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Abstract: *This study investigates the factors influencing the intention of SMEs and startups in Vietnam to adopt smart digital financial solutions, addressing the limited empirical evidence in emerging economies. Using the TOE framework, the research applies a mixed-methods design. The qualitative phase includes expert interviews to refine measurement scales for the Vietnamese context, while the quantitative phase is based on a survey of 220 firms analyzed using SEM-PLS with SmartPLS 4.0. Findings show that all three TOE dimensions significantly affect adoption intention, with technological factors, especially cost, complexity, and compatibility, exerting the strongest influence. The study contributes by clarifying the relative importance of TOE components in SMEs and startups and provides practical implications for businesses and policymakers aiming to promote effective and sustainable adoption of digital financial solutions.*

Abstract: This study analyzes the influence of sustainability governance and digital transformation on corporate performance in Indonesia, exploring the role of business ethics as a moderating variable. The study sample includes 156 public companies listed on the Indonesia Stock Exchange (IDX) during the 2022-2023 period. Data were analyzed using panel data regression. The results reveal that sustainability governance has a positive and significant impact on improving corporate performance. Meanwhile, the influence of digital transformation on performance shows dynamic results: insignificant in the main model, but significant in the sensitivity analysis. A key finding of this study is the critical role of business ethics, which is proven to strengthen (positively moderate) the relationship between both independent variables—sustainability governance and digital transformation—on corporate performance. Further analysis shows variations between sectors. The energy sector recorded the highest sustainability governance score, driven by regulatory pressure, while the basic industry and chemical sectors excelled in adopting digital transformation, supported by the national initiative Making Indonesia 4.0. Overall, this study confirms that the strategic integration of sustainability principles, digital initiatives, and a strong ethical foundation is a determining factor in building long-term competitiveness and sustainable corporate performance.

Abstract: This study examines how Experiential Learning contributes to Employability among Indonesian university students, testing the mediating role of Digital Skill and clarifying conceptual ambiguity regarding potential moderation effects. While the direct pathway is robust, inconsistent evidence regarding psychological moderators leaves the boundary conditions of this crucial educational relationship unresolved. A cross-sectional survey of 469 Indonesian university students with internship experience was conducted, analyzed using structural equation modeling. Results show Experiential Learning significantly enhances Work Readiness directly and indirectly via Digital Skill. Crucially, the hypothesized moderating role of Self-Efficacy was not supported, and Self-Efficacy had no direct effect on Work Readiness. These findings suggest that the experiential learning pathway operates as a stable, non-conditional mechanism. The study provides clarification on the pathway's robustness, demonstrating that psychological factors may offer limited explanatory value. It highlights the need to prioritize competence-based interventions and continuous improvement of experiential learning environments to boost graduate employability

Abstract: Making effective hiring decisions remains critical for organisational competitiveness, thus requiring the identification and signalling of reliable, qualified, and suitable candidates. Human capital theory (HCT) and matching theory provide the theoretical underpinnings for this procedure by stressing the monetary worth of education, experience, and skills and the degree to which candidate traits correlate with job needs. This research utilised a machine-learning methodology to analyse principal determinants of recruitment choices. More specifically, due to the limited availability of such research in the Global South, specifically South Africa, the study utilised a validated secondary dataset from Kaggle to model the influence of various predictors: recruitment strategy, educational level, personality score, skills score, interview score, and demographic variables. Moreover, a quantitative, positivist research approach was adopted, and three machine-learning algorithms—logistic regression, a decision tree, and XGBoost—were compared to determine the strongest predictor set and model performance. Consistent with the expectations of both theoretical lenses, the findings revealed that recruitment strategy, followed by educational level and personality score, are the most influential predictors of hiring decisions, indicating that both job–candidate fit and human capital attributes significantly shape outcomes. Additionally, XGBoost outperformed the other algorithms across all evaluation metrics, demonstrating superior predictive accuracy. This study advances theoretical understanding by demonstrating how matching theory and human capital theory can be operationalised through machine-learning techniques, and pragmatically by providing human resource management (HRM) professionals with data-driven insights that enhance fair, efficient, and strategic hiring.

Abstract: Artificial Intelligence (AI) is increasingly recognized as a powerful force for change in entrepreneurship, enabling innovation through improved decision-making, greater operational effectiveness, and the creation of new business models. This study uses data from Scopus, Web of Science, and ScienceDirect, along with a systematic analysis of 78 academic articles published between 2013 and 2024. The review identifies four main thematic clusters: platform-based scaling strategies, customer integration, AI-driven entrepreneurial cognition, and innovation process efficiency. This study introduces the AI-Enabled Innovation Capabilities framework, which highlights four key dimensions: cognitive augmentation, operational intelligence, customer-centric accuracy, and scalability with ecosystem leverage. This framework shows how AI facilitates several kinds of innovation, such as strategic, product, process, and business model innovations, by offering a capability-based viewpoint that goes beyond conventional linear innovation models. By emphasizing both the revolutionary potential and the contextual challenges of AI adoption, the study adds to the literature on entrepreneurship and advocates for more investigation into the responsible and inclusive integration of AI.

Abstract: This study investigates the relationship between supply chain resilience and firm performance in food and beverage companies operating in West Java, Indonesia, in the midst of the COVID-19 pandemic and the acceleration of technological disruptions. Using a quantitative research approach, data were collected from 193 respondents representing various business scales and analyzed through a second-order conceptual model withl of likert scale questionaires forms and occured by using SMART PLS 4. The sampling method for this research was carried out using a random sampling approach. The empirical results demonstrate that supply chain resilience alone does not directly and significantly enhance firm performance. Instead, mediating variables play an essential role in linking resilience to business outcomes. Specifically, competitive advantage and digital capability emerge as significant mediators, exhibiting high and medium mediation effects, respectively. Conversely, digital innovation shows no significant influence, either directly or indirectly, on performance improvement. These findings suggest that resilient supply chains must be supported by strategic differentiation and digital competence to generate sustainable value. The study contributes to the growing body of knowledge in supply chain and strategic management by integrating resilience, competitiveness, and digital transformation within a unified framework. From a managerial perspective, the findings offer valuable insights for business leaders and policymakers to strengthen adaptive capabilities, enhance innovation readiness, and design proactive strategies to maintain competitiveness and achieve long-term business sustainability amid uncertainty and technological change.

NOTE FROM THE EDITORS

As an interdisciplinary indexed journal, *The Journal of Global Business and Technology (JGBAT)* serves academicians and practitioners in the fields of global business and technology management and their related areas. JGBAT is also an appropriate outlet for manuscripts designed to be of interest, concern, and applied value to its audience of professionals and scholars. Readers will note that our attempt to bridge the gap between theory and practice has been successful.

We cannot thank our reviewers enough for having been so professional and effective in reiterating to contributors the need to provide managerial applications of their research. As is now obvious, the majority of the articles include a section on managerial implications of research. We wish to reiterate once again our sincere thanks to JGBAT reviewers for having induced contributors to answer the "so what?" question that every *Journal of Global Business and Technology* article is required to address.

Thank you for your interest in the journal and we are looking forward to receiving your submissions. For submissions guidelines and requirements, please refer to the Manuscript Guidelines at the end of this publication.

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FACTORS INFLUENCING SMES' AND STARTUPS' INTENTION TO ADOPT SMART DIGITAL FINANCIAL SOLUTIONS: APPLYING THE TOE FRAMEWORK

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ABSTRACT

This study investigates the factors influencing the intention of SMEs and startups in Vietnam to adopt smart digital financial solutions, addressing the limited empirical evidence in emerging economies. Using the TOE framework, the research applies a mixed-methods design. The qualitative phase includes expert interviews to refine measurement scales for the Vietnamese context, while the quantitative phase is based on a survey of 220 firms analyzed using SEM-PLS with SmartPLS 4.0. Findings show that all three TOE dimensions significantly affect adoption intention, with technological factors, especially cost, complexity, and compatibility, exerting the strongest influence. The study contributes by clarifying the relative importance of TOE components in SMEs and startups and provides practical implications for businesses and policymakers aiming to promote effective and sustainable adoption of digital financial solutions.

Keywords: SMEs, startups, smart digital financial solutions, TOE framework, Vietnam

INTRODUCTION

The rapid advancement of digital technologies over the past decade has been reshaping the global financial ecosystem and transforming the way firms manage their operations. Developments in data analytics, cloud computing, process automation and open banking have accelerated the emergence of smart digital financial solutions. These tools not only help optimize cash flows and strengthen transparency, but also enhance firms' forecasting capabilities and risk management performance (Ozili, 2020). For SMEs and startups, groups that typically face constraints in capital, human resources and financial capacity, such technologies are especially crucial, as they reduce transaction costs, expand access to finance and improve operational efficiency (OECD, 2023).

Despite these benefits, the readiness and intention to adopt smart digital financial tools remain uneven across SMEs and startups. Some firms proactively pursue financial digitalization, while many others remain cautious due to limited technological infrastructure, a shortage of digitally skilled personnel or concerns about operational risks. The 2024 National Digital Transformation Report indicates that only around 35 percent of SMEs and startups in Vietnam have adopted at least some digital financial tools, and fewer than 15 percent use advanced solutions such as automated cash flow systems or predictive analytics. This highlights a clear gap between potential and actual adoption.

From an academic perspective, most studies on financial technology adoption focus on individual consumers or financial institutions, while SMEs and startups, key drivers of innovation, have not received proportional attention (Nguyen et al., 2022). Classical models such as the Technology acceptance model (TAM), the Theory of planned behavior (TPB), and the Unified theory of acceptance and use of technology (UTAUT) primarily explain behavior at the individual level, and therefore do not fully capture organizational decision making, which is shaped simultaneously by technological attributes, internal resources and competitive pressures (Baker, 2012).

In this context, the Technology Organization and Environment (TOE) framework is regarded as a suitable analytical lens for examining technology adoption at the organizational level (Tornatzky and Fleischer, 1990). TOE has been successfully applied in various domains, including e-commerce (Nguyen et al., 2022), cloud computing (Gangwar et al., 2015), blockchain (Clohessy et al., 2019) and artificial intelligence in SMEs (Badghish and Soomro, 2024). These applications demonstrate its ability to capture the full spectrum of technological characteristics, organizational readiness and environmental pressures.

However, the application of the TOE framework to examine SMEs and startups' intention to adopt smart digital financial solutions in Vietnam remains limited. Existing domestic studies mainly focus on consumer-oriented Fintech, digital banking or e-commerce, while systematic investigations of the factors influencing firms' intention to adopt smart digital financial tools are still scarce. This gap is particularly noteworthy given that Vietnam's business landscape consists of 98% SMEs and startups, yet only about 20 percent of them have access to advanced digital financial services (VCCI, 2023).

Addressing these limitations, this study makes three primary contributions. First, at the theoretical level, it extends the TOE framework into the domain of smart digital financial solutions, a context that differs from traditional IT or e-commerce adoption by involving higher financial sensitivity and regulatory exposure. By empirically comparing the relative strength of technological, organizational, and environmental dimensions, the study refines our understanding of how TOE operates under financial innovation conditions in emerging markets. Second, at the contextual level, it provides rare empirical evidence from Vietnam, an emerging fintech ecosystem where SMEs dominate the economic structure but face structural capital constraints. Third, at the practical level, the findings offer actionable insights for policymakers and solution providers aiming to design financially accessible and institutionally supportive digital finance ecosystems for SMEs and startups.

LITERATURE REVIEW AND HYPOTHESIS

Smart digital financial solutions

Smart digital financial solutions refer to a set of tools, platforms and technology applications designed to digitalize, automate and optimize a firm's financial activities (Liu et al., 2024). These solutions typically integrate key technologies such as advanced data analytics, forecasting models, process automation (RPA), cloud computing and open banking connectivity. Together, they help firms strengthen cash flow control,

improve transparency, reduce manual errors and enhance the quality of financial decision making (Ozili, 2020).

For SMEs and startups, smart digital financial solutions are particularly valuable, as these firms often face constraints related to resources, financial and accounting capacity and access to capital. The adoption of financial technologies enables them to reduce operating costs, expand access to financial services and improve risk management capabilities, thereby reinforcing their competitiveness in an increasingly digitalized business environment (OECD, 2023).
In this study, smart digital financial solutions are conceptualized as a technological innovation that SMEs and startups consider adopting, and intention to use is viewed as a critical stage preceding actual implementation behavior.

TOE framework

The Technology Organization Environment (TOE) framework proposed by Tornatzky and Fleischer (1990) is a comprehensive theoretical model widely employed to explain how organizations evaluate, adopt and implement technological innovations. The central premise of the framework is that adoption outcomes do not arise solely from the characteristics of the technology but from the combined influence of technological conditions, internal organizational factors and the external environment in which the firm operates. By acknowledging this multi-layered structure, the TOE framework provides a more holistic and realistic explanation of organizational adoption behaviour

The technological context describes the technical attributes of the innovation, including relative advantage, compatibility, complexity and cost. These characteristics shape firms' perceptions of usefulness, practicality and implementation feasibility, thereby influencing whether managers view the innovation as worthwhile. The organizational context reflects the internal conditions that support or constrain adoption, such as leadership commitment, employee capabilities, firm size, resource availability and the overall readiness for transformation. The environmental context encompasses external forces and institutional conditions, including competitive intensity, customer expectations, regulatory requirements and government support policies, all of which create pressures or incentives that influence adoption decisions (Arifia, 2024; Konopik at al., 2021).

