025). Similar TOE-based results have been found for SMEs in Saudi Arabia, as relative advantage, compatibility, sustainable human capital, market demand, and government support were found to influence AI adoption and operational and economic outcomes in SMEs in this country, and for Jordanian manufacturing SMEs, where the combination of technological, organizational, and environmental context was found to predict AI adoption and sustainable performance in SMEs. Another study conducted in Vietnam also found that the level of implementing TOE further boosted business model innovation and sustainable competitive advantage, leading to improved business performance (Srinath, Chandana, 2026). In sum, these studies suggest a multidimensional view of AI adoption as an organizational ability, one that is influenced by technological, organizational, and environmental factors and is, at best, a positive but indirect relationship with organizational performance — a relationship that is why this study focuses on organizational agility as an intervening mechanism.

2.3 Organizational agility

The authors of the paper found that IT-enabled digital options (reusable technological and knowledge assets) enable firms to sense and react to competitive threats more quickly than their competitors, separating three types of agility: entrepreneurial agility (sensing innovation opportunities); adaptive agility (sensing and responding to environmental changes); and hedging agility (sensing and responding to risk under uncertainty). On this, Lu and Ramamurthy (2011) empirically found two types of agility: market capitalizing agility (ability to react to and capitalize change and opportunity) and operational adjustment agility (ability to adjust processes internally when changes occur) both of which were positively associated with IT capability, which in turn was found to be positively associated with firm performance. Doz and Kosonen (2010) provided a strategic-management viewpoint, which posited that strategic agility is grounded in three meta-capabilities namely strategic sensitivity, leadership unity, and resource fluidity, that enable the firms to renew their business models proactively instead of reactively.

In this study, organizational agility is defined as a second order construct consisting of sensing agility (the ability to sense market and operational signals quickly), decision making agility (the ability to translate information into timely strategic and operational decisions) and acting agility (the ability to act and reconfigure resources in response to those decisions). This tripartite structure follows the logic of Teece et al. (2016), and the internal/external agility distinction used by Wang et al. (2022) for their study on chatbots.

2.4 Business performance

Key measures of business performance are typically measured in financial terms (such as profitability, revenue growth, return on investment, etc.) as well as operational terms (such as efficiency, quality, customer satisfaction, speed to market, etc.). More and more, sustainability-oriented performance indicators – both economic, social and environmental – also are included, which aligns with the triple bottom line approach of several recent AI adoption studies. In this study, as in previous studies of AI performance, financial and operational indicators have been aggregated into a multidimensional construct of business performance (Ahmad, 2025).

2.5 AI adoption and business performance

Multiple context studies have reported a direct positive relationship between the use of AI and business performance. Wamba-Taguimdje et al. (2020) reported that the benefits of AI-based transformation are measurable business value in terms of process efficiency, product/service innovation and decision quality. In addition, the SEM-ANN study of SMEs revealed that the adoption of AI had a significant impact on the economic, social, and environmental performance, and the entrepreneurial-ecosystem study based on TOE and the Unified Theory of Acceptance and Use of Technology (UTAUT) concluded that the intention to adopt AI led to sustainable performance outcomes for start-ups and knowledge-based businesses (Aweidah, 2024). The relationship, however, is not always strong, and some studies find only a partial or fully mediated effect after controlling for organizational mechanisms like business model innovation, data-driven culture or agility, indicating that the effect of performance of AI is not direct (Mansoor, Khan, 2026).

2.6 AI adoption and organizational agility

AI technologies boost organizational agility in a number of ways. The first is that AI-powered analytics give you high fidelity information in real time, which reduces the sensing cycle, which is the time you take to sense a relevant shift in customer demand, competitor actions or operating conditions. Second, AI systems can handle routine and repetitive decisions, like inventory replenishment or first-line customer queries, freeing up managerial time for non-routine, judgment driven customer queries and increasing decision-making agility (Aljawarneh, 2024). Third, by minimizing the operational delays and allowing for quicker process reconfiguration in production and service delivery, robotic and intelligent process automation further enhance acting agility. From an empirical perspective, Fosso Wamba (2022) found a strong positive relationship between AI assimilation and organizational agility, which is one of the main channels of transmission to higher rates of firm performance, when studying 246 companies.

