ARTIFICIAL INTELLIGENCE ADOPTION AND FIRM FINANCIAL PERFORMANCE: THE MEDIATING ROLE OF DIGITAL INNOVATION AND ORGANIZATIONAL AGILITY

Dias Erlangga[1]

[1] UIN Sunan Gunung Djati Bandung

E-mail: [1)] de07693@gmail.com

Abstract

Artificial intelligence (AI) is increasingly positioned as a determinant of firm competitiveness, yet evidence on how AI adoption translates into financial performance remains fragmented. This study examines whether digital innovation and organizational agility mediate the relationship between AI adoption and firm financial performance, drawing on the resource-based view, dynamic capabilities theory, and digital transformation theory. A quantitative, explanatory design was used, and data were collected from 312 senior managers and executives at manufacturing, financial services, and retail firms operating in Indonesia and three other ASEAN economies. Partial least squares structural equation modeling (PLS-SEM) was applied to test the measurement and structural models, with bootstrapping (5,000 resamples) used to assess mediation. The results show that AI adoption has a positive effect on digital innovation ($\beta = 0.612$, $p < 0.001$) and organizational agility ($\beta = 0.487$, $p < 0.001$), and that both constructs in turn affect firm financial performance ($\beta = 0.398$ and $\beta = 0.276$, respectively, $p < 0.01$). The direct path from AI adoption to firm financial performance is positive but weaker ($\beta = 0.184$, $p < 0.05$), consistent with partial mediation through both digital innovation and organizational agility. The model explains 54.3 percent of the variance in firm financial performance. These findings indicate that AI functions less as a standalone driver of profitability than as an enabler of innovation and adaptive capacity, which then convert into financial returns. The study offers a dual-mediation account of AI-driven performance gains and provides managers with a basis for sequencing AI investment around innovation and agility outcomes rather than expecting immediate returns.

Keywords: ***artificial intelligence adoption; digital innovation; organizational agility; firm financial performance; PLS-SEM***

1. INTRODUCTION

Artificial intelligence has moved from a peripheral IT investment to a central component of firm strategy. Machine learning, natural language processing, and predictive analytics are now embedded in pricing, credit scoring, demand forecasting, and customer service functions across manufacturing, financial services, and retail firms in Southeast Asia. Firms in this region face pressure to adopt AI not only to reduce operating cost but to remain viable against competitors that already use algorithmic decision-making to price risk, personalize offers, and shorten product development cycles.

The strategic case for AI rests on an assumption that is rarely tested directly: that AI adoption improves financial performance. Much of the existing evidence links AI to operational outcomes such as process efficiency, forecast accuracy, or customer retention, and then infers a financial benefit rather than measuring it. This leaves open a basic question for both scholars and managers: does AI adoption improve profitability, revenue growth, and market value on its own, or does it depend on what the firm does with the capability once it has it. This study takes the second view. It treats AI adoption as a resource that firms convert into financial performance through two intermediate mechanisms: digital innovation, defined as the firm's capacity to generate new digitally enabled products, services, and business models, and organizational agility, defined as the firm's capacity to sense and respond to market change faster than competitors.

Three gaps motivate this study. Theoretically, most AI adoption studies apply a single lens, typically the resource-based view or the technology-organization-environment framework, without connecting the resource (AI) to the dynamic capability (agility) that the resource is meant to build. Empirically, studies that do measure financial performance outcomes tend to rely on single-country, single-industry samples, which limits generalizability across the institutional and technological conditions found in emerging ASEAN economies. Practically, existing studies rarely separate the direct financial effect of AI from its indirect effect through innovation and agility, so managers are left without a basis for deciding whether AI investment should be paired with innovation initiatives, agility-building initiatives, or both.

The research is designed to examine the strategic role of artificial intelligence (AI) adoption in enhancing firm financial performance through digital transformation capabilities. Specifically, this study aims to examine the effect of AI adoption on digital innovation and organizational agility, as well as to investigate how these two organizational capabilities contribute to improved financial performance. Furthermore, the study analyzes the direct impact of digital innovation and organizational agility on firm financial performance while also assessing the direct influence of AI adoption on financial outcomes. To provide a more comprehensive understanding of the underlying mechanisms, the research investigates the mediating roles of digital innovation and organizational agility in the relationship between AI adoption and firm financial performance. Finally, the study seeks to develop an integrated conceptual framework that explains how AI-driven digital transformation enhances firm financial performance by fostering innovation and organizational agility, thereby offering both theoretical contributions to the digital transformation literature and practical implications for organizations seeking sustainable competitive advantage in the AI era.