One of the strengths of the TOE framework is its ability to integrate these three domains into a unified explanatory model. This makes it particularly suitable for studying technology adoption at the organizational level, especially in contexts where individual perceptions alone cannot fully capture the complexity of decision-making. Unlike individual-based models such as TAM or UTAUT, which focus primarily on psychological determinants, the TOE framework incorporates structural, strategic and environmental dimensions that are essential for understanding how firms approach technological change (Baker, 2012). As a result, the framework has demonstrated strong empirical validity across a diverse range of technological domains, including e-commerce (Nguyen et al., 2022), cloud computing (Gangwar et al., 2015), blockchain (Clohessy et al., 2019) and, more recently, artificial intelligence adoption in SMEs (Badghish and Soomro, 2024).

Given this extensive empirical grounding, applying the TOE framework to examine SMEs' and startups' intention to adopt smart digital financial solutions is well justified. The adoption of such solutions is inherently an organizational decision, shaped simultaneously by the perceived attributes of the technology, the firm's internal capabilities and constraints and the broader business environment in which these enterprises operate. The TOE framework therefore offers an analytically robust foundation for capturing these interrelated influences and for explaining why adoption patterns may differ across firms even within the same industry or market conditions.

Hypothesis

Technological context

Perceived benefits capture the extent to which firms believe that smart digital financial technologies create superior value compared with their existing processes. Contemporary digital transformation theory argues that adoption decisions are largely driven by expected value creation, efficiency improvement and performance enhancement (Konopik et al., 2021). When managers clearly perceive improvements in financial visibility, operational accuracy and processing speed, they are more likely to consider the innovation worthwhile. For SMEs and startups, benefits such as improved cash flow management, reduced errors and shorter processing time represent tangible performance gains that significantly strengthen adoption intention (Konopik et al., 2021).

H1a: *Perceived benefits of smart digital financial solutions have a positive effect on SMEs' and startups' intention to adopt them.*

Compatibility refers to the extent to which digital financial solutions align with a firm's existing processes, strategic objectives, and technological infrastructure. When a new technology integrates smoothly into current workflows and does not require major structural adjustments, firms tend to perceive lower implementation risk and disruption. This perceived fit increases managerial confidence and reduces resistance to change, making firms more inclined to adopt the technology (Arifia, 2024).

H1b: *Compatibility has a positive effect on the intention to adopt smart digital financial solutions.*

Perceived complexity reflects the degree to which a firm views the technology as difficult to understand, implement, or operate. When complexity is perceived to be high, firms often anticipate longer integration timelines, additional training requirements, and a higher likelihood of operational disruption. These concerns increase both switching costs and opportunity costs, thereby diminishing managerial confidence in the technology. Prior innovation-adoption research consistently demonstrates that complexity functions as a major barrier that undermines adoption intention (Zhang et al., 2020). In essence, when a technology is regarded as "unintuitive" or "hard to use," firms tend to postpone or even reject adoption, regardless of the potential strategic benefits it may offer.

H1c: *Complexity has a negative effect on the intention to adopt smart digital financial solutions.*

Cost encompasses not only the initial investment in digital technologies but also the ongoing operating expenses and the resources needed for employee training. For SMEs and startups, which typically operate under tight budget constraints, these financial burdens become particularly salient. High implementation and maintenance costs can easily outweigh the perceived benefits, making cost one of the most critical barriers to digital transformation efforts (Awa et al., 2017). When the required investment is viewed as excessive or risky, firms are more likely to delay adoption or opt for lower-tech alternatives despite their strategic limitations.

H1d: *Cost has a negative effect on the intention to adopt smart digital financial solutions.*

Organizational context

Top management plays a critical role in shaping a firm's strategic direction and ensuring that the necessary resources are allocated for technological initiatives. When senior leaders demonstrate clear commitment through their support, decisions and investment priorities, they help reduce the perceived risks associated with adopting new systems (Kim and Kiymaz, 2024). This commitment also strengthens organizational

readiness, creating an environment where innovation is more likely to be accepted and successfully implemented (Clohessy and Acton, 2019).

H2a: *Top management support has a positive effect on the intention to adopt smart digital financial solutions.*

The technological capabilities and digital skills of employees play a central role in determining how effectively a firm can absorb and operate new technologies. When the workforce possesses adequate knowledge and experience with digital tools, firms are better equipped to handle implementation challenges and are more confident in managing potential risks. SMEs and startups with digitally competent employees therefore tend to show a higher willingness to adopt smart digital financial solutions (Aboelmaged and Hashem, 2019).

H2b: *Employee competence has a positive effect on the intention to adopt smart digital financial solutions.*

Environmental context

In the TOE framework, the environmental context reflects the external forces that pressure or motivate firms to adopt innovations, including customers, competitors and the regulatory environment. For SMEs and startups, prior studies show that competitive pressure is often not expressed through market size or the number of rivals, but rather through shifts in customer expectations and behavior (Saadah and Setiawan, 2023). These firms commonly operate in niche markets where customers demand faster, more transparent and more digitalized services. For this reason, customer demand is considered an indirect yet most appropriate indicator for capturing competitive pressure in the SME context. When customers develop higher expectations for digital financial convenience, firms are more inclined to adopt new technologies to maintain competitiveness. Based on this reasoning, the study proposes the following hypothesis:

H3a: *Customer demand has a positive effect on the intention to adopt smart digital financial solutions.*

In addition to competitive forces, regulatory conditions are also a critical part of the environmental context. Numerous TOE studies emphasize that government support, including digital transformation policies, tax incentives, training programs, financial assistance and the clarity of regulatory frameworks, serves as a composite indicator of how supportive the legal environment is toward innovation (Hojnik and Ruzzier, 2016; Susanti et al., 2023). For SMEs and startups that face substantial resource constraints, government initiatives help lower experimentation costs and reduce legal risks, thereby encouraging these firms to adopt digital financial technologies. Accordingly, the following hypothesis is proposed:

H3b: *Government support has a positive effect on the intention to adopt smart digital financial solutions.*

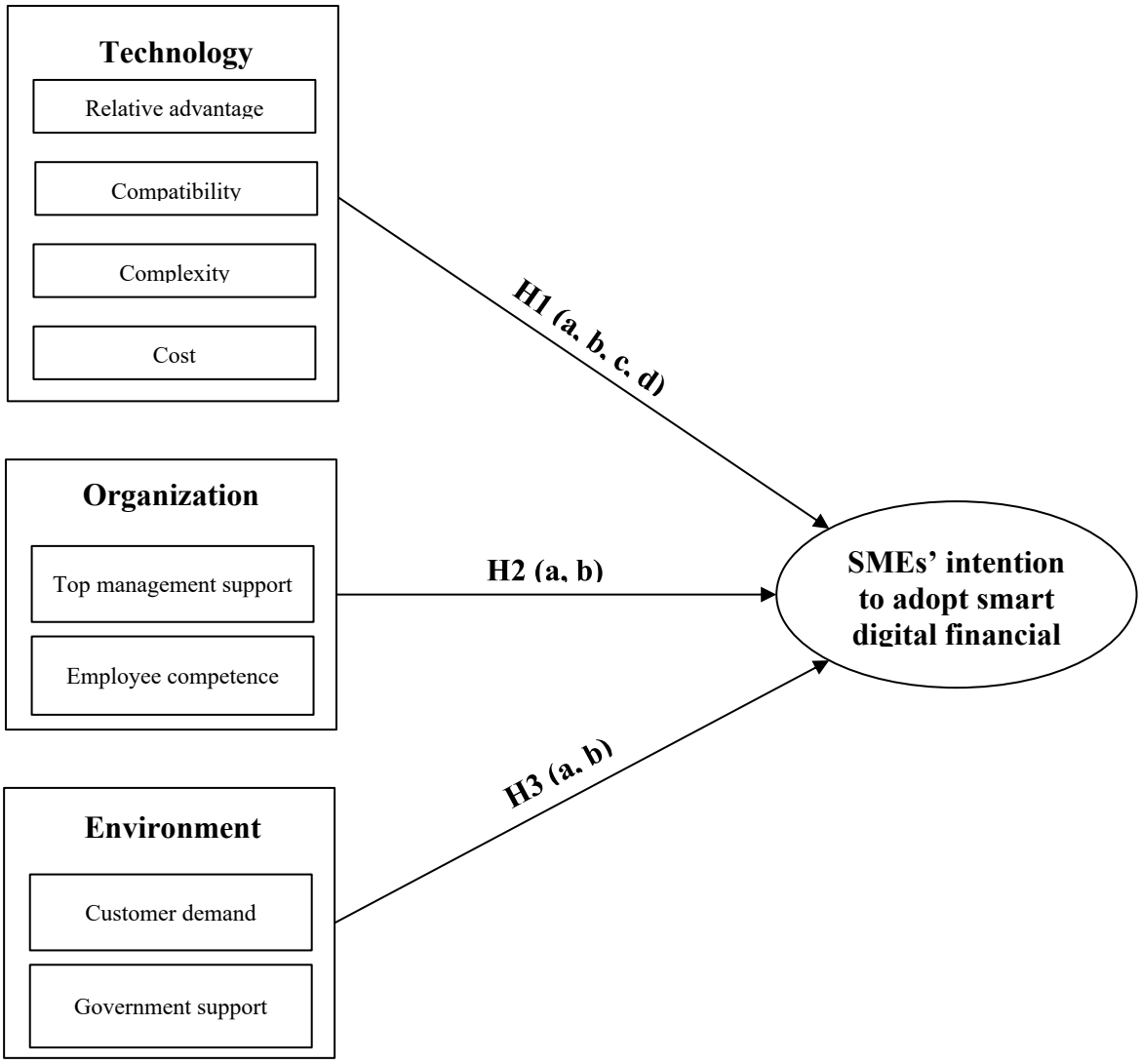

Figure 1. Research Model

Source: Author's proposal (2025)

DATA COLLECTION AND METHODOLOGY

Data collection

The study focuses on SMEs and startups operating in the trade and service sectors, which are widely recognized as among the most dynamic and innovation-driven segments of the economy. These firms face intense competitive pressure and continuous shifts in market conditions, resulting in heightened demand for technological upgrading and financial digitalization. They also encounter persistent challenges related to financial management, capital access and forecasting capability, thereby making the adoption of smart digital financial solutions particularly salient.

Data were collected from 220 firms through a combination of online surveys and in-person distribution at business events, industry networks and startup communities. To enhance coverage and reduce potential perceptual bias, each firm was invited to complete one or two questionnaires. Over a three-month period, from July 2025 to October 2025, the study obtained 357 valid responses that satisfied the

required quality criteria. All constructs were measured using a five-point Likert scale (5 = strongly agree; 4 = agree; 3 = neutral; 2 = disagree; 1 = strongly disagree).

Methodology

The study employs a mixed-methods approach using an explanatory sequential design, in which the qualitative phase is conducted first to ensure that the measurement scales are appropriate for the context of SMEs and startups in Vietnam. In this phase, the research team conducted in-depth interviews with 11 experts and managers selected through purposive sampling to gather practical insights related to technological, organizational and environmental factors. The choice of 11 participants aligns with recommended sample sizes for qualitative research. Hennink and Kaiser (2022) indicate that most studies reach thematic saturation with approximately 9 to 17 interviews, depending on participant homogeneity and topic complexity. Accordingly, the sample size of 11 experts is considered adequate to ensure informational completeness and depth for this study.

The interview data were analyzed using thematic content analysis to identify ambiguities and contextual nuances that required refinement in the measurement items. The results indicate that the core components of the TOE framework remain valid and do not necessitate additional constructs; however, several observed items required linguistic adjustments to enhance clarity and conceptual precision. These refinements were incorporated into the survey instrument prior to the quantitative phase, thereby ensuring methodological coherence and strengthening the reliability of the measurement model.

The quantitative analysis is based on a firm-level sample of 220 SMEs and startups operating in the trade and service sectors. A non-probability convenience sampling approach was adopted, supported by access through professional networks and business associations, as no comprehensive sampling frame exists that identifies firms according to their digital financial adoption practices. The unit of analysis is the firm, and questionnaires were directed specifically to top managers, founders, owners, financial directors, or individuals responsible for digital transformation and financial management, as these respondents possess strategic oversight and sufficient knowledge of the firm's technological capabilities and adoption decisions. In cases where multiple responses were obtained from the same enterprise, answers were reviewed for consistency and aggregated to ensure a single firm-level representation. Sample adequacy was evaluated using established PLS-SEM guidelines: with eight predictors of Behavioral Intention, the "10-times rule" suggests a minimum of 80 observations, while power analysis ($f^2 = 0.15$, $\alpha = 0.05$, power = 0.80) indicates a minimum of approximately 109 observations. The final sample of 220 firms exceeds both thresholds, providing sufficient statistical power for model estimation. Although non-probability sampling limits strict population-level generalization, the targeted key-informant approach strengthens the validity of firm-level inference within a variance-based SEM framework.

The quantitative phase was then carried out using Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the survey data. PLS-SEM is well-suited for studies involving complex models with multiple latent variables and does not require data to follow a normal distribution (Hair et al., 2019). SmartPLS 4.0 was used to estimate both the measurement model and the structural model.
In evaluating the measurement model, scale reliability was assessed using Cronbach's alpha and composite reliability, while convergent validity was examined through factor loadings and the Average Variance Extracted (AVE). Discriminant validity was verified using the Fornell–Larcker criterion and the HTMT ratio, ensuring that the latent constructs were conceptually distinct.

For the structural model, multicollinearity was assessed using variance inflation factors (VIF), followed by the estimation of path coefficients and statistical significance testing via bootstrapping with 5,000 resamples. The model's explanatory power, effect sizes and predictive relevance were evaluated using the R^2, f^2 and Q^2 indices. The PLS-SEM results provide empirical evidence of the extent to which

technological, organizational and environmental factors influence SMEs' and startups' intention to adopt smart digital financial solutions.