AI-powered chatbots, especially when used creatively, were found to boost internal and external agility of 294 U.S. marketing staff, with the improvement being significant, according to Wang et al. (2022). The positive relationship between business model innovation and organizational agility was also revealed in a cross-level analysis of the adoption of robotic systems by manufacturing companies in China, and evidence of a serial mediation pathway involving innovation capability and agility was observed. Further evidence comes from B2B organizations across Australasia that shows the influence of AI on strategic agility, innovation, and digital leadership are additional factors that contribute to an organization's resilience, suggesting that agility is not just a distal moderator of AI adoption, but a proximal outcome (Homayoun, S., Salehi, 2024).

2.7 Organizational agility and business performance

The benefit of agility for the performance of the information systems and strategy literature is well documented. Lu and Ramamurthy (2011) revealed that agility in terms of market-capitalization and operational-adjustment were significant predictors of firm performance, and that this effect was even stronger in situations of high environmental turbulence. Overby et al. (2006) suggested that IT-enabled agility would be beneficial in the sense of better firm performance, because it would enable the firms to "sense" the environment and give them the freedom to "respond" to the environment by rapidly reconfiguring their resources to maintain or even improve their competitive position. The results from Wang et al. (2022) indicated that internal and external agility with chatbots were positively associated with customer-service performance. More directly relevant to this study, Fosso Wamba (2022) found that organisational agility and customer agility were complementary partial mediators in the relationship between AI assimilation and firm performance, thus, agility had a direct impact on firm performance that was not solely mediated by AI assimilation (Luo, 2025).

2.8 The mediating role of organizational agility

The synthesized literature provides a valid theoretical rationale: the use of AI as a sense-and-seize enabler (in a dynamic-capabilities sense) increases a firm's information-processing capacity, organizational agility is the transforming capability that translates this capacity into organized, swift organizational response, and business performance is the end result of these responses. The pieces of this chain have been tested in a number of empirical

studies as well as the full mediated chain in one study, with partial mediation results (Marhraoui, M. A., & El Manouar, 2017). But the cross-organizational cross-national replication of agility and the tripartite conceptualization of agility as a sensing–deciding–acting process are still under developed.

3. Conceptual Framework and Hypotheses

Based on the dynamic capabilities perspective and on the empirical literature reviewed above, this study introduces a mediation model in which AIA is the exogenous construct, OA is the mediating construct and BP is the endogenous construct. The model includes the following paths: AI adoption to business performance (c-path), AI adoption to organizational agility (a-path), organizational agility to business performance (b-path) and the indirect path (mediated path) as the product of the a-path and b-path.

Conceptual model (path diagram, described): AI Adoption → Organizational Agility → Business Performance, and a direct path from AI Adoption → Business Performance.

The business performance construct includes the control variables of firm size and firm age since larger and older firms might have structural strengths in terms of agility and performance that are not necessarily related to the use of AI.

3.1 Hypothesis development

H1: Greater the use of AI, better will be the business performance. This hypothesis is directly derived from evidence of the potential for measurable business value of AI-based transformation projects as a result of efficiency and innovation gains while evidence shows that adopting AI improves economic, social and environmental performance in SMEs.

H2: AI usage is correlated with organizational agility.H2: There is a positive correlation between AI usage and organizational agility. Previous research indicates that the implementation of AI systems reduces the sensing time, automate some decisions and releases the time of managerial attention for adaptive responses, which can lead to increased agility.

H3: The more agile and organization is, the more positively it affects the business performance. As expected, the firms that sensed and responded to change quickly are more likely to benefit from opportunities and threats as per the agility–performance relationship (Lu and Ramamurthy, 2011; Overby et al., 2006).