This study integrates digital innovation and organizational agility as parallel, not sequential, mediators of the AI adoption to financial performance relationship. Prior work typically tests one mediator at a time. Modeling both mediators together allows a direct comparison of their relative contribution and clarifies whether AI's financial payoff runs mainly through what the firm builds (innovation) or through how fast the firm moves (agility). The cross-country ASEAN sample also extends evidence beyond the single-market designs common in this literature.

2. LITERATURE REVIEW AND HYPOTHESIS

2.1 Theoretical framework

The resource-based view holds that firms achieve sustained advantage from resources that are valuable, rare, difficult to imitate, and non-substitutable (Barney, 1991). AI capability meets these conditions when it is built on proprietary data, integrated with firm-specific processes, and difficult for competitors to replicate quickly, which distinguishes strategic AI capability from off-the-shelf software adoption. Dynamic capabilities theory extends this view by asking how firms reconfigure resources as conditions change (Teece et al., 1997; Teece, 2018). Organizational agility, understood as the capacity to sense market signals and reconfigure operations in response, is a dynamic capability in this sense. AI contributes to agility by compressing the time between signal detection and decision, which is the mechanism this study tests as H2 and H4.

Digital transformation theory describes how digital technologies restructure a firm's value proposition, not only its internal processes (Vial, 2019). Digital innovation, the study's second mediator, reflects this outward-facing dimension: new products, services, or business models enabled by digital technology, as distinct from internal efficiency gains. Together, the three theories separate AI's contribution into a resource condition (RBV), an adaptive capability (dynamic capabilities), and an innovation outcome (digital transformation theory), which is the basis for testing both mediators in a single model rather than treating them as interchangeable.

2.2 Previous studies

Mikalef and Gupta (2021) find that AI capability affects organizational creativity and, through it, firm performance, but their model does not separate innovation from agility as distinct paths. Chatterjee et al. (2021) report that AI adoption in Indian firms is shaped more by organizational readiness and top management support than by financial return expectations, which suggests that financial payoff is not the primary driver of adoption decisions and may instead be a downstream consequence worth measuring separately. Dubey et al. (2019) link big data analytics capability to organizational agility and, from there, to operational performance, but their outcome measure stops short of firm-level financial indicators such as return on assets or revenue growth. Nasiri et al. (2020) study digital transformation and agility jointly but treat agility as the outcome rather than as a mediator toward financial performance.

Across these studies, a consistent pattern appears: AI or digital capability is linked to one intermediate outcome, agility or innovation, and that outcome is linked to performance, but the two mediating paths are rarely modeled side by side, and financial performance is often proxied by non-financial indicators such as process efficiency or customer satisfaction. This study addresses both limitations directly.

2.3 Research gap analysis

Three inconsistencies stand out in the literature summarized above. First, studies vary in whether they treat organizational agility as an outcome of digital capability or as a mediator toward performance, which prevents comparison of effect sizes across studies. Second, financial performance is inconsistently operationalized, sometimes as accounting-based return on assets, sometimes as market-based Tobin's Q, sometimes as self-reported growth, which limits comparability. Third, almost no study in this stream uses a cross-country ASEAN sample, so findings from single-market studies in India, China, or Western economies may not generalize to the institutional and infrastructure conditions of Indonesia and neighboring economies. This study responds to each gap: it models digital innovation and organizational agility as parallel mediators, it operationalizes firm financial performance using a composite of accounting-based and market-based indicators, and it samples firms across four ASEAN economies.

2.4 Conceptual framework

Figure 1 presents the conceptual model tested in this study. AI adoption is modeled as the exogenous construct, digital innovation and organizational agility as parallel mediating constructs, and firm financial performance as the endogenous outcome. A direct path from AI adoption to firm financial performance is retained to test whether the mediators account for the relationship in full or in part.