RESULTS AND DISCUSSION

Results

Cronbach's Alpha

The reliability assessment results presented in Table 1 indicate that all measurement scales meet the acceptable reliability thresholds established in contemporary international standards. Specifically, the Cronbach's alpha coefficients of the constructs range from 0.766 to 0.925, exceeding the minimum threshold of 0.70 recommended by Hair et al. (2017). This confirms the reliability of each observed variable and demonstrates that the overall measurement scale is appropriate. In addition, the composite reliability (CR) values for all latent constructs exceed 0.80, ranging from 0.865 to 0.952, further reinforcing the reliability of the scales. The consistently high CR values indicate strong internal consistency among the items used in the study.

Table 1. Construct reliability and validity

Variables	Cronbach's alpha	Rho_A	Composite reliability (CR)	Average variance extracted (AVE)
BI	0,922	0,923	0,951	0,866
CD	0,907	0,911	0,941	0,843
COM	0,856	0,863	0,912	0,776
COST	0,800	0,800	0,882	0,714
CPLX	0,766	0,767	0,865	0,681
EC	0,823	0,823	0,894	0,739
GS	0,925	0,926	0,952	0,869
RA	0,822	0,828	0,894	0,737
TMS	0,891	0,896	0,932	0,821

Note: BI = Behavioral Intention; CD = Customer Demand; COM = Compatibility; COST = Perceived Cost; CPLX = Complexity; EC = Employee Competence; GS = Government Support; RA = Relative Advantage; TMS = Top Management Support.

Source: Author's research findings (2025)

Convergent validity assessment

The results reported in Table 1 indicate that all constructs satisfy the criterion for convergent validity. The Average Variance Extracted (AVE) values range from 0.681 to 0.869, all of which exceed the widely accepted threshold of 0.50. As noted by Hair et al. (2017), an AVE value above 0.50 signifies that the latent construct accounts for more than half of the variance in its observed indicators, thereby demonstrating adequate explanatory power. An AVE below this level would suggest that error variance dominates the explained variance. Based on these results, it can be concluded that the constructs used in the study exhibit strong convergent validity.

Discriminant validity assessment

To assess discriminant validity, the square root of the AVE for each latent construct must exceed its correlations with other constructs. In SmartPLS, following the Fornell–Larcker criterion, the square roots of the AVE values appear on the diagonal of the correlation matrix, while the inter-construct correlations are placed below the diagonal. As shown in Table 2, the diagonal values (bolded) are consistently greater than the corresponding off-diagonal correlations, indicating that the measurement scales satisfy the requirement for discriminant validity.

Table 2. Fornell-Larcker criterion

Variables	BI	CD	COM	COST	CPLX	EC	GS	RA	TMS
BI	0,930								
CD	0,558	0,918							
COM	0,530	0,420	0,881						
COST	-0,527	-0,413	-0,325	0,845					
CPLX	-0,550	-0,367	-0,351	0,414	0,825				
EC	0,583	0,467	0,459	0,316	0,455	0,859			
GS	0,593	0,502	0,426	0,433	0,491	0,543	0,932		
RA	0,439	0,372	0,330	0,251	0,228	0,347	0,345	0,859	
TMS	0,318	0,271	0,096	0,145	0,167	0,172	0,200	0,119	0,906

Note: BI = Behavioral Intention; CD = Customer Demand; COM = Compatibility; COST = Perceived Cost; CPLX = Complexity; EC = Employee Competence; GS = Government Support; RA = Relative Advantage; TMS = Top Management Support. *Source: Author's research findings (2025)*

In addition, discriminant validity was further examined using the Heterotrait–Monotrait Ratio (HTMT). The results indicate that all construct pairs exhibit HTMT values below the threshold of 0.90, which is consistent with accepted guidelines. This provides additional evidence that the constructs in the model are empirically distinct (Table 3).

Table 3. Heterotrait-Monotrait ratio (HTMT)

Variables	BI	CD	COM	COST	CPLX	EC	GS	RA	TMS
BI									
CD	0,607								

COM	0,592	0,475							
COST	0,612	0,482	0,389						
CPLX	0,652	0,439	0,431	0,530					
EC	0,667	0,538	0,545	0,389	0,574				
GS	0,642	0,545	0,475	0,504	0,583	0,624			
RA	0,501	0,428	0,392	0,309	0,284	0,422	0,392		
TMS	0,349	0,299	0,110	0,168	0,195	0,204	0,214	0,140	

Note: BI = Behavioral Intention; CD = Customer Demand; COM = Compatibility; COST = Perceived Cost; CPLX = Complexity; EC = Employee Competence; GS = Government Support; RA = Relative Advantage; TMS = Top Management Support.

Source: Author's research findings (2025)

These results indicate that the measurement scales used in the study satisfy the required standards of reliability and discriminant validity.

Structural model assessment

According to Hair et al. (2017), multicollinearity may arise when tolerance falls below 0.20 or when the Variance Inflation Factor (VIF) exceeds 5. The VIF is computed as the inverse of tolerance, where tolerance is defined as $1 – R^2$. Therefore, when R^2 is below 0.80, multicollinearity is generally not a concern. The results presented in Table 4 show that all VIF values are below the threshold of 5, confirming that the structural model does not exhibit multicollinearity.

Table 4. Outer loadings and collinearity statistics (VIF)

Variables	BI	CD	COM	COST	CPLX	EC	GS	RA	TMS	VIF
BI1	0,934									3,545
BI2	0,927									3,256
BI3	0,930									3,545
CD1		0,920								3,050
CD2		0,920								2,842
CD3		0,913								3,012
COM1			0,870							2,149
COM2			0,882							2,148
COM3			0,891							2,111
COST1				0,841						1,664
COST2				0,845						1,695
COST3				0,849						1,793
CPLX1					0,831					1,662
CPLX2					0,829					1,553
CPLX3					0,816					1,496
EC1						0,871				2,024
EC2						0,842				1,681

EC3						0,865				1,959
GS1							0,928			3,494
GS2							0,930			3,300
GS3							0,940			3,977
RA1								0,881		1,974
RA2								0,860		1,994
RA3								0,835		1,674
TMS1									0,917	3,111
TMS2									0,898	2,593
TMS3									0,903	2,432

Note: BI = Behavioral Intention; CD = Customer Demand; COM = Compatibility; COST = Perceived Cost; CPLX = Complexity; EC = Employee Competence; GS = Government Support; RA = Relative Advantage; TMS = Top Management Support.

Source: Author's research findings (2025)

Model fit assessment

The goodness of fit of the model was assessed using the coefficient of determination (R^2). As reported in Table 5, the R^2 value for the BI variable is 0.629, with an adjusted R^2 of 0.620. These values meet the statistical criteria for model adequacy and indicate that the independent variables in the model explain approximately 62.0% to 62.9% of the variance in BI.

Table 5. R-square

	R-square	R-square adjusted
BI	0,629	0,620

Note: BI = Behavioral Intention.

Source: Author's research findings (2025)

The overall fit of the model was evaluated using the SRMR, d_ULS, and d_G indices. As shown in Table 6, the SRMR value is 0.051, which is lower than the recommended threshold of 0.08 proposed by Hu and Bentler (1998), indicating a good fit between the model and the empirical data. The values of d_ULS (1.002) and d_G (0.573) are stable, reflecting consistency in the estimation process. In addition, the Chi-square statistic of 1,284.395 and the NFI value of 0.804 fall within acceptable ranges; notably, the NFI exceeds the 0.80 benchmark, providing further support for the overall fit of the PLS-SEM model.

Table 6. Model_Fit

	Saturated model	Estimated model
SRMR	0,051	0,051
d_ULS	1,002	1,002
d_G	0,573	0,573
Chi-square	1284,395	1284,395
NFI	0,804	0,804

Source: Author's research findings (2025)

Hypothesis testing

Using the bootstrapping technique with 5,000 resamples (Hair et al., 2016), the estimated path coefficients are reported in Table 7. The results indicate that all hypothesized relationships in the model are statistically significant.

Among the factors influencing BI, COST demonstrates the strongest effect, with β = 0.189 (T = 4.912; p = 0.000), followed by CPLX (β = 0.176; T = 4.441; p = 0.000) and EC (β = 0.174; T = 3.992; p = 0.000). The variables COM and TMS also exhibit meaningful effects, with coefficients of β = 0.168 and β = 0.144, respectively (both p = 0.000).

Although CD, GS, and RA show more modest coefficient values (β ranging from 0.111 to 0.133), these relationships remain statistically significant (p < 0.05), confirming their supplementary role in shaping BI.

Overall, these findings show that all hypotheses are supported, indicating that each construct in the model exerts a positive influence on BI, albeit with varying magnitudes of impact across factors.

Table 7. Hypothesis testing

Hypothesis	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Kết luận
CD → BI	0,111	0,039	2,840	0,005	Accept
COM → BI	0,168	0,041	4,107	0,000	Accept
COST → BI	-0,189	0,039	4,912	0,000	Accept
CPLX → BI	-0,176	0,040	4,441	0,000	Accept
EC → BI	0,174	0,043	3,992	0,000	Accept
GS → BI	0,129	0,050	2,579	0,010	Accept
RA → BI	0,133	0,037	3,557	0,000	Accept
TMS → BI	0,144	0,031	4,712	0,000	Accept

Note: BI = Behavioral Intention; CD = Customer Demand; COM = Compatibility; COST = Perceived Cost; CPLX = Complexity; EC = Employee Competence; GS = Government Support; RA = Relative Advantage; TMS = Top Management Support.

Source: Author's research findings (2025)

Discussion

The SEM-PLS results indicate that all three dimensions of the TOE framework exert statistically significant effects on the intention to adopt smart digital financial solutions (BI), with a clearly differentiated pattern of influence across groups. Overall, these findings are consistent with Tornatzky and Fleischer (1990), who argue that organizational innovation behavior emerges from the interplay between technological characteristics, organizational capabilities, and environmental conditions. A notable feature in the Vietnamese context is the relatively high sensitivity to cost and complexity, suggesting that SMEs and startups continue to face substantial resource constraints when implementing digital financial solutions.
The Technological dimension exerts the strongest influence on BI, aligning with observations from prior TOE studies in emerging markets (Oliveira and Martins, 2011; Awa et al., 2017). Among its components, compatibility (COM) shows the largest positive effect, reinforcing Rogers' (2003) assertion that the

alignment of a technology with existing systems reduces perceived risk and facilitates adoption intention. By contrast, implementation cost (COST) and complexity (CPLX) both demonstrate sizable negative effects, consistent with the findings of Baker (2012) and Gangwar et al. (2015), indicating that financial and operational barriers remain significant deterrents for SMEs and startups. Unlike firms in developed economies that often benefit from diversified financing channels, Vietnamese startups rely heavily on internal funds, short-term bank credit, or informal capital networks. Under such conditions, investment decisions are evaluated primarily through short-term cash-flow impact rather than long-term strategic gains. Consequently, even if smart digital financial solutions promise efficiency improvements, high upfront costs increase perceived financial vulnerability, making firms more price-sensitive than strategy-oriented. Meanwhile, relative advantage (RA), although positively associated with BI, exhibits a relatively weak effect. This may reflect a pragmatic managerial mindset prevalent in emerging markets, where survival and liquidity stability take precedence over long-term strategic optimization. Managers may acknowledge the benefits of advanced analytics or automation; however, unless these benefits translate into immediate operational feasibility, they are insufficient to drive adoption intention.

Within the Organizational dimension, both top management support (TMS) and employee competence (EC) show positive effects, albeit at moderate levels. This pattern aligns with Low et al. (2011) and Zhu et al. (2006), which suggest that organizational characteristics primarily serve as enabling conditions rather than dominant drivers of technological intention. Notably, employee competence exerts a stronger influence than managerial support, underscoring the importance of digital skills and absorptive capacity, consistent with the findings of Singh et al. (2019) and Baker (2012). However, compared with studies conducted in more advanced economies, the overall impact of organizational factors in Vietnam is markedly lower, implying that adoption decisions among SMEs and startups remain strongly shaped by external forces and technological considerations rather than internal readiness.

In the Environmental dimension, both customer demand (CD) and government support (GS) positively influence BI, highlighting the role of market conditions and regulatory frameworks in driving innovation behaviors. These findings correspond with the conclusions of Oliveira and Martins (2011) and Baker (2012), both of which emphasize the importance of market pressure in catalyzing digital innovation among SMEs and startups. Nevertheless, the effect of GS is weaker than that of CD, reflecting a characteristic feature of Vietnam: the fintech policy framework is still evolving and primarily functions to stabilize the environment rather than to act as a direct catalyst for adoption. This observation is consistent with Nguyen and Pham (2021), who note that Vietnamese firms often view policy support as a foundational condition, while market demands serve as the immediate source of pressure driving technology adoption.
Taken together, the results depict a three-layer influence structure: Technology as the decisive driver, Environment as the enabling force, and Organization as the supporting foundation. This configuration accurately reflects the current trajectory of digital transformation among Vietnamese SMEs and startups. The model not only aligns with the classical TOE framework but also highlights a notable shift in innovation behavior within emerging markets, where technological advancement and market demand increasingly serve as the two primary engines of adoption, while organizational capability plays a stabilizing role that ensures feasibility and sustainability during implementation. These insights offer a meaningful contribution to the existing literature, particularly in the context of the accelerating expansion of fintech and digital transformation in Vietnam.

CONCLUSION AND RECOMMENDATION

Conclusion

The study was conducted to address an existing gap in both academic research and practical understanding regarding SMEs' and startups' intention to adopt smart digital financial solutions in Vietnam, a topic that has received limited attention despite the growing importance of digital financial technologies

in enterprise management. Building on the Technology–Organization–Environment (TOE) framework, the research model examined the effects of eight factors across the three contextual dimensions on the intention to adopt digital financial technologies.