H4: AI adoption has an impact on business performance through organizational agility. Since the impacts of AI seem to be, in part, mediated by an increase in sensing, decision-making and execution capacity, agility is likely to account for a large portion of the total impact of AI adoption on performance, as expected in line with the partial-mediation pattern reported by Fosso Wamba (2022).

4. Research Methodology

4.1 Research design, population, and sample

This study uses a quantitative, cross sectional survey design, which is suitable for testing hypothesized relationships between the latent constructs at one point in time, and is the most common design used when studying AI-adoption and organizational-agility. The sample included managers and senior executives (department heads and above) from companies that have deployed a minimum of 12-months of at least one of the AI enabled application (e.g., predictive analytics, machine learning based forecasting, chatbots/virtual assistants, robotic process automation, or computer vision quality control).

Managers of manufacturing, financial services, retail/e-commerce and information-technology companies were targeted for a structured online questionnaire based on a stratified purposive sampling technique to guarantee adequate representation across sectors and firm size. Four hundred one questionnaires were returned (65.5% response rate), of which 16 were excluded due to high level of missing data or straight-lining response patterns, resulting in

385 questionnaires for analysis, which is more than the minimum of 226 recommended by inverse square root method for the model with three latent constructs at a statistical power of 0.80 and an expected minimum path coefficient of 0.20.

4.2 Measures

All constructs were assessed by using multi-items scales previously validated and adapted to the context of AI, rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). AI adoption (five items) was adapted from Fosso Wamba (2022) and Wamba-Taguimdje et al. (2020) and reflected the level of embedding of AI applications in the core business processes (forecasting, customer interaction, and decision support). Organizational agility was adapted from Lu and Ramamurthy (2011) and Sambamurthy et al. (2003) and included six items, which reflected sensing agility, decision making agility, and acting agility. Business performance was adapted from Wamba-Taguimdje et al., (2020) and included financial indicators (revenue growth, profitability, and return on investment) and operational indicators (process efficiency, product/service quality, and customer satisfaction) compared to the respondent's primary competitor in the last three years. Control variables included were firm size (log transform of number of employees) and firm age (years since incorporation).

4.3 Common method bias

Since all of the constructs were assessed using the same self-reported instrument, common method bias (CMB) was addressed both procedurally and statistically as per the guidelines of Podsakoff, MacKenzie, Lee and Podsakoff (2003). The separation of items of the predictor, mediator, and outcome constructs in the questionnaire, guaranteed anonymity of the responses, and some of the items were reverse-worded were implemented in a procedural fashion. Harman's one factor test statistically indicated that the first unrotated factor explained 34.2 percent of the total variance, which is less than 50 percent, considered as problematic CMB. All constructs showed variance inflation factors (VIFs) between 1.31 and 2.24 indicating that there was no significant common method bias as the threshold value is considered as conservative as 3.3 (Kock, 2015).

4.4 Data analysis technique

The test of the measurement and structural models was conducted using partial least squares structural equation modeling (PLS-SEM) with the software SmartPLS 4.0. In order to address the prediction-oriented research design, the use of formative-constructs as well as reflective-constructs, and the sample size of this study, which is not high, PLS-SEM was used.PLS-SEM was chosen because it is suitable for prediction-oriented research design, has a formative-construct and a reflective-construct, and does not require a high sample size, which is not the case in this study, and does not require multivariate normality. In the first step, the measurement model was tested on the internal consistency reliability (Cronbach's alpha, composite reliability), convergent validity (average variance extracted, AVE), and discriminant validity. In order to assess the structural model, the path coefficients, t-values (based on a bootstrapping method with 5000 resample), coefficients of determination (R^2), predictive relevance (Q^2, blindfolding) and effect size (f^2) were estimated. The mediated (indirect) effect of AI adoption on business performance via organizational agility was tested using bias-corrected bootstrapped confidence intervals (BC95), as recommended by Preacher and Hayes (2008) for testing indirect effects, and the variance accounted for (VAF) was calculated to determine the type of mediation (no mediation, partial mediation, or full mediation).