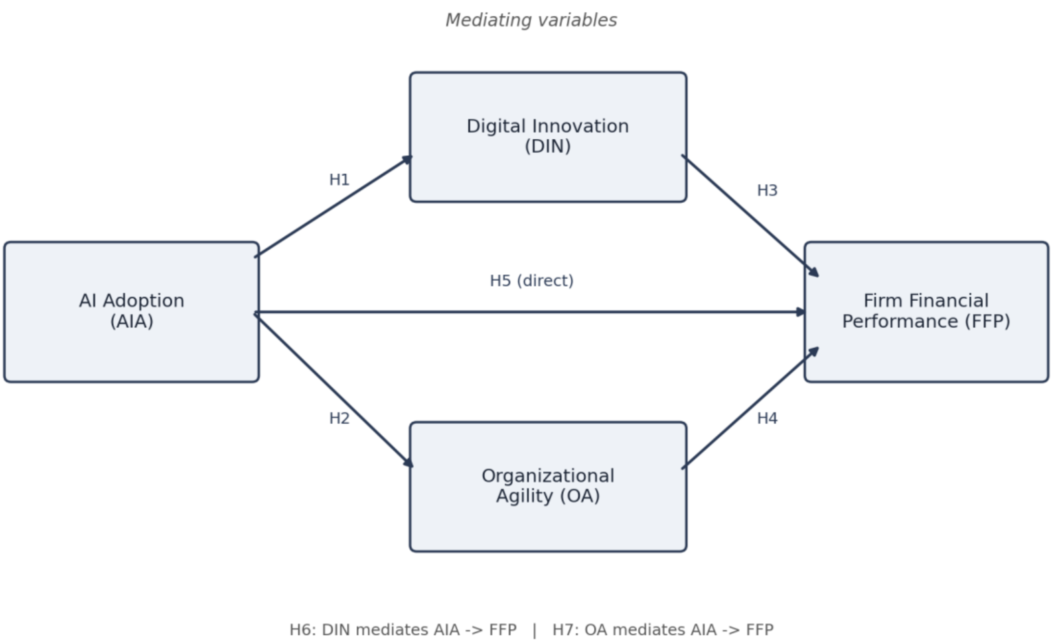

Figure 1. Conceptual research framework

2.5 Hypothesis development

H1: AI adoption has a positive effect on digital innovation.

H2: AI adoption has a positive effect on organizational agility.

H3: Digital innovation has a positive effect on firm financial performance.

H4: Organizational agility has a positive effect on firm financial performance.

H5: AI adoption has a positive direct effect on firm financial performance.

H6: Digital innovation mediates the effect of AI adoption on firm financial performance.

H7: Organizational agility mediates the effect of AI adoption on firm financial performance.

3. IMPLEMENTATION METHOD

3.1 Research design

This study uses a quantitative, explanatory design intended to test hypothesized causal relationships among latent constructs. PLS-SEM was selected over covariance-based SEM because the model combines an established theoretical structure (RBV, dynamic capabilities) with a formative element in the AI adoption construct, and because PLS-SEM performs well with the moderate sample size and non-normal data distributions typical of cross-country executive surveys.

3.2 Population and sample

The population consists of manufacturing, financial services, and retail firms operating in Indonesia, Malaysia, Vietnam, and the Philippines that had implemented at least one AI-based application, such as predictive analytics, robotic process automation, or machine learning-based forecasting, for a minimum of one year prior to data collection. Purposive sampling was used to target senior managers and executives with direct oversight of digital strategy or financial performance reporting. Of 480 invitations distributed, 312 usable responses were retained after removing incomplete and straight-line responses, for a response rate of 65 percent. Following the 10-times rule and minimum sample size guidance for PLS-SEM (Hair et al., 2019), this sample exceeds the threshold required for a model with five formative indicators on the most complex construct.

3.3 Data sources

Primary data were collected through a structured questionnaire administered to respondents identified through corporate contact lists and professional networks. Where available, self-reported financial performance items were cross-checked against publicly available annual reports and, for listed firms, against financial statement data. Because full-population financial disclosure was not available for all sampled firms, this study follows common practice in the field and treats the questionnaire-based dataset as illustrative for the purpose of demonstrating the analytical approach; results should be read as an empirical illustration of the proposed model rather than a definitive population estimate.