The findings indicate that all three contextual dimensions statistically significant effects on BI. The Technological context demonstrates the strongest influence, particularly through factors related to implementation cost and perceived complexity, reflecting SMEs' practical concerns regarding technical feasibility and limited resource capacity. The Organizational context, represented by top management support and employee competence, shows moderate influence, functioning primarily as a set of enabling conditions. The Environmental context, which includes customer demand and government support, also exhibits meaningful effects, highlighting the role of market pressure and institutional frameworks in shaping SMEs' innovation behavior.

Overall, SMEs' intention to adopt digital financial solutions emerges from the interaction of three layers of influence: (i) the capability and suitability of the technology, (ii) the organization's readiness and internal capacity, and (iii) signals and pressures from the external environment. These findings align with the initial research goals and extend the application of the TOE framework to the domain of smart digital finance, an area that remains relatively nascent in the Vietnamese context.

Although this study focuses on Vietnam, the pattern of findings may reflect broader conditions found in many emerging economies. The strong impact of cost and complexity suggests that firms in this context are primarily concerned with financial feasibility and operational risk. In other words, before thinking about long-term strategic benefits, managers first ask whether they can afford the technology and whether it can be implemented smoothly.

This priority may be linked to structural conditions. In environments where access to capital is limited and regulatory systems are still developing, firms tend to be cautious. Even if a digital solution promises efficiency gains, high upfront investment or implementation difficulty can discourage adoption. In contrast, in countries with more stable financial systems and stronger institutional support, firms may place greater weight on strategic advantage or organizational capability rather than immediate cost concerns.

Cultural context may also play a role. In societies where businesses are more risk-averse, perceived complexity and financial uncertainty may have a stronger deterrent effect. In settings that emphasize long-term orientation, firms may be more willing to absorb short-term costs in exchange for future gains. Similarly, the influence of environmental pressures, such as customer demand, may vary depending on how digitally mature the market is.

Recommendations

(1) Recommendations for SMEs and startups

First, SMEs and startups should prioritize assessing technological feasibility prior to implementation. The results indicate that cost and integration capability are the two most critical determinants of adoption. Firms therefore need to evaluate the total lifecycle cost of the technology, its ability to interface with existing systems and the operational complexity it may introduce.

Second, strengthening the digital capability of employees is essential. Since employee competence has a clear influence on the intention to adopt digital financial solutions, firms should invest in internal training, encourage continuous learning of new technologies and develop specialized teams responsible for financial and technological functions.

Third, firms should proactively respond to evolving customer needs. As customers increasingly expect digitalized experiences, SMEs and startups should accelerate the adoption of digital financial tools in payment processing, invoice management, cash-flow forecasting and customer service to enhance competitiveness.

(2) Recommendations for digital financial solution providers

First, solution providers should design products that simplify the user experience and minimize perceived complexity. Since complexity has a substantial influence on adoption intention, solutions need to be intuitive, easy to implement and capable of integrating quickly with existing accounting systems, ERP platforms or other operational tools used by SMEs.Second, providers should develop flexible pricing models. Given the limited resources of SMEs and startups, solution packages should be cost-effective and scalable, potentially offered through monthly subscription plans or usage-based pricing tailored to the size and needs of each firm.

(3) Recommendations for regulatory agencies

First, regulatory agencies should enhance the legal framework and standardize data practices. The finding that government support influences BI underscores the role of institutional conditions in reducing perceived risk and strengthening confidence among SMEs and startups. Continued improvements are needed in areas such as electronic identification, enterprise data sharing, digital payments and information security.

Second, targeted programs to support financial digital transformation for SMEs and startups should be expanded. Policy instruments such as incentive schemes, financial support funds, training programs and shared digital platforms can help reduce investment costs and strengthen operational capacity for firms.
Third, broader financial digital literacy initiatives should be promoted. Government bodies and business associations should collaborate on communication campaigns aimed at raising awareness and reducing firms' perceived risks related to adopting digital financial solutions.

Limitations and directions for future research

This study has several limitations. First, the data were collected mainly from specific locations and groups of firms, which may limit the extent to which the sample represents the diversity of the overall SME and startup ecosystem in Vietnam. Second, the study focuses on measuring intention based on employees' perceptions and does not observe actual post-adoption behavior after the technology has been implemented. Third, the research model incorporates organizational factors at the micro level but does not account for macro-level characteristics such as financial capacity, organizational structure or firm size-factors that may create substantial differences across enterprises and influence their ability to absorb innovations. This limitation partly reflects the nature of SMEs and startups, in which macro-level variation is often less pronounced, but it also reveals a gap regarding the role of organizational macro-environment in digital transformation.

Future research may extend in several directions: (i) integrating macro-level characteristics such as financial capacity, organizational structure or firm size to provide a more comprehensive assessment of firms' innovation readiness; (ii) examining actual usage behavior after implementation to test the sustainability of adoption intention; (iii) comparing SMEs, startups and large enterprises to identify differences in technological adoption mechanisms; and (iv) incorporating dynamic factors such as digital organizational culture, organizational learning capability or innovation capacity to better capture the full process of digital transformation.

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DIGITAL TRANSFORMATION, SUSTAINABLE GOVERNANCE, AND STRENGTHENING THEIR IMPACT BY BUSINESS ETHICS

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ABSTRACT

This study analyzes the influence of sustainability governance and digital transformation on corporate performance in Indonesia, exploring the role of business ethics as a moderating variable. The study sample includes 156 public companies listed on the Indonesia Stock Exchange (IDX) during the 2022-2023 period. Data were analyzed using panel data regression. The results reveal that sustainability governance has a positive and significant impact on improving corporate performance. Meanwhile, the influence of digital transformation on performance shows dynamic results: insignificant in the main model, but significant in the sensitivity analysis. A key finding of this study is the critical role of business ethics, which is proven to strengthen (positively moderate) the relationship between both independent variables—sustainability governance and digital transformation—on corporate performance. Further analysis shows variations between sectors. The energy sector recorded the highest sustainability governance score, driven by regulatory pressure, while the basic industry and chemical sectors excelled in adopting digital transformation, supported by the national initiative Making Indonesia 4.0. Overall, this study confirms that the strategic integration of sustainability principles, digital initiatives, and a strong ethical foundation is a determining factor in building long-term competitiveness and sustainable corporate performance.

Keywords: Sustainable Governance, Digital Transformation, Business Ethics, Firm Performance and Indonesia Stock Exchange.

JEL Code: M14, G34, O33, L25 and Q56.

INTRODUCTION

Amid global demands for sustainability and environmental responsibility, companies are increasingly faced with the need to adopt sustainable governance practices and establish an environmentally friendly organizational culture. Corporate engagement in sustainability is no longer seen merely as a social responsibility but also as a key factor influencing overall corporate performance (Bhattacharyya & Nair, 2019) not in reference list. Improved corporate performance is more optimal if accompanied by a corresponding increase in social and environmental responsibility. Corporate performance plays a crucial

role that every company must pursue, as it reflects a company's ability to manage and allocate resources, thus requiring effective business governance practices. Therefore, investors consider corporate sustainability information to be on par with financial information in terms of relevance, and stakeholders should consider this sustainability aspect in their decision-making process (Agustia et al., 2019) not in reference list.

One issue of concern related to sustainability is the management of hazardous and toxic waste. Explain it first According to data from the Ministry of Energy and Mineral Resources (ESDM) (2018), 10 companies in the energy sector were the largest waste producers in Indonesia. These 10 companies produced a total of 30,967.51 tons of hazardous and toxic waste (LB3). PT Kimu Sukses Abadi (2022) not in reference list also committed an environmental pollution violation. According to a report published on the official Bekasi Regency portal, Acting Regent Dani Ramdan discovered several violations related to environmental pollution by PT Kimu Sukses Abadi (year) not in reference list , including the lack of documents related to environmental management and environmental approval from the surrounding community, as well as the lack of a B3 waste storage facility.

Beyond environmental issues, corporate governance performance also significantly impacts company performance. Deficiencies in corporate governance practices can lead to negative company performance (Naeem et al., 2022). Furthermore, Naeem et al (2022) not in reference list stated that when corporate governance is implemented well, companies are more likely to integrate sustainability practices into their operations and policies, resulting in improved company performance. Well-managed and efficient corporate governance empowers the board of directors to monitor and oversee executive actions. This ensures that decisions are aligned with the long-term interests of the company and its shareholders, which in turn positively impacts the company's financial performance (Ataay, 2018). not in reference list This is in line with research by Neves et al. (2023), which shows that implementing good corporate governance practices can positively contribute to company performance by bringing transparency, accountability, and sustainability into business practices.

Recently, the concept of corporate governance has evolved intoGovernance Sustainability and is gaining widespread recognition (source). The emergence of corporate scandals has increased public expectations for corporate ethical responsibility. In relation to good governance,Governance Sustainability has become crucial for a company's sustainable development (Ledi & Ameza–Xemalordzo, 2023). The use of ACGS explain it in full for the first time to measure good corporate governance is still relatively rare among public companies in Indonesia. At the 14th CG Conference and Award held by the Indonesia Institute for Corporate Directorship (IICD), the IICD assessed the quality of corporate governance using the ACGS method for 200 issuers with the largest market capitalization listed on the Indonesia Stock Exchange. The IICD subsequently announced that of the 200 issuers, only 50 received awards for implementing the best corporate governance practices in 2022 (IICD, 2023) not in reference list. This also motivated this research, as the use of ACGS actually includes dimensions ofGovernance Sustainability within the four ACGS principles, namely Sustainability and Resilience. Previous research has largely relied on traditional governance models (Chien, 2023; Yin & Sheng, 2019; Jatana, 2023) not in reference list. According to Ledi and Ameza–Xemalordzo (2023), not in reference list current governance is insufficient if it only utilizes an organizational structure that emphasizes operational and economic performance. Therefore, governance changes are necessary.

Based on the need for changes in corporate governance standards, this study proposes a more comprehensive measurement model by incorporating three new dimensions:Governance Sustainability based on POJK explain it for the first time No. 51 of 2017 with six indicators; Sustainability and Resilience according to ACGS (2023) not in reference list with nineteen indicators; and IT Governance with thirteen indicators. Furthermore, this study modifies existing indicators and adds new indicators to the IT Governance dimension, such as training and development related to information technology and the use of

social media. Thus, this research is expected to provide novelty in measuring corporate governance that is more oriented towards sustainability, as well as being a real contribution in strengthening the theory and practice of modern corporate governance that is able to address environmental, social, and technological challenges simultaneously.

Despite the recognition of the urgency of sustainable governance, previous research still suffers from fundamental limitations. Existing studies tend to rely on traditional governance models that focus narrowly on economic and operational performance, and are fragmented in their measurement approaches, such as separating environmental, corporate governance (GCG), and information technology (IT) aspects. Consequently, there is no comprehensive framework that holistically integrates these three key dimensions into a single governance measurement model oriented towards long-term sustainability. This study aims to fill this gap by proposing and testing a new measurement model that integrates three pillars: regulatory-based Sustainable Governance, the Sustainability and Resilience principles of the ACGS, and extended IT Governance. In doing so, this study addresses the need for more adaptive governance standards that not only ensure accountability and transparency but also explicitly internalize environmental responsibility, organizational resilience, and digital readiness into corporate oversight structures.

LITERATURE REVIEW

Theoretical underpinnings You can put this section at the end of your literature review

Stakeholder theory states that every company cannot be separated from the interests of various parties involved in its operations. These parties include shareholders, employees, suppliers, creditors, and community members. This theory emphasizes that companies have an obligation to be responsible and provide benefits to all stakeholders, given that their survival and success depend heavily on their support (Ningwati et al., 2022). Accordingly, stakeholder theory is used in this study to explain that companies adoptingGovernance Sustainability have an obligation to be responsible and carry out their duties to ensure that the company integrates sustainability into its strategies, decisions, and operations, while taking into account the interests of stakeholders through oversight and control structures (Neves et al., 2023).

Meanwhile, agency theory is based on the assumption that individuals are individualistic, opportunistic, and self-interested. Under this assumption, the relationship between shareholders as principals (owners of company assets) and managers as agents is a standard "principal-agent" relationship in which all parties act to maximize their own interests; this process determines agency cost conflicts (Jensen & Meckling, 1976). Furthermore, Jensen & Meckling (1976) added that agency theory treats policymakers as rational actors seeking to maximize utility but subject to constraints such as bounded rationality and incomplete information. Agency theory is primarily used to analyze corporate governance issues, particularly regarding the influence of ownership form, concentration, and board members on company strategy and performance. Furthermore, the concept of sustainable corporate governance is now increasingly recognized. This concept requires companies to consider internal and external stakeholders in the decision-making process, meet social expectations, assume greater responsibility, and maintain a balance between the management team and all stakeholders (Ma et al., 2022; Bellaqa et al., 2023).

Conceptualizing sustainable corporate governance, digital transformation and business ethics

Naeem et al. (2022) not in reference list assert that sustainable corporate governance refers to an approach to managing a company based on the triple-bottom line principle, encompassing economic, social, and environmental aspects. Similarly, Epifani and Valente (2023) emphasize that effective and sustainable governance must be aligned with the Sustainable Development Goals (SDGs). On the other hand, digital

transformation involves the use of advanced technologies, such as data analytics, mobile computing, social media, or smart devices, to drive significant business change. This transformation also includes optimizing traditional technologies, such as enterprise resource planning (ERP) systems, to more effectively support business strategy (Zhang et al., 2024). By integrating new and traditional technologies, organizations can increase operational efficiency, accelerate data-driven decision-making, enhance customer experience, and create a competitive advantage in the marketplace. This is not simply a technological adaptation, but a strategic approach to transforming the way business is conducted (Chanias, 2017; Wahat et al., 2023).