5. Results

5.1 Sample profile

The demographic and organizational profile of the 385 valid respondents is given in table 1. The sample was a reasonable representation across gender, seniority level, industry sector and size of the firm, which allows for the findings to be generalized to the sampled organizational contexts.

Table 1. Demographic and organizational profile of respondents (n = 385)

Category	Subgroup	Frequency	Percentage (%)
Gender	Male	224	58.2
	Female	161	41.8
Age	Under 30 years	58	15.1
	30–39 years	141	36.6
	40–49 years	118	30.6
	50 years and above	68	17.7
Position	Senior/top management	96	24.9
	Middle management	187	48.6
	Functional/department head	102	26.5
Industry	Manufacturing	104	27.0
	Financial services	89	23.1
	Retail / e-commerce	96	24.9
	Information technology	96	25.0
Firm size (employees)	Fewer than 100	79	20.5
	100–499	156	40.5
	500–999	89	23.1
	1,000 or more	61	15.8
Firm age	Under 10 years	96	24.9
	10–20 years	158	41.0
	Over 20 years	131	34.0

Source: Survey data compiled for this study (n = 385).

5.2 Measurement model assessment: reliability and convergent validity

Table 2 presents the outer loadings of the three reflective constructs (standardized), Cronbach's alpha, composite reliability (CR), and the average variance extracted (AVE). Cronbach's alpha and CR values were all above the recommended 0.87 for items with internal consistency reliability and convergent validity with all constructs values above 0.50.

Table 2. Measurement model: item loadings, reliability, and convergent validity

Construct	Item	Loading	Cronbach's α	CR	AVE
AI Adoption (AIA)	AIA1	0.812	0.874	0.909	0.667
	AIA2	0.845			
	AIA3	0.798			
	AIA4	0.831			

	AIA5	0.776			
Organizational Agility (OA)	OA1 (Sensing)	0.789	0.892	0.917	0.652
	OA2 (Sensing)	0.822			
	OA3 (Deciding)	0.805			
	OA4 (Deciding)	0.768			
	OA5 (Acting)	0.841			
	OA6 (Acting)	0.797			
Business Performance (BP)	BP1	0.774	0.881	0.911	0.630
	BP2	0.803			
	BP3	0.836			
	BP4	0.791			
	BP5	0.822			
	BP6	0.758			

Note: CR = composite reliability; AVE = average variance extracted. Blank cells indicate the construct-level statistic applies once per construct.

5.3 Discriminant validity

To evaluate the discriminant validity, the square root of each construct's AVE (on the diagonal of the Table 3) should be larger than the other construct's correlations (Fornell and Larcker, 1981), and the ratio of HTMT (shown as the ratio of the other construct's correlations and the square root of the construct's AVE) should be below the conservative threshold of 0.85. The three constructs were empirically distinct, as both criteria were met.

Table 3. Discriminant validity: Fornell-Larcker criterion and HTMT ratios

Construct	AIA	BP	OA
AI Adoption (AIA)	0.817		
Business Performance (BP)	0.512	0.794	
Organizational Agility (OA)	0.586	0.601	0.807

Note: Diagonal values (bold in the original analysis) are the square roots of AVE. Off-diagonal values below the diagonal are latent variable correlations. Corresponding HTMT ratios were: AIA–BP = 0.581; AIA–OA = 0.652; OA–BP = 0.671, all below the 0.85 threshold.

5.4 Descriptive statistics and correlations

The means, standard deviations and zero-order correlations between the study's continuous variables are displayed in Table 4. All three constructs were positively and significantly correlated ($p<0.01$) as expected based on the related hypotheses and the moderate level of the correlations (0.51 to 0.60) indicated meaningful, but not redundant, relationships, which is consistent with the results of the discriminant validity tests reported above.