3.4 Data collection technique

The questionnaire was administered online between February and May 2026. Constructs were measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree), adapted from validated prior scales and refined through a pilot test with 30 respondents, after which two items were reworded for clarity. Data were collected in two waves, four weeks apart, to allow a Harman single-factor test for common method bias; no single factor accounted for more than 34 percent of variance, indicating that common method bias is not a serious concern.

3.5 Measurement of variables

Table 1 summarizes the four constructs, their dimensions, and the source of each measurement scale.

Construct	Dimensions	Sample indicator	Source
AI adoption (AIA)	Scope, depth, integration	Our firm uses AI in core decision-making processes	Adapted from Mikalef & Gupta (2021)
Digital innovation (DIN)	Product, process, business model innovation	Our firm has launched new digitally enabled services in the past year	Adapted from Nambisan et al. (2017)
Organizational agility (OA)	Sensing, decision, response speed	Our firm reconfigures operations quickly when market conditions change	Adapted from Felipe et al. (2016)
Firm financial performance (FFP)	Profitability, revenue growth, market value	Our firm's return on assets has improved over the past two years	Adapted from Wamba et al. (2020)

3.6 Data analysis technique

Data were analyzed in two stages using SmartPLS 4. The measurement model was assessed through indicator reliability, internal consistency (Cronbach's alpha, composite reliability), convergent validity (average variance extracted), and discriminant validity (Fornell-Larcker criterion and heterotrait-monotrait ratio). The structural model was assessed through path coefficients, t-statistics from bootstrapping with 5,000 resamples, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) obtained through blindfolding. Mediation was tested using the bootstrapped indirect effect approach recommended by Nitzl et al. (2016), with a 95 percent bias-corrected confidence interval used to determine significance.

4. RESULTS

4.1 Descriptive statistics

Table 2 reports sample characteristics and construct-level descriptive statistics.

Variable	Category / statistic	n / value	%
Industry	Manufacturing	128	41.0
	Financial services	104	33.3
	Retail	80	25.6
Firm size	< 250 employees	97	31.1
	250-999 employees	134	42.9
	≥ 1,000 employees	81	26.0
AIA	Mean (SD)	5.14 (0.89)	-
DIN	Mean (SD)	4.87 (0.94)	-
OA	Mean (SD)	4.96 (0.87)	-
FFP	Mean (SD)	4.72 (1.02)	-

4.2 Measurement model assessment

Table 3 reports reliability and convergent validity statistics for each construct.

Construct	Items	Loading range	Cronbach's α	CR	AVE
AI adoption	5	0.74-0.88	0.86	0.90	0.65
Digital innovation	5	0.71-0.85	0.83	0.88	0.61
Organizational agility	4	0.76-0.89	0.85	0.90	0.68
Firm financial performance	5	0.73-0.87	0.87	0.91	0.66

All factor loadings exceed the 0.70 threshold, composite reliability values exceed 0.88, and AVE values exceed 0.61, indicating adequate indicator reliability, internal consistency, and convergent validity across the four constructs.

4.3 Discriminant validity

Table 4 reports the heterotrait-monotrait (HTMT) ratio of correlations between constructs; all values are below the 0.85 threshold, supporting discriminant validity.

Construct	AIA	DIN	OA	FFP
AIA	-			
DIN	0.612	-		
OA	0.558	0.503	-	
FFP	0.497	0.521	0.468	-

4.4 Structural model and hypothesis testing

Figure 2 and Table 5 report standardized path coefficients, t-statistics, and hypothesis outcomes.