Furthermore, corporate management is also linked to ethical aspects. Management aims to develop information for use by various parties. If the information is used for good purposes and conveyed honestly, no ethical issues arise (Source). However, if the information influences a person's decision to act in a certain way, and that action benefits or harms the party providing or receiving the information, then providing this information becomes a significant ethical issue (Gorfie & Wube, 2023). not in reference list Furthermore, Rudi et al. (2023) emphasized that business ethics is a subset of applied ethics that focuses on monitoring and assessing ethical rules and moral standards within an organization. The goal is to evaluate how well or poorly a business handles ethical and moral conflicts, whether in production, marketing, or finance. Therefore, the researchers added three new dimensions to the existing corporate governance measurement: the first dimension, derived from POJK No. 51 guidelines, with six indicators; the second dimension, Sustainability and Resilience (ACGS 2023), with twenty-nine indicators; and the third dimension, IT Governance, with twelve indicators (Wahab et al., 2023).

While these reviews have illustrated each domain, there is a critical gap in the synthesis that dynamically connects them. Most of the literature addresses sustainable governance, digital transformation, and business ethics in separate silos, resulting in a partial understanding. For example, studies such as Naeem et al. (2022) and Epifani & Valente (2023) focus on the sustainability governance framework but under-explore how digital technologies can be enablers or even disruptors for achieving the triple-bottom line principle. On the other hand, digital transformation literature (such as Zhang et al., 2024) often emphasizes efficiency and competitive advantage without deeply examining the environmental impacts (e.g., data center energy consumption) or social risks (e.g., the digital divide) that these issues pose—issues that are at the heart of business ethics (Gorfie & Wube, 2023). This inconsistency creates a theoretical gap: how these three elements interact synergistically or conflictingly in the context of modern corporations. Therefore, this study not only compiles but also integrates these three dimensions by proposing that business ethics serves as a crucial moderating mechanism. Business ethics is not just an add-on, but rather a principle that moderates how digital transformation is implemented to support, not compromise, sustainable governance, thus creating a coherent and mutually reinforcing holistic governance model.

The Impact of Sustainable Governance on Corporate Performance

Wahyudin et al. (2022) in their research showed that entities or organizations that conduct their operations adhering to good corporate governance principles can help create an environment that supports efficiency, accountability, and sustainability, which in turn positively contributes to performance. This aligns with Brown and Caylor (2009), who found that corporate profitability and shareholder returns increase when companies have better governance. Ledi and Ameza–Xemalordzo (2023) also stated that when companies implement good corporate governance practices, this not only improves the company's image in the eyes of the public and stakeholders but also improves the company's overall performance. A good corporate image can attract more investors, customers, and business partners, which in turn can drive company growth and profitability. Kuzey et al. (2023) in their research stated that corporate governance has a significant impact on a company's sustainability performance, especially in emerging markets, where companies need to rely on good internal governance to drive sustainability performance.

This comparison demonstrates a strong consensus that good governance is positively related to performance, but there are important nuances in the mechanisms and focus. Wahyudin et al. (2022) and Brown & Caylor (2009) emphasize improving economic and financial performance, while Kuzey et al. (2023) specifically link it to sustainability performance, particularly in emerging markets, shifting the focus away from solely short-term profitability. A key gap in this discussion is the lack of exploration of the role of digital transformation as a catalyst linking corporate governance to sustainability performance. Without considering the digital dimension, arguments about efficiency and accountability (Wahyudin et al., 2022) become less concrete in the modern context, as technology enables real-time data transparency, carbon footprint tracking, and accurate social impact measurement all key elements underpinning effective sustainable governance.Based on the explanation above, the first hypothesis in this study is as follows:

H_1: Sustainable governance has a positive impact on company performance.

The Impact of Digital Transformation on Company Performance

Zhang et al. (2023) in their research explained that digital transformation strategies have a positive impact on company performance. The higher the environmental uncertainty, the greater the positive contribution of information digitalization to company performance. This transformation contributes to company performance by creating operational efficiency, improving customer experience, and strengthening competitiveness, although the impact varies depending on the company's internal preparedness, industry sector, and ability to face the dynamics of the business environment (Wahab et al., 2023).

Wang et al. (2020) also stated that the implementation of digital transformation has a positive relationship with company performance in both the short and long term. The implementation of digital technology and related changes in business strategy can result in improvements in a company's financial aspects. In the short term, digital transformation can increase operational efficiency, reduce costs, and improve business processes, which directly impact revenue increases or operational cost reductions. In the long term, digital transformation provides sustainable benefits by creating innovations that can expand markets, introduce new products or services, and enhance a company's competitiveness in the global market (Azinheira et al., 2023).

Research by Zhang et al. (2023) and Wang et al. (2020) agree that digital transformation drives performance, but they highlight different contingency variables: Zhang emphasizes environmental uncertainty as a moderating factor, while Wang distinguishes between short-term (efficiency) and long-term (innovation) impacts. A striking discrepancy between these two findings is the implicit assumption that these positive impacts are linear and universal, without critically examining how a company's sustainability orientation can influence the direction and outcomes of its digital transformation. However, without integrated sustainability principles, digital initiatives can actually produce negative consequences such as increased energy consumption or e-waste, ultimately harming long-term performance. Thus, the relationship between digital transformation and company performance is incomplete without considering business ethics and sustainable governance as guides that direct the impacts of digitalization toward truly sustainable outcomes. Based on the explanation above, the second hypothesis in this study is as follows:

H_2: Digital transformation has a positive impact on company performance.

Business Ethics Moderates the Effect ofGovernance Sustainability on Corporate Performance

Lusmeida et al. (2024) not in reference list revealed that business ethics is a key factor that can strengthen the influence of sustainable governance on company performance. The main obstacle to

implementing sustainable performance is shareholder orientation, which prioritizes short-term profits over investments in sustainability, which tend to yield long-term results. (Source) If sustainable governance is implemented without strong business ethics, shareholder pressure can hinder sustainable practices, leading to decisions that are more oriented towards short-term profitability (Source).

Choi and Jung (2008) not in reference list in Waweru (2020) not in reference list stated that business ethics plays a crucial role in improving company performance. Siswati and Pudjowati (2023) not in reference list in their research explained that by implementing good business ethics, companies can improve operational efficiency and build trust with stakeholders, thereby optimizing company performance. The findings of Lusmeida et al. (2024), who positioned business ethics as a positive moderator, make it clear that sustainability without an ethical foundation is vulnerable to distortion by short-term shareholder pressures. However, studies such as Choi & Jung (2008) and Siswati & Pudjowati (2023) tend to discuss business ethics as a direct independent variable, resulting in a less dynamic picture of its interaction with other strategic variables such as sustainable governance. This gap highlights the need for a more holistic understanding: business ethics is not simply a driver of performance, but rather a value system that governs and directs how strategic elements such as sustainable governance and digital transformation are operationalized to achieve true and sustainable performance. Based on the explanation above, the third hypothesis in this study is as follows:

H_3: Business Ethics Strengthens the Influence of Sustainable Governance on Corporate Performance

Business Ethics Moderates the Impact of Digital Transformation on Corporate Performance

Floridi (2018) not in reference list stated that companies that focus on moral principles and responsibility in their use of technology can play a significant role in determining how they adopt and implement digital transformation. Xu et al. (2024) in their research stated that business ethics significantly influence digital transformation, particularly in the areas of transparency, data security, and responsible innovation. Companies with high ethical standards tend to be more transparent in their use of technology, maintain customer data security, and avoid information manipulation, which impacts company performance. These ethical principles serve as a strategic compass, where integrity in algorithms and fairness in automation can actually create sustainable competitive advantage (Mittelstadt et al., 2016). Furthermore, a commitment to business ethics mitigates the reputational and legal risks that often accompany rushed digital innovation, creating a more stable foundation for transformation (Brennan & Johnson, 2022). In the context of data security, a robust ethical framework not only complies with regulations like GDPR but also builds customer trust, a critical asset in the digital economy (Martin, 2019). Therefore, business ethics serves as a critical enabler and moderator, ensuring that digital transformation not only improves efficiency but also strengthens the social legitimacy and long-term resilience of companies (Stahl et al., 2022). Based on the explanation above, the fourth hypothesis in this study is as follows:

H_4: Business Ethics Strengthens the Impact of Digital Transformation on Corporate Performance

RESEARCH METHOD

This research is a causal associative study. Causal associative research is a type of research designed to explain the cause-and-effect relationship between two or more variables. This study aims to understand how one variable (the independent variable) indicate the independent variables influences another variable (the dependent variable) indicate the dependent variables for your study (Sugiyono, 2019). This study used content analysis to assess the variables of sustainability governance, digital transformation, business ethics, and corporate performance, considering three main reasons. First, this study focused on

finding specific information related to the selected indicators, rather than simply counting the number of words or sentences. Second, companies often present information in the form of numbers and tables, which cannot be processed with text-based software. Third, an adequate keyword dictionary is not yet available, given the variety of corporate reporting styles despite the existence of guidelines such as the GRI. Sustainability governance, digital transformation, business ethics, and corporate performance were analyzed to score the indicators using a 0–3 scale, designed to provide deeper insight into report quality, rather than simply counting text elements. The rationale for using multiple sampling techniques is to ensure a representative and efficient sample: purposive sampling selects companies that meet basic criteria (listed on the IDX and have complete reports), the Slovin formula determines the minimum sample size, stratified random sampling maintains the proportions per sector, and systematic random sampling selects the final sample using structured random sampling. Scoring 0–3 in the content analysis is based on the level of completeness and quality of disclosure, with operationally defined thresholds (e.g., 0=no disclosure, 1=general disclosure, 2=quantitative disclosure, 3=disclosure with targets/policies). To minimize subjectivity, intercoder reliability is tested using statistics such as Cohen's Kappa Coefficient or percentage of agreement, and any discrepancies are discussed until consensus is reached. The analysis process involved several steps. First, indicators were developed based on literature and guidelines related to environmental and social sustainability practices. Second, the content of the 2022–2023 annual and sustainability reports was analyzed, with each indicator scored according to the level of implementation disclosed in the report. Infrequently reported indicators were then removed to refine the list (Papoutsi & Sodhi, 2020). not in reference list

RESULT AND DISCUSSION

The data used in this study is secondary data obtained from financial reports, annual reports, sustainability reports, and official company websites. The study population includes all companies listed on the Indonesia Stock Exchange (IDX). Sample selection was carried out in four stages. First, the sample was determined using a purposive sampling method with specific criteria. Next, probability sampling was conducted using the Slovin formula. The third stage used a proportionate stratified random sampling technique, and the final stage applied systematic random sampling. The observation period was set from 2022 to 2023. Details of the sample selection can be seen in Table 1.

Table 1. Sample Selection

No.	Sector	Number of Population	Proportion	Number of Samples
1.	Basic Material	93	36.5%	57
2.	Consumer Non-Cyclicals	87	34.1%	53
3.	Consumer Cyclicals	43	16.9%	26
4.	Energy	22	8.6%	14
5.	Industrials	10	3.9%	6
	Total	255	100%	156

Table 1 shows that from a total population of 255 companies, 156 samples were obtained, representing five sectors: Basic Materials, Consumer Non-Cyclicals, Consumer Cyclicals, Energy, and Industrials. Descriptive statistical analysis was used to provide an overview of the research data by calculating minimum, maximum, mean, and standard deviation values. The results of this analysis are presented in Table 2.

Table 2. Descriptive Statistical Analysis

	Minimum	**Maximum**	**Mean**	**Std. Deviation**
TKK	1.021	2.652	1.687	0.217
TD	0.000	1.688	0.819	0.514
KP	0.875	2.750	1.775	0.303
EB	0.916	2.833	2.058	0.427
LEV	-1.979	29.31	0.928	1.057
SIZE	3.210	3.520	3.375	0.053
Total Observasi	312			

Furthermore, this study also identified sectors with the highest implementation ofGovernance Sustainability and digital transformation. Table 3 presents the average scores for each sector. Based on the table, the Energy sector achieved the highestGovernance Sustainability (SGO) score, at 1.89. This reflects regulatory pressures and the need for an energy transition to more environmentally friendly sources. However, the Digital Transformation (DTR) score for this sector remains relatively low (0.79), indicating that the energy sector's primary focus remains on complying with sustainability regulations, while digitalization has not yet become a priority.

Table 3. Governance Sustainability and Digital Transformation Statistics by Sector

No.	Sector	TKK	TD
1	Basic Material	1,63	0,82
2	Consumer Non-Cyclicals	1,68	0,73
3	Consumer Cyclicals	1,70	0,91
4	Energy	1,89	0,79
5	Industrial	1,74	1,21

In contrast, the Basic Materials sector recorded the lowest TKK score (1.63), even though its activities are closely linked to the exploitation of natural resources and have the potential to cause significant environmental impacts. This low score is due to a focus on mass production and cost efficiency, which makes sustainability investments an additional burden. Furthermore, the sector's capital-intensive nature and reliance on traditional production processes make implementing environmentally friendly technologies expensive and time-consuming. The TD score for this sector reached 0.82, which is still relatively low, indicating that digitalization has not yet become a primary focus.

Meanwhile, the Industrials sector achieved the highest TD score, at 1.21. This confirms that the industrial sector is more advanced in adopting digitalization than other sectors. This high score can be explained by the sector's competitive nature and focus on productivity, efficiency, and quality. The widespread implementation of automation, Internet of Things (IoT), big data analytics, artificial intelligence, and smart manufacturing technologies is being implemented to optimize production processes, supply chains, and customer service. The government's Making Indonesia 4.0 program is also driving the acceleration of digitalization in this sector. Furthermore, the TKK score in the industrial sector is relatively high (1.74), indicating a balance between sustainability and digitalization.

Next, hypothesis testing was conducted to assess the influence of independent variables on company performance. The results of the main model testing are shown in Table 4.