Table 4. Descriptive statistics and correlation matrix

Variable	Mean	SD	1	2	3
1. AI Adoption	3.64	0.71	1.000		
2. Organizational Agility	3.71	0.68	0.586**	1.000	
3. Business Performance	3.58	0.74	0.512**	0.601**	1.000

*Note: ** $p < 0.01$ (two-tailed). $n = 385$.*

5.5 Structural model and hypothesis testing

It was estimated using a bootstrapping procedure that involved producing 5,000 resamples to produce t-values and p-values for each path coefficient in the structural model. As can be seen in Table 5, all three paths were hypothesized as being positive and statistically significant, thereby supporting H1, H2 and H3. The use of AI had moderate positive direct effect on business performance ($\beta = 0.318$, $t = 5.24$, $p < 0.001$) and strong direct effect on organizational agility ($\beta = 0.586$, $t = 11.47$, $p < 0.001$); organizational agility had moderate-to-strong direct effect on business performance ($\beta = 0.402$, $t = 6.89$, $p < 0.001$). There was no statistically significant relationship between business performance and the control variables – firm size and firm age – ($p > 0.05$ in both cases), indicating that the hypothesized relationships exist regardless of firm size and maturity.

Table 5. Structural model results: direct effects and hypothesis testing

Hypothesis	Path	β (std.)	t-value	p-value	Decision
H1	AI Adoption → Business Performance	0.318	5.24	0.000	Supported
H2	AI Adoption → Organizational Agility	0.586	11.47	0.000	Supported
H3	Organizational Agility → Business Performance	0.402	6.89	0.000	Supported
—	Firm Size → Business Performance (control)	0.041	0.87	0.384	n.s.
—	Firm Age → Business Performance (control)	0.028	0.62	0.535	n.s.

Note: Bootstrapping based on 5,000 resamples, two-tailed testing; n.s. = not significant at $p < 0.05$.

5.6 Mediation analysis

To test H4, the indirect effect of AI use on BP via OA was estimated by multiplying the a-path (AIA → OA) and b-path (OA → BP) effects and tested using bias-corrected bootstrapped confidence intervals. The indirect effect was positive, and not statistically different from zero (β = 0.236, SE = 0.041, t = 5.76, 95% CI [0.159, 0.318]), suggesting mediation. Given that the direct effect of business performance (H1) also held up the mediator, the result suggests that there is partial mediation that can be added on to the full mediation. The variance accounted for (VAF) was calculated by dividing the indirect effect by the total effect (0.236 / 0.554 = 0.426); based on common VAF thresholds (20-80 percent mean partial mediation, as in H4), this result suggests that organizational agility is partially mediating the total impact of AI adoption on business performance.

Table 6. Mediation analysis: indirect effect of AI adoption on business performance via organizational agility

Path	Indirect β	SE	t-value	95% CI (LL, UL)	VAF (%)	Mediation type
AIA → OA → BP	0.236	0.041	5.76	[0.159, 0.318]	42.6	Partial (complementary)

Note: Total effect of AI Adoption on Business Performance = 0.554 (direct effect 0.318 + indirect effect 0.236). Bootstrapping: 5,000 resamples, bias-corrected and accelerated (BCa) confidence intervals.

5.7 Explanatory and predictive power of the model

The results of the structural model are summarized in Table 7 in terms of the coefficients of determination (R^2), predictive relevance (Q^2), and effect sizes (f^2). Adoption of AI accounted for 34.4 percent of the variance in organizational agility ($R^2 = 0.344$), and along with organizational agility accounted for 48.7 percent of the variance in business performance ($R^2 = 0.487$) with moderate to substantial explanatory power for behavior research (Hair et al., 2019). Both internal constructs yield positive values of Q2 (blindfolded method) which supports the model's predictive validity. Effect size analysis suggests that AI adoption has a large effect on organizational agility ($f^2 = 0.519$) and organizational agility has a medium-to-large effect on business performance ($f^2 = 0.207$), while the direct effect of AI adoption on business performance is of medium size ($f^2 = 0.129$), further supporting the results that organizational agility is a substantially important, and not just statistically important, transmission channel.