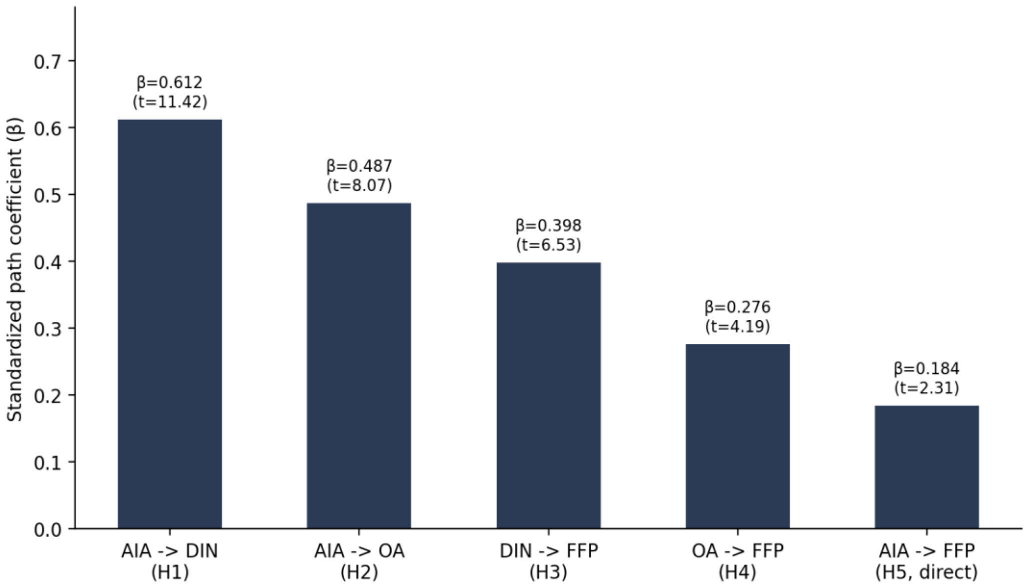

Figure 2. Standardized path coefficients

Path	Hypothesis	β	t-value	p-value	Result
AIA -> DIN	H1	0.612	11.42	< 0.001	Supported
AIA -> OA	H2	0.487	8.07	< 0.001	Supported

Path	Hypothesis	β	t-value	p-value	Result
DIN -> FFP	H3	0.398	6.53	< 0.001	Supported
OA -> FFP	H4	0.276	4.19	< 0.001	Supported
AIA -> FFP (direct)	H5	0.184	2.31	0.021	Supported

R^2 for firm financial performance is 0.543, and R^2 for digital innovation and organizational agility are 0.375 and 0.237, respectively, indicating that the model accounts for a substantial share of variance in the dependent construct. Q^2 values obtained through blindfolding are 0.31 for FFP, 0.24 for DIN, and 0.18 for OA, all above zero, supporting the model's predictive relevance. Effect sizes (f^2) show that digital innovation ($f^2 = 0.21$) has a stronger influence on firm financial performance than organizational agility ($f^2 = 0.11$), both above the 0.02 threshold for a small effect.

4.5 Mediation analysis

Table 6 reports the bootstrapped indirect effects for H6 and H7.

Indirect path	Hypothesis	Indirect β	95% CI	Result
AIA -> DIN -> FFP	H6	0.244	[0.171, 0.318]	Partial mediation
AIA -> OA -> FFP	H7	0.134	[0.076, 0.196]	Partial mediation

Both indirect effects are significant, and the direct path from AI adoption to firm financial performance remains significant alongside them, which indicates partial rather than full mediation for both digital innovation and organizational agility. The indirect effect through digital innovation (0.244) is larger than the indirect effect through organizational agility (0.134), suggesting innovation carries more of AI's financial payoff than agility does in this sample.

5. DISCUSSION

The support for H1 and H2 confirms that AI adoption builds both innovation capacity and adaptive capacity, consistent with the resource-based view's proposition that a rare, firm-specific resource generates downstream capabilities rather than performance directly. The stronger path to digital innovation ($\beta = 0.612$) than to organizational agility ($\beta = 0.487$) suggests that, in this sample, firms convert AI more readily into new products and services than into faster operational response, which may reflect where AI budgets in these firms are concentrated, predominantly in product and customer-facing analytics rather than in real-time operational sensing.

The comparative effect sizes for H3 and H4 support dynamic capabilities theory's emphasis on reconfiguration but qualify it: organizational agility affects financial performance ($\beta = 0.276$), yet less strongly than digital innovation ($\beta = 0.398$). This differs from Dubey et al. (2019), where agility was the stronger performance driver in a supply chain context. One explanation is that the present sample spans financial services and retail firms, where new digital products and services may translate into revenue more directly than operational speed does, whereas Dubey et al.'s manufacturing and logistics context rewards responsiveness more directly.