Table 4. Main Model Test Results

Variable	Prediction	Coefficient	P-value	Decision
C	-	9.407	0.092	
TKK	+	1.805	***0.000	H1 Accepted
TD	+	0.011	0.821	H2 Decline
EB*TKK	+	0.244	***0.004	H3 Accepted
EB*TD	+	0.040	**0.041	H4 Accepted
LEV	-	0.006	0.759	
SIZE	+	1.515	0.352	
R^2	0.972			
Adj-R^2	0.942			
F-Statistic	32.71			
Prob(F-Statistic)	0.000			
(*) Sig. 10%, (**) Sig. 5%, (***) Sig. 1% *Description: TKK=Sustainability Governance, TD=Digital Transformation, EB=Business Ethics, LEV=Leverage, SIZE=Company Size*				

Source: processed data (2025)

Table 4 displays the results of the main model testing in this study, which includes the F-statistic, coefficient of determination (Adj. R^2), and partial statistical test (t-statistic). The F-test is used to assess whether all independent variables in the model sustainable governance, digital transformation, business ethics, leverage, and company size jointly influence company performance.

The results of the main model testing can be interpreted as indicating that this research model has a coefficient of determination (R^2) of 0.972 and an Adj-R^2 of 0.942, meaning that the independent variables accurately explain 94.2% of the variation in company performance. Furthermore, the high Adj-R^2 value is due to the model's accommodation of other unobserved variables in each entity.

The F-statistic value of 32.71, with a Prob (F-statistic) of 0.000 <0.05, indicates that simultaneously, the variables of sustainable governance, digital transformation, business ethics, leverage, company size, and the interaction of these variables significantly influence company performance.

The Impact of Sustainable Governance on Company Performance

The results of the study of the main model indicate that the first hypothesis (H1) is accepted, meaning thatGovernance Sustainability (SGG) has a significant and positive effect on company performance, both in terms of environmental and social performance. This finding strengthens the evidence that implementing goodGovernance Sustainability can improve company performance through responsible management of environmental and social issues. In Indonesia, the urgency of implementingGovernance Sustainability has increased with the enactment of OJK Regulation No. 51/POJK.03/2017 concerning the implementation of sustainable finance, which requires financial services institutions, issuers, and public companies to integrate sustainability aspects into their business practices (OJK, 2017).

This finding supports Stakeholder Theory, which argues that companies are accountable not only to shareholders but also to other stakeholders such as the community, government, and the environment (Freeman, 1984). By implementing goodGovernance Sustainability, companies demonstrate their

commitment to meeting stakeholder expectations through socially and environmentally responsible business practices, thereby enhancing their reputation and long-term performance.

Furthermore, these results align with Agency Theory, which states that disclosure and implementation ofGovernance Sustainability can mitigate conflicts of interest between managers (agents) and capital owners (principals). Transparent sustainability management serves as a monitoring mechanism that encourages management to act in the best interests of capital owners and other stakeholders (Jensen & Meckling, 1976).

Wahyudin et al. (2022), Kuzey et al. (2023), and Brown and Caylor (2009) also emphasize that implementing good corporate governance principles can create a work environment that supports efficiency, accountability, and sustainability, ultimately improving company performance. Ledi and Ameza–Xemalordzo (2023) reinforce these findings by demonstrating that good governance practices not only improve a company's image in the eyes of the public and stakeholders but also have a direct impact on overall company performance. This positive image can attract more investors, customers, and business partners, thus supporting long-term growth and profitability.

The Impact of Digital Transformation on Company Performance

The results of the study of the main model indicate that the second hypothesis (H2) is rejected, so it has no statistically significant effect on company performance. This finding indicates that the digital transformation implemented by the company has not been able to provide a real impact on improving environmental and social performance. This is because the digital transformation measurement indicators used emphasize more on technology adoption (ERP, AI, IoT, mobile applications, robots, etc.), rather than on how these technologies are integrated to support business strategy, innovation, or increasing customer value. The content analysis results show that of the 16 digital transformation measurement indicators, only 3 indicators have high scores, namely:

1) Indicator number 4 in the Paradigm Characteristics dimension, regarding companies adopting automation and digitalization in their production processes, has an average score of 1.58. This indicates that companies have adopted automation and digitalization in their production processes because they are directly linked to operational efficiency and cost reduction. This technology is also considered a core investment in the manufacturing industry, so its implementation is prioritized over other, more "additional" technologies such as AI chatbots or big data analytics. With automation, companies can increase productivity and reduce human error, which ultimately impacts company performance.
2) Indicator number 11 in the Influencing Scope dimension, regarding the company's use of internal applications that allow employees to communicate and share information digitally, has an average score of 1.31. The use of internal applications such as company email, intranet, collaboration applications (e.g., Microsoft Teams, Slack), or digital HR systems is relatively easier to implement and costs less than AI-based automation. Companies also recognize that the use of internal applications will have an impact on increasing the effectiveness of communication and coordination that supports employee productivity. Digital transformation in this area is usually carried out more quickly because the risk is low, the technology is mature, and it immediately makes employees' work easier.
3) Indicator number 13 in the Technology or Equipment dimension, regarding the company's use of a centralized data storage system to efficiently manage production and supply chain information, has an average score of 1.35. The implementation of this indicator shows that companies are increasingly aware of the importance of data management and supply chain integration. With a centralized data storage system (e.g., ERP, cloud database, or data warehouse), production, logistics, and supply chain information can be managed in real time, thereby reducing data duplication and accelerating decision-making. This implementation also forms the main foundation for advanced technologies such as big data analytics or AI.

Many low indicators relate to advanced technologies such as AI, IoT, big data, cloud computing, and robotics. Implementing these technologies requires high investment costs, both in hardware, software, and digital infrastructure. Companies tend to delay their implementation due to uncertain ROI (return on investment).

Technologies such as AI for energy efficiency (Indicator 7), chatbots for customer service (Indicator 8), or mobile supply chain applications (Indicators 14–15) require a workforce with digital literacy and high technical expertise. Many traditional manufacturing companies lack the necessary human resources, resulting in limited adoption.

Currently, the government has issued several regulations related to digital transformation, such as the ITE Law and Government Regulation No. 71 of 2019 concerning the Implementation of Electronic Systems and Transactions (PSTE), Law No. 27 of 2022 concerning Personal Data Protection (PDP), and POJK No. 38/2016 and POJK No. 11/2022 concerning IT Governance and Making Indonesia 4.0 in the industrial sector.

However, most of these regulations focus on compliance, data security, and operational efficiency through digitalization, rather than directly on reducing emissions, energy efficiency, or improving social impact. Thus, companies are encouraged to adopt digital technologies for greater security, transparency, and efficiency, but this transformation has not yet been directed toward generating tangible environmental or social outcomes. This explains why, in the context of research, despite ongoing digitalization, its impact on sustainability performance remains insignificant. Furthermore, these findings reinforce the Resource-Based View (RBV) argument that technologies adopted in isolation without integration into a firm's core capabilities and sustainability strategy will not generate sustainable competitive advantage. Therefore, the rejection of H2 reveals a crucial theoretical gap: digital transformation should be viewed not as a direct driver, but as an enabler whose effectiveness is fully moderated by strategic factors such as business ethics and sustainable governance, as proposed in this research model.

The Moderating Effect of Business Ethics on the Influence of Sustainable Governance and Company Performance

The results in Table 4 of the main model indicate that the third hypothesis (H3) is accepted. This means that business ethics significantly strengthens the influence ofGovernance Sustainability on company performance. In other words, even if a company already implementsGovernance Sustainability practices, the presence of strong business ethics will further maximize its positive impact on the company's environmental and social performance.

This finding aligns with Waweru's (2020) not in reference list view that business ethics plays a crucial role in improving company performance. Business ethics provides a value framework that encourages management and employee behavior to adhere to moral principles and social responsibility, ultimately supporting the consistent implementation ofGovernance Sustainability.

Furthermore, Siswati and Pudjowati (2023) not in reference list also emphasized that the implementation of good business ethics can improve operational efficiency and build trust with stakeholders, such as investors, customers, and the government. This established trust is crucial for supporting smooth company operations and strengthening reputation, which in turn positively impacts the optimization of overall company performance.

Practically, these results demonstrate that the implementation ofGovernance Sustainability alone is insufficient without the support of a culture of good business ethics. Business ethics serves as a core value that guides organizational and management behavior in consistently and responsibly implementing

sustainability principles (Gorfie & Wube, 2023). not in reference list In the Indonesian context, the urgency of strengthening business ethics is increasingly important given the frequent occurrence of ethical violations, corrupt practices, and abuse of authority, which can undermine the implementation ofGovernance Sustainability (Rudi et al., 2023).

These findings align with Stakeholder Theory, which emphasizes that a company's sustainability success is significantly influenced by how it manages its moral responsibility to stakeholders through ethical behavior (Freeman, 1984). Companies that internalize business ethics tend to be more trusted by investors, customers, and the public, thereby building a reputation that supports long-term performance.

In the regulatory context, Indonesia has also provided a legal framework related to business ethics andGovernance Sustainability through various regulations, such as Law No. 40 of 2007 concerning Limited Liability Companies, which requires companies to implement Good Corporate Governance (GCG) principles, and POJK No. 51/POJK.03/2017 concerning the Implementation of Sustainable Finance. In addition, the Code of Corporate Governance released by the National Committee for Governance Policy (KNKG) also encourages companies to build a strong culture of business ethics as part of good governance.

The Moderating Effect of Business Ethics on the Influence of Digital Transformation and Company Performance

The research results indicate that the fourth hypothesis (H4) is accepted. This means that although the direct effect of digital transformation on company performance was proven to be insignificant, the implementation of strong business ethics was proven to strengthen the relationship between digital transformation and company performance significantly. In other words, business ethics acts as a moderating factor that maximizes the benefits of digital transformation in supporting a company's operational, social, and environmental performance.

These results support Floridi's (2018) not in reference list view, which asserts that business ethics plays a crucial role in the relationship between digital transformation and company performance. According to Floridi, companies that utilize moral principles and responsibility as the foundation for their technology use will be better able to ensure that digital transformation is carried out safely, transparently, and beneficial to all stakeholders.

Furthermore, Xu et al. (2024) also confirmed that business ethics significantly influence digital transformation, particularly in the aspects of transparency, data protection, and responsible innovation. Companies with high ethical standards tend to be more transparent in data processing, maintain customer data security, and avoid misuse of technology that could harm the public. This ultimately strengthens stakeholder trust, minimizes legal risk, and supports business continuity in the digital era.

CONCLUSION

This study found thatGovernance Sustainability positively impacts corporate performance, while digital transformation did not show a significant effect in the main model, although sensitivity test results confirmed a positive effect. Furthermore, business ethics was shown to strengthen the influence ofGovernance Sustainability and digital transformation on corporate performance. The most dominant governance dimensions were POJK 51, sustainability and resilience, and IT governance, while board structure, ownership, and ethics-compliance variables were insignificant. These findings imply thatGovernance Sustainability should be viewed as a core corporate strategy, particularly in the energy sector, which faces strong regulatory pressures and global demands for decarbonization. Meanwhile, the implementation of digital transformation has had a significant impact on the industrial sector, which can serve as a model for other sectors in strengthening competitiveness. The existence of business ethics also emphasizes the importance of a moral foundation so that the implementation of sustainability and

digitalization truly provides added value, rather than simply fulfilling regulatory obligations. From a policy perspective, this study's results emphasize the need for more outcome-oriented regulations, directly linking digital transformation to ESG achievement and sustainability reporting.

For managers, these findings emphasize that investments in sustainable governance and digital infrastructure must be strategically integrated with a company's ethical framework to not only achieve regulatory compliance but also create tangible long-term value. Specifically, the energy sector should prioritize strengthening the sustainability dimension in reporting and operations, while the industrial sector can lead the way in designing digital transformation roadmaps that explicitly aim to improve environmental and social performance. For policymakers, regulatory enhancements, such as fiscal incentives or integrated reporting guidelines that directly link digital transformation indicators to ESG target achievement, are needed, thus encouraging companies to shift from a compliance-based approach to a purpose-driven approach to digital transformation.

The novelty of this research lies in the development of a more comprehensive Governance Sustainability measurement instrument by incorporating three new dimensions: POJK 51/2017, the sustainability and resilience dimension of ACGS 2023, and IT Governance. With the modifications and addition of indicators, this study presents a measurement model that is more relevant to the Indonesian context and able to address global challenges. However, this study has limitations, including the relatively short observation period (2022–2023), the potential for subjectivity in content analysis, the limited application of digital transformation indicators that still focus on advanced technology, and the failure to consider external factors such as macroeconomic conditions, government policies, and organizational culture. Therefore, future research is recommended to expand the sample size, extend the observation period, consider other mediating or moderating variables, complement the quantitative approach with qualitative data, and develop digital transformation indicators that are more relevant to improving company performance.

Future research is recommended to adopt a mixed-methods approach, complementing quantitative analysis with in-depth interviews with practitioners, to understand the organizational cultural context and implementation barriers not measured in secondary data. The research period should be extended in a longitudinal study (e.g., 5-10 years) to observe the dynamics and long-term impacts of the interaction between sustainable governance, digital transformation, and business ethics. Furthermore, the development of more contextual digital transformation indicators that encompass aspects of digital governance, data maturity, and the socio-ecological impacts of technology, as well as the inclusion of mediating variables such as innovation capability or stakeholder engagement, could provide a more comprehensive explanation of the mechanisms of performance improvement.

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APPENDIX

Table 1. Summary of statistics

This table summarizes variables, including performance measures and firm-specific control variables.