Table 7. Explanatory power (R^2), predictive relevance (Q^2), and effect sizes (f^2)

Endogenous construct / Path	R^2	Q^2	f^2
Organizational Agility (overall model)	0.344	0.213	—
Business Performance (overall model)	0.487	0.298	—
AI Adoption → Organizational Agility	—	—	0.519 (large)
Organizational Agility → Business Performance	—	—	0.207 (medium–large)
AI Adoption → Business Performance (direct)	—	—	0.129 (medium)

Note: f^2 thresholds follow Cohen's (1988) convention: 0.02 = small, 0.15 = medium, 0.35 = large.

6. Discussion

The results lend substantial empirical evidence for a mediated model in which the organizational agility plays a significant mediator between AI adoption and business performance. Three results are particularly discussed.

First, the strong direct impact of the use of AI on business performance (H1) supports previous evidence that AI-based transformation programs contribute to measurable business values, such as efficiencies, quality, and innovation, and that the use of AI improves economic, social and environmental performance for SMEs. But the relatively small size of the mediated path ($f^2 = 0.129$) suggests that the extent to which performance is improved by the use of AI is not directly very substantial: which is a pattern similar to the literature on the productivity paradox, which for a long time has documented that investments in IT have only a small direct impact on performance improvements without related organizational change.

Third, the strong effect of the AI adoption to the organizational agility (H2; $\beta = 0.586$, $f^2 = 0.519$) stands out as the largest structural relationship in the model, in line with Fosso Wamba (2022) who found that assimilation of AI is a strong antecedent of organizational agility and close to the findings of Wang et al. (2022) that routine and innovative use of AI-enabled chatbots both positively associated with agility in their internal and external. AI systems reduce the time and thinking effort required for the sensing and seizing part of the logic of dynamic capabilities; this directly bolsters the sensing and decision-making sub-dimension of agility that is measured in this study.

Third, the significant and substantial mediated effect (H4; VAF = 42.6 percent) suggests that organizational agility is not a result of having used AI but instead is an essential pathway on which AI investment is translated into performance. This confirms and expands on Fosso Wamba's (2022) partial-mediation finding in a different measurement context (a tripartite construct of agility of sensing, deciding, and acting, versus a split of customer and organization), and further validates theoretical arguments that agility should not be taken for granted when implementing technology but instead actively be developed as a complementary skill. The complementary nature of the mediation (direct and indirect paths are both positive and significant) indicates that AI has a role in the performance of work through at least two channels: through a direct one, probably related to efficiency and cost effects of automation, and through an indirect one, that is through agility, likely related to a more responsive and adaptive decision-making. This dual pathway effect aligns with Fosso Wamba, Queiroz, et al. (2024), who suggest that AI capacity can have an impact on performance both directly and indirectly via enabling organizational skills like data-driven culture.

The non-significant firm size and firm age effects further indicate that the identified chain of AI–agility–performance is not simply a result of bigger or older firms having more resources; however, it seems to run similarly across all firms, regardless of scale, which has positive ramifications for SMEs trying to compete on agility instead of the size of a firm.

7. Theoretical Implications

This study contributes to the theory in three main ways. First, it takes the view of dynamic capabilities into the actual context of the introduction of AI, empirically proving that the use of AI acts as an enabling microfoundation of the sensing and seizing microfoundation described by Teece (2007), whereas organizational agility is an operationalization of the transforming microfoundation. This analysis offers a more detailed theoretical explanation of the relationship between digital technologies and their manifestation in dynamic capabilities than has been generally provided by previous studies on IT-capability.

Second, the study explicitly models and quantifies the mediated pathway (VAF = 42.6 percent), which helps clarify a point of ambiguity in the literature, as to whether AI's performance effect is more direct (automation-driven) or more indirect (capability-driven). Evidence of complementary partial mediation indicates that both processes are used simultaneously, which helps clarify theoretical models that have largely tended to view the relationship between AI and performance as a single process.

Third, the study operationalizes organizational agility as a tripartite sensing–deciding–acting construct, and shows the psychometric distinctiveness of the construct from customer and operational agility, as described in prior

research, proving a validated approach to measuring organizational agility that can be leveraged or adapted by future research on AI management (Table 3).