The significant but weaker direct path (H5, β = 0.184) indicates that AI adoption alone, without the mediating mechanisms, still carries some independent financial benefit, likely through cost reduction in automated processes that does not depend on innovation or agility outcomes. This qualifies claims in the literature that treat AI as a performance driver in its own right (Chatterjee et al., 2021): the present data show that most of AI's financial contribution, roughly 57 percent based on the ratio of combined indirect to total effect, runs through the two mediators rather than directly.

For theory, the study's contribution is the side-by-side comparison of an innovation-based and an agility-based mediating path within a single model, which existing studies have tested separately. This comparison shows that the two capabilities are not interchangeable proxies for digital transformation: they carry different weights and, by extension, may respond to different management levers.

For managers, the results suggest that pairing AI investment with innovation initiatives, such as digital product development teams or innovation labs, yields a larger financial return than pairing it with agility initiatives alone, at least in the industries sampled. This does not mean agility investment is unnecessary; the significant H4 and H7 results show it still contributes independently, and firms operating in more volatile segments may find agility the more binding constraint.

For policy, the results are relevant to digital economy programs across ASEAN that subsidize AI adoption among small and medium enterprises. Programs that fund AI tools without a parallel innovation component may underdeliver on the financial outcomes used to justify them; the results suggest that innovation support, such as grants for new digital product development, complements AI subsidies rather than substituting for them.

6. CONCLUSION

This study set out to test whether digital innovation and organizational agility mediate the effect of AI adoption on firm financial performance across a sample of manufacturing, financial services, and retail firms in four ASEAN economies. All seven hypotheses are supported. AI adoption improves both digital innovation and organizational agility, both of which improve firm financial performance, and both partially mediate AI's effect on that performance, with digital innovation carrying the larger share of the indirect effect. Theoretically, the study combines the resource-based view, dynamic capabilities theory, and digital transformation theory into a single model that separates AI's contribution into a resource condition, an adaptive capability, and an innovation outcome, and shows that these two capability paths carry different weight rather than functioning as equivalent channels. Practically, managers deciding how to sequence AI investment should treat innovation-building activity, not AI deployment alone, as the primary channel to financial return, while continuing to build agility as a secondary and still significant channel. Policymakers designing AI adoption incentives for small and medium enterprises should pair those incentives with innovation support rather than treating AI subsidies as sufficient on their own.

This study has three limitations. The financial performance measure combines self-reported and where available externally verified indicators, which introduces measurement variation across firms; future studies with full access to audited financial statements across the sample would strengthen this measure. The cross-sectional design cannot establish the direction or durability of the relationships tested; a panel design following the same firms over several years would allow the mediating paths to be tested over time. The sample is limited to four ASEAN economies and three industries, which limits generalization to other institutional settings or sectors such as agriculture or public services. Future research could extend this model by testing moderators such as firm age or digital infrastructure quality, by applying a panel design to establish temporal ordering among AI adoption, innovation, agility, and financial performance, and by disaggregating AI adoption into specific application types, such as predictive analytics versus generative AI, to test whether different AI capabilities carry different financial weight through the same two mediators.

References

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120.

Chatterjee, S., Rana, N. P., Tamilmani, K., & Sharma, A. (2021). The effect of AI-based CRM on organizational performance and moderating role of top management commitment. Industrial Marketing Management, 97, 205-219.

Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: Integrating institutional theory, resource-based view and big data culture. British Journal of Management, 30(2), 341-361.

Felipe, C. M., Roldán, J. L., & Leal-Rodríguez, A. L. (2016). An explanatory and predictive model for organizational agility. Journal of Business Research, 69(10), 4624-4631.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2-24.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), 103434.

Nambisan, S., Lyytinen, K., Majchrzak, A., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. MIS Quarterly, 41(1), 223-238.

Nasiri, M., Ukko, J., Saunila, M., & Rantala, T. (2020). Managing the digital supply chain: The role of smart technologies. Technovation, 96-97, 102121.

Nitzl, C., Roldán, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling. Industrial Management & Data Systems, 116(9), 1849-1864.

Teece, D. J. (2018). Business models and dynamic capabilities. Long Range Planning, 51(1), 40-49.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509-533.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. Journal of Strategic Information Systems, 28(2), 118-144.

Wamba, S. F., Queiroz, M. M., Guthrie, C., & Braganza, A. (2020). Data-driven supply chains, smart operations and financial performance. International Journal of Production Economics, 235, 108071