Variables	*Obs.*	*Mean*	*Median*	*Std.Dev.*	*Min.*	*Max.*	25	50	75
ESG	1001	19.28	17.77	8.37	9.09	50.83	14.46	17.77	20.66
Environ	834	13.03	10.85	9.23	1.55	51.94	8.53	10.85	14.73
Social	777	15.54	12.28	12.78	3.13	67.19	5.26	12.28	18.42
Governance	1001	45.98	44.64	5.63	10.71	67.86	44.64	44.64	48.21
SalesGr	996	0.19	0.12	0.52	−1.00	9.34	0.02	0.12	0.24
Leverage	1001	0.20	0.17	0.16	0.00	0.83	0.07	0.17	0.31
Profitability	1001	0.08	0.08	0.06	−0.13	0.44	0.04	0.08	0.12
R&D	1001	0.00	0.00	0.01	0.00	0.09	0.00	0.00	0.00
DivPayout	1001	0.48	0.18	3.85	0.00	109.88	0.08	0.18	0.28
LnAsset	1001	10.71	10.62	1.67	6.90	15.67	9.47	10.62	11.79
FirmAge	999	41.91	31.00	28.59	2.00	155.00	23.00	31.00	55.00
Market-to-book ratio	1001	0.77	0.50	0.72	0.02	5.06	0.25	0.50	1.09

Table 2. Correlation analysis

This table provides a correlation analysis of the variables used.

	ESG	*Environ*	*Social*	*Governance*	*Sales Gr*	*Leverage*	*Profitability*	*R&D*	*Div Payout*	*LnAsset*	*Firm Age*	*Market-to-book ratio*
ESG	1											
Environ	0.94**	1										
Social	0.84**	0.66**	1									
Governance	0.60**	0.60**	0.50**	1								
SalesGr	−0.04	0.02	−0.02	0.02	1							
Leverage	−0.01	0.04	0.02	0.12**	0.03	1						
Profitability	0.04	0.08*	−0.04	0.07*	0.06	−0.37**	1					
R&D	0.04	0.09**	0.05	0.02	−0.03	−0.19**	0.18**	1				
DivPayout	0.11**	0.10**	0.08*	0.10**	−0.02	0.02	−0.05	−0.02	1			
LnAsset	0.39**	0.37**	0.54**	0.32**	0.03	0.39**	−0.29**	−0.05	0.04	1		
FirmAge	0.11**	0.038	0.11**	0.014	−0.03	0.01	−0.13**	−0.02	0.08*	0.01	1	
Market-to-book ratio	0.05	.108**	0.11**	0.10**	0.02	−0.43**	0.48**	0.29**	−0.04	−0.19**	−0.06*	1

Notes: Significant at * p<0.05 (t >. 1.96), **p<0.01 (t>. 3.29).

Table 3. Determinants of founder CEOs

This table reports the determinants of founder CEOs using the firm-specific control variables. A logit regression model is employed.

Variables	*Founder CEOs*
C	3.38***
	(4.56)
SalesGr	−0.21
	(−1.40)
Leverage	1.81***
	(3.39)
Profitability	0.15
	(0.10)
R&D	3.59
	(0.69)
LnAsset	−0.39***
	(−6.84)
LnAge	0.24**
	(2.21)
Market-to-book ratio	−0.51***
	(−3.90)
ForeignOwn	0.54***
	(2.87)
Industry effect	Yes
Pseudo. R squared	0.07

Notes: Significant at * p<0.1 (t>1.64), ** p<0.05 (t >. 1.96), *** p<0.01 (t>. 3.29).

Table 4. Comparison between founder CEOs and non-founder CEOs

This table compares performance measures and firm-specific control variables for founder and non-founder CEOs groups.

	Firms with founder CEOs			Firms with non-founder CEOs			*Difference* Tests *p-value*	
	N	*Mean*	*Median*	*N*	*Mean*	*Median*	*t-test*	*Mann-Whitney U test*
ESG	487	18.29	17.36	514	20.22	17.77	0.00	0.02
Environ	415	11.66	10.85	419	14.39	11.63	0.00	0.00
Social	388	13.22	8.77	389	17.85	12.28	0.00	0.00
Governance	487	45.49	44.64	514	46.45	44.65	0.01	0.00
SalesGr	487	0.16	0.14	509	0.21	0.11	0.17	0.04
Leverage	487	0.21	0.18	514	0.19	0.14	0.07	0.00
Profitability	487	0.08	0.07	514	0.09	0.08	0.01	0.08
R&D	487	0.01	0.00	514	0.01	0.0001	0.15	0.00
DivPayout	487	0.52	18.68	514	0.44	16.98	0.76	0.34
LnAsset	487	10.53	10.35	514	10.89	10.83	0.00	0.00
FirmAge	486	42.30	32.00	513	41.53	30.00	0.67	0.05
Market-to-book ratio	487	0.67	0.42	514	0.87	0.58	0.00	0.00
ForeignOwn	487	0.22	0.00	508	0.18	0.00	0.19	-

Notes: Significant at * p<0.1 (t>1.64), ** p<0.05 (t >. 1.96), ***p<0.01 (t>. 3.29).

Table 5. The relationship between founder CEOs and ESG performance using the fixed effect model

This table reports the impact of founder CEOs and other control variables on the firm's *ESG*, *Environmental*, *Social*, and *Governance* performance. The results are interpreted using the panel fixed effect model (Fahlenbrach, 2009).

Variables	*ESG*		*Environmental*		*Social*		*Governance*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
C	20.22***	−18.37***	14.37***	−19.96***	17.90***	−38.25***	46.44***	29.28***
	(55.18)	−(7.30)	(32.33)	−(6.35)	(28.35)	−(9.37)	(188.28)	(16.10)
Founder CEOs	−1.94***	−1.01**	−2.69***	−1.66***	−4.73*	−2.38***	−0.95***	−0.26
	−(3.69)	−(2.06)	−(4.27)	−(2.75)	−(5.29)	−(3.05)	−(2.68)	−(0.73)
SalesGr		−0.40		0.23		−0.78		−0.21
		−(0.83)		(0.38)		−(0.74)		−(0.61)
Leverage		−5.20***		0.15		−4.90		2.75**
		−(2.83)		(0.06)		−(1.56)		(2.07)
Profitability		18.37***		19.87***		18.16***		17.81***
		(3.67)		(3.25)		(2.27)		(4.92)
R&D		27.66		78.14*		86.51*		−8.02
		(0.93)		(1.91)		(1.86)		−(0.37)
DivPayout		0.23***		0.22***		0.21**		0.13***
		(3.86)		(3.26)		(2.47)		(3.01)
LnAsset		2.59***		2.32***		4.08***		1.28**
		(13.96)		(9.95)		(13.75)		(9.53)
FirmAge		1.83***		1.03**		1.57**		0.25
		(4.97)		(2.17)		(2.56)		(0.95)
Market-to-book ratio		0.79*		1.29**		2.87***		0.75**
		(1.81)		(2.25)		(3.91)		(2.37)
ForeignOwn		−0.56		0.36		1.67		0.49
		−(0.89)		(0.44)		(1.60)		(1.06)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R squared	0.01	0.272	0.03	0.134	0.22	0.06	0.01	0.16
# of Obs	1,001	1,001	1,001	1,001	1,001	1,001	1,001	1,001
# of Firms	215	215	215	215	215	215	215	215

Notes: Significant at * p<0.1 (t>1.64), ** p<0.05 (t >. 1.96), ***p<0.01 (t>. 3.29).

Table 6. The effect of growth opportunities on the relationship between founder CEOs and ESG performance using the fixed effect model

This table reports the effect of growth opportunities on the relationship between founder CEOs and *ESG*, *Environmental*, *Social,* and *Governance* performance. The results are interpreted using the panel fixed effect model (Fahlenbrach, 2009).

Variables	*ESG 9(1)*	*Environ (2)*	*Social (3)*	*Governance (4)*
C	−18.90***	−20.89***	−38.56***	29.02***
	−(7.50)	−(6.64)	−(9.35)	(15.91)
Founder CEOs× Market-to-book ratio	−1.72**	−2.52***	−0.63	−0.85*
	−(2.50)	−(2.73)	−(0.55)	−(1.69)
Founder CEOs	0.25	0.05	−1.92*	0.36
	(0.36)	(0.06)	−(1.71)	(0.70)
Salesgr	−0.40	0.22	−0.78	−0.21
	−(0.83)	(0.37)	−(0.75)	−(0.61)
Leverage	−5.16***	0.17	−4.89	2.77**
	−(2.82)	(0.07)	−(1.56)	(2.08)
Profitability	18.49***	20.00***	18.31**	17.87***
	(3.70)	(3.28)	(2.29)	(4.94)
R&D	27.37	72.52*	85.81*	−8.16
	(0.92)	(1.78)	(1.84)	−(0.38)
DivPayout	0.23***	0.21***	0.21**	0.13***
	(3.77)	(3.13)	(2.44)	(2.94)
LnAsset	2.57***	2.29***	4.07***	1.27***
	(13.87)	(9.88)	(13.71)	(9.46)
FirmAge	1.90***	1.18**	1.62***	0.29
	(5.16)	(2.47)	(2.61)	(1.08)
Market-to-book ratio	1.39***	2.21***	3.10***	1.04***
	(2.80)	(3.33)	(3.67)	(2.89)
ForeignOwn	−0.56	0.24	1.64	0.49
	−(0.88)	(0.29)	(1.57)	(1.07)
Fixed effect	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes
Adj. R squared	0.28	0.23	0.38	0.17

Notes: Significant at * p<0.1 (t>1.64), ** p<0.05 (t >. 1.96), ***p<0.01 (t>. 3.29).

Table 7. The effect of foreign ownership on the relationship between founder CEOs and ESG performance using the fixed effect model

This table reports the effect of foreign ownership on the relationship between founder CEOs and *ESG*, *Environmental*, *Social,* and *Governance* performance. The results are interpreted using the panel fixed effect model (Fahlenbrach, 2009).

Variables	*ESG*	*Environ*	*Social*	*Governance*
	(1)	*(2)*	*(3)*	*(4)*
C	−18.36***	−19.67***	−38.03***	29.29***
	−(7.34)	−(6.31)	−(9.32)	(16.16)
Founder CEOs×ForeignOwn	4.21***	5.72***	3.05	2.43***
	(3.50)	(3.67)	(1.52)	(2.78)
Founder CEOs	−1.81***	−2.64***	−2.91***	−0.72*
	−(3.36)	−(4.03)	−(3.41)	−(1.85)
SalesGr	−0.40	0.15	−0.79	−0.22
	−(0.84)	(0.25)	−(0.76)	−(0.62)
Leverage	−5.15***	−0.58	−5.20*	2.78**
	−(2.82)	−(0.23)	−(1.66)	(2.10)
Profitability	19.61***	20.60***	18.49**	18.52***
	(3.93)	(3.39)	(2.32)	(5.12)
R&D	25.32	72.76	85.02*	−9.37
	(0.86)	(1.79)	(1.83)	−(0.44)
DivPayout	0.23***	0.22***	0.21**	0.13***
	(3.85)	(3.22)	(2.44)	(2.99)
LnAsset	2.64***	2.36***	4.09***	1.31***
	(14.29)	(10.20)	(13.79)	(9.77)
FirmAge	1.82***	1.13**	1.65***	0.25
	(4.98)	(2.38)	(2.67)	(0.94)
Market-to-book ratio	0.71	1.25**	2.83***	0.70**
	(1.64)	(2.19)	(3.85)	(2.23)
ForeignOwn	−2.87***	−2.79**	−0.02	−0.84
	−(3.14)	−(2.36)	−(0.01)	−(1.27)
Fixed effect	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes
Adj. R squared	0.28	0.23	0.38	0.17

Notes: Significant at * p<0.1 (t>1.64), ** p<0.05 (t >. 1.96), ***p<0.01 (t>. 3.29).

Table 8. Robustness check on the relationship between founder CEOs, growth opportunities, and ESG performance using the panel GMM model

This table reports the results of our robustness check on the relationship between founder CEOs, growth opportunities, and *ESG*, *Environmental*, *Social*, and *Governance* performance. Arellano and Bond (1991) Panel GMM is used in our analysis to account for endogeneity problems.

Panel A. The relationship between founder CEOs and ESG performance

Variables	*ESG*	*Environ*	*Social*	*Governance*
	(1)	*(2)*	*(3)*	*(4)*
C	−18.25***	−19.96***	−38.25***	29.36***
	−(7.24)	−(6.35)	−(9.37)	(16.11)
Founder CEOs	−1.01**	−1.66***	−2.38***	−0.26
	−(2.06)	−(2.75)	−(3.05)	−(0.74)
SalesGr	−0.33	0.23	−0.78	−0.17
	−(0.67)	(0.38)	−(0.74)	−(0.47)
Leverage	−5.36***	0.15	−4.90	2.64**
	−(2.90)	(0.06)	−(1.56)	(1.98)
Profitability	18.17***	19.87***	18.16**	17.67***
	(3.62)	(3.25)	(2.27)	(4.87)
R&D	27.73	78.14*	86.51*	−7.98
	(0.93)	(1.91)	(1.86)	−(0.37)
DivPayout	0.23***	0.22***	0.21**	0.13***
	(3.86)	(3.26)	(2.47)	(3.01)
LnAsset	2.60***	2.32***	4.08***	1.28***
	(13.98)	(9.95)	(13.75)	(9.55)
FirmAge	1.79***	1.03**	1.57**	0.23
	(4.86)	(2.17)	(2.56)	(0.86)
Market-to-book ratio	0.77*	1.29**	2.87***	0.73**
	(1.77)	(2.25)	(3.91)	(2.33)
ForeignOwn	−0.54	0.36	1.67	0.50
	−(0.85)	(0.44)	(1.60)	(1.10)
Fixed effect	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes
Adj. R squared	0.27	0.22	0.38	0.17

Notes: Significant at * p<0.1 (t>1.64), ** p<0.05 (t >. 1.96), ***p<0.01 (t>. 3.29).