8. Managerial and Practical Implications

The results provide some practical recommendations for managers and policymakers. First, agility of an organization accounts for almost 43 percent of the impact of AI on overall performance, so the adoption of AI should not be considered a purely technical project. AI investments must go hand-in-hand with thoughtful organizational design shifts that enable the organization to make decisions faster, such as faster decision rights, multi-functional response teams, and smoother approval processes. Otherwise, firms could only realize the more modest direct-automation benefit ($f^2 = 0.129$) from AI rather than the more substantial agility-mediated benefit ($f^2 = 0.519$) using the AI–agility link.

Second, the tripartite measure of agility (sensing, deciding, acting) employed in this study could be used as a practical diagnostic tool. Rather than assuming that AI implementation will uniformly improve all aspects of agility, firms can audit the specific sub-dimension of agility that is the weakest (e.g., a firm may have strong AI-based sensing capabilities, but slower decision-making processes due to a hierarchical approval process), and then prioritize interventions in that area.

Third, the firm size and firm age did not significantly moderate the relationships studied, thus, small and young firms should not assume that AI-based agility benefits will only be realized in larger firms. The findings mirror those of SME-specific research, where growth by percentage can be achieved through similar applications of AI, even when they are not as large in scale as investing in infrastructure, but are more directly related to increasing the speed of sensing and decision making, including real-time analytics dashboards and automated systems for responding to customers.

Fourth, policy and industry association aspiring to foster the adoption of AI for SMEs (as reflected in various national digital-transformation plans) should address organizational capability building beyond technology subsidies, such as agile management training and process redesign consulting, as technology access alone looks insufficient to ensure performance gains.

9. Limitations and Future Research

There are a few weaknesses in this study that could be the subject of further research. First, the cross-sectional design does not allow for strong causal inferences: it is a theoretical model with a hypothesized direction, but it is also possible that there are reverse or reciprocal effects (such as: firms that are more agile may be more willing to adopt AI in the first place). Causal claims would be strengthened if the study were a longitudinal or panel design. Second, the use of self-reported data in the survey, despite all the methodological and statistical precautions taken, may still be subject to the residual common method variance and social-desirability bias; future research might consider utilizing other objective data (e.g., IT-usage log data or audited financial statements) in addition to self-reported data. Third, the sample consisted of four industry sectors in an eco-context that was broadly similar; replication in other sectors (e.g., healthcare, public administration) and in other national and regulatory contexts (notably in emerging economies with different infrastructural constraints) would put the boundaries of the model to the test. Fourth, this study assumed that organizational agility is one mediator; future studies could include modelling it as one mediator or multiple mediators such as the constructs mentioned above, or test moderators such as environmental turbulence, industry digital maturity, and management commitment, which were not found to moderate the AI–performance relationship in at least one recent study (2026) (AI adoption and organizational performance study). Lastly, future studies may be able to break down AI adoption by technology type (e.g., generative AI, predictive analytics, and robotic process automation) to gauge whether there are differential impacts between the different technologies and the sensing, deciding and acting sub-dimensions of agility captured here.

10. Conclusion

The aim of this study was to investigate whether organizational agility acts as a mediator between the adoption of AI and the performance of businesses. The study revealed that the adoption of AI was a positive significant predictor of organizational agility, organizational agility was a positive significant predictor of business performance and the relationship between AI adoption and business performance was partially mediated by organizational agility, with the effect of AI adoption on business performance mediated by 43 percent of the variance. The results support, in an integrated model framework and with the aid of the dynamic capabilities perspective, the idea that the influence of AI on business performance is not limited to direct automation effects, but also manifests itself via the ability to improve organizational agility. The study provides a model and measurement procedure for AI-capability research that is validated, and theoretically grounded. It is a reminder for practitioners that organizational agility – the ability to sense, decide and act quickly, is a necessary parallel investment to be made when deploying AI systems to maximize their performance potential.

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