Panel B. The effect of growth opportunities on the relationship between Founder CEOs and ESG performance

Variables	*ESG*	*Environ*	*Social*	*Governance*
	(1)	*(2)*	*(3)*	*(4)*
C	−18.79***	−20.89***	−38.56***	29.10***
	−(7.44	−(6.64)	−(9.35)	(15.92)
Founder CEOs×Market-to-book ratio	−1.71**	−2.52***	−0.63	−0.83*
	−(2.47)	−(2.73)	−(0.55)	−(1.66)
Founder CEOs	0.23	0.05	−1.92*	0.35
	(0.33)	(0.06)	−(1.71)	(0.68)
SalesGr	−0.34	0.22	−0.78	−0.17
	−(0.69	(0.37)	−(0.75)	−(0.48)
Leverage	−5.30*	0.17	−4.89	2.67*
	−(2.87)	(0.07)	−(1.56)	(2.00)
Profitability	18.31***	20.00***	18.31**	17.74***
	(3.66)	(3.28)	(2.29)	(4.90)
R&D	27.43	72.52*	85.81*	−8.12
	(0.35)	(1.78)	(1.84)	−(0.38)
DivPayout	0.23***	0.21***	0.21**	0.13***
	(3.77)	(3.13)	(2.44)	(2.94)
LnAsset	2.57***	2.29***	4.07***	1.27***
	(13.89)	(9.88)	(13.71)	(9.47)
FirmAge	1.87***	1.18**	1.62***	0.27
	(5.06)	(2.47)	(2.61)	(1.00)
Market-to-book ratio	1.37***	2.21***	3.10***	1.02***
	(2.75)	(3.33)	(3.67)	(2.85)
ForeignOwn	−0.54	0.24	1.64	0.51
	−(0.40)	(0.29)	(1.57)	(1.10)
Fixed effect	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes
Adj. R squared	0.28	0.22	0.38	0.17

Notes: Significant at * p<0.1 (t>1.64), ** p<0.05 (t >. 1.96), ***p<0.01 (t>. 3.29).

Panel C. The effect of foreign ownership on the relationship between Founder CEOs and ESG performance

Variables	*ESG* *(1)*	*Environ* *(2)*	*Social* *(3)*	*Governance* *(4)*
C	−18.28***	−19.67***	−38.03***	29.35***
	−(7.29)	−(6.31)	−(9.32)	(16.16)
Founder CEOs×ForeignOwn	4.17***	5.72***	3.05	2.40***
	(3.45)	(3.67)	(1.52)	(2.74)
Founder CEOs	−1.80***	−2.64***	−2.91***	−0.72*
	−(3.35)	−(4.03)	−(3.41)	−(1.84)
SalesGr	−0.35	0.15	−0.79	−0.18
	−(0.72)	(0.25)	−(0.76)	−(0.51)
Leverage	−5.25***	−0.58	−5.20*	2.70**
	−(2.86)	−(0.23)	−(1.66)	(2.03)
Profitability	19.45***	20.60***	18.49**	18.41***
	(3.89)	(3.39)	(2.32)	(5.08)
R&D	25.39	72.76*	85.02*	−9.32
	(0.86)	(1.79)	(1.83)	−(0.43)
DivPayout	0.23***	0.22***	0.21**	0.13***
	(3.85)	(3.22)	(2.44)	(2.99)
LnAsset	2.65***	2.36***	4.09***	1.31***
	(14.29)	(10.20)	(13.79)	(9.78)
FirmAge	1.80***	1.13**	1.65***	0.23
	(4.89)	(2.38)	(2.67)	(0.87)
Market-to-book ratio	0.70	1.25**	2.83***	0.69**
	(1.61)	(2.19)	(3.85)	(2.20)
ForeignOwn	−2.83***	−2.79**	−0.02	−0.81
	−(3.09)	−(2.36)	−(0.01)	−(1.22)
Fixed effect	Yes	Yes	Yes	Yes
Industry effect	Yes	Yes	Yes	Yes
Adj. R squared	0.28	0.23	0.38	0.17

Notes: Significant at * p<0.1 (t>1.64), ** p<0.05 (t >. 1.96), ***p<0.01 (t>. 3.29).

THE DIGITAL BRIDGE TO EMPLOYABILITY: A MODERATED MEDIATION ANALYSIS OF EXPERIENTIAL LEARNING, DIGITAL SKILL, AND SELF-EFFICACY ON WORK READINESS

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ABSTRACT

This study examines how Experiential Learning contributes to Employability among Indonesian university students, testing the mediating role of Digital Skill and clarifying conceptual ambiguity regarding potential moderation effects. While the direct pathway is robust, inconsistent evidence regarding psychological moderators leaves the boundary conditions of this crucial educational relationship unresolved. A cross-sectional survey of 469 Indonesian university students with internship experience was conducted, analyzed using structural equation modeling. Results show Experiential Learning significantly enhances Work Readiness directly and indirectly via Digital Skill. Crucially, the hypothesized moderating role of Self-Efficacy was not supported, and Self-Efficacy had no direct effect on Work Readiness. These findings suggest that the experiential learning pathway operates as a stable, non-conditional mechanism. The study provides clarification on the pathway's robustness, demonstrating that psychological factors may offer limited explanatory value. It highlights the need to prioritize competence-based interventions and continuous improvement of experiential learning environments to boost graduate employability

Keywords: Work Readiness; Experiential Learning; Digital Skill; Self-Efficacy; Moderated Mediation; Graduate Employability

INTRODUCTION

Amidst the highly competitive global economic landscape of the 21st century, the demand for "work-ready talent" has become a key priority for organizations (OECD, 2024). Consequently, higher education institutions (HEIs) are under immense pressure not only to confer degrees but also to ensure their graduates possess a comprehensive set of attributes. This attribute set is known as Work Readiness, a multidimensional construct encompassing (Enstroem & Schmaltz, 2024; Fugate et al., 2004; Peersia et al., 2024). However, despite this urgency, reports of a persistent "mismatch" between graduate competencies and actual industry demands continue to surface (The future of jobs report, 2025).

This skills mismatch is rooted in long-standing criticisms of the traditional higher education model. Many HEI curricula are criticized for focusing excessively on theoretical knowledge dissemination and rote learning, while neglecting the development of practical and contextual capabilities (Adegbite & Govender, 2021; Jackson & Bridgstock, 2021). Consequently, graduates often experience a "reality shock" upon

entering the workforce, where they are expected to adapt rapidly, solve complex problems, and collaborate effectively within teams (Ferry & Westerlund, 2023).

As a strategic response to bridge this theory-practice gap, the Experiential Learning paradigm has been widely adopted (Azeez & Aboobaker, 2024). This approach is increasingly supported by co-creation models and challenge-based learning initiatives that foster collaboration between academia and the labor market to address real-world professional challenges (Amante et al., 2024). Drawing from Kolb, (1984) Experiential Learning Theory, profound and meaningful learning occurs through a four-stage cycle: concrete experience, reflective observation, abstract conceptualization, and active experimentation. Empirical studies consistently demonstrate that participation in experiential learning programs is one of the strongest predictors of enhanced Work Readiness, as these programs compel students to apply, test, and refine their competencies within authentic professional contexts (Alrazeeni et al., 2021; Shore & Dinning, 2023)

While the positive relationship between Experiential Learning and Work Readiness is well-documented (Shore & Dinning, 2023), modern research has begun to shift from *whether* experiential learning impacts work readiness to the more critical question of *how* this influence occurs (Adegbite, 2024). The process is considerably more complex and contingent upon the specific competencies honed and acquired during the experience (Azeez & Aboobaker, 2024). Therefore, identifying the mediating mechanisms that explain the transformation process from experience to readiness is theoretically and practically crucial for designing effective Experiential Learning programs.

Amid the demands of Industry 4.0 and the digital economy, one of the most logical and crucial mediating mechanisms is Digital Skill. Digital Skill, which encompasses the ability to seek, evaluate, use, and create information using digital technologies (Helsper & Van Laar, 2021), has evolved from a mere IT skill into a foundational language in nearly every modern workplace (Reddy et al., 2023). Experiential Learning programs provide an authentic arena for students to apply, test, and validate their Digital Skill on real-world problems. It is this enhancement of Digital Skill that, in turn, directly contribute to their Work Readiness (Van Laar et al., 2019).

The robustness of this [X → M → Y] mediation path is no longer a mere theoretical proposition; it has been empirically validated by recent Q1 research. using conceptually identical constructs (Work-Integrated Learning and Digital Literacy, successfully demonstrated that Digital Literacy plays a significant mediating role. This finding (Adegbite, 2024) confirming that Digital Skill (or Literacy) is a critical bridge in the work readiness model. However, this validated model still leaves a significant question unanswered.

While the model successfully answers *how* the mechanism operates, it failed to answer the crucial question of *when* this effect holds true. The effectiveness of Experiential Learning is not universal; its impact likely hinges on specific individual characteristics or conditions. Previous research has attempted to test potential moderators, such as life-career knowledge, namely *Life-Career Knowledge*. However, their findings indicated that this moderation hypothesis failed (was rejected). the model remains incomplete because its true boundary conditions have yet to be identified.

Therefore, this study proposes a moderator that is Self-Efficacy. Drawing from Social Cognitive Theory (Bandura, 1986), Self-Efficacy is an individual's belief in their capability to succeed in specific tasks. Within this context, Self-Efficacy functions as a psychological filter. Students with high Self-Efficacy will tend to be proactive, persistent, and view challenges during their internship as opportunities, thereby maximizing their impact on Work Readiness.

Based on the identified research gap, this study aims to refine and extend the model proposed by (Adegbite, 2024). Specifically, the objectives are: (1) To confirm the influence of Experiential Learnin on

Work Readiness; (2) To confirm the mediating role of Digital Skill in the X-Y relationship within the Indonesian context; and (3) To test the moderating role of Self-Efficacy on the X-Y relationship, which we hypothesize will be significant. Thus, this research will produce a more comprehensive and robust moderated mediation model to explain the determinants of graduate work readiness.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Work Readiness (Y) as a Key Construct

The central construct in this research is Work Readiness. Work Readiness is defined as a multidimensional set of attributes that enables graduates to effectively integrate and contribute within the workplace (Herbert et al., 2020). It is crucial to note that Work Readiness transcends mere technical proficiency (hard skills); it is a holistic construct that also encompasses generic skills (such as communication, teamwork, and problem-solving), personal attributes (like professionalism, work ethic, and resilience), and an understanding of organizational expectations and dynamics (Inderanata & Sukardi, 2023; Lawton et al., 2024). Within the context of graduate mismatch, the achievement of high Work Readiness is considered the most critical ultimate outcome of higher education interventions (Sakitri et al., 2024).

Experiential Learning and its Theoretical Foundation

To cultivate such holistic Work Readiness, the most potent pedagogical intervention is Experiential Learning. Experiential Learning (e.g., internships, WIL) is not merely the placement of students in industry; it is an active learning process with a robust theoretical foundation. Its cornerstone is Kolb, (1984) Experiential Learning Theory. Kolb (1984) argued that deep learning occurs through a continuous four-stage cycle: (1) Concrete Experience, (2) Reflective Observation, (3) Abstract Conceptualization, and (4) Active Experimentation. This process affirms that learning is not the passive transfer of knowledge, but rather an active process of "creating knowledge through the transformation of experience" (Kolb, 1984).

The Direct Influence of Experiential Learning on Work Readiness

The relationship between Experiential Learning and Work Readiness can be directly explained via (Kolb (1984) cycle. Experiential Learning programs compel students to exit their passive roles and enter this cycle. They confront Concrete Experiences (e.g., handling client complaints or project deadlines). They must engage in Reflective Observation (Why did my approach fail?). They Conceptualize (comparing classroom theory with reality). And they Experiment (trying new approaches). It is this active process that plays a central role in developing the various dimensions of Work Readiness, from problem-solving to resilience (Lau et al., 2020). Numerous empirical studies have consistently found a positive and significant correlation between participation in WIL/EL and enhanced Graduate Employability or Work Readiness (Adegbite, 2024; Adegbite & Govender, 2021; Mahajan et al., 2022). Furthermore, the adoption of innovative pedagogical methodologies is crucial as it fosters deeper student engagement and promotes the development of critical problem-solving skills necessary for professional success (Amante, 2024). Therefore, the first hypothesis is formulated:

H1: Experiential Learning has a positive and significant influence on Work Readiness.

The first hypothesis (H1) establishes the direct relationship. However, to unpack the "black box" of the X→Y path, its intervening mechanisms must be tested. The first path in this mechanism is the relationship between Experiential Learning and Digital Skill. We argue that Experiential Learning programs

(such as internships) serve as a practical "arena" or "laboratory." It is here that students are compelled to transition from theoretical knowledge of digital tools to practical application in professional contexts (Chonsalasin & Khampirat, 2022). They must utilize collaborative software (e.g., Teams, Slack), project management platforms (e.g., Trello, Asana), or industry-specific data analysis software not taught in the classroom. This intensive "learning by doing" process within EL is what directly hones, validates, and enhances the student's Digital Skill (M) (Hampton et al., 2021). Therefore, the second hypothesis is proposed:

H2: Experiential Learning has a positive and significant influence on Digital Skill (M).

The second path in the mediation mechanism is the relationship between Digital Skill and Work Readiness. In the modern labor market, Digital Skill is no longer considered an optional or specialized competency but rather a fundamental baseline (Adegbite, 2024). Employers across all sectors now assume graduates possess the ability to adapt to new technologies, analyze data, and communicate digitally (Dewi, 2021). These skills directly contribute to Work Readiness by enabling graduates to work more efficiently, contribute to virtual teams, and demonstrate self-directed learning all core attributes that define "work readiness" in the 21st century (Scheepers et al., 2024; McGunagle & Zizka, 2020) Thus, the third hypothesis is:

H3: Digital Skill has a positive and significant influence on Work Readiness.

Based on the H2 and H3 arguments, we propose the full mediation hypothesis. The logic is as follows: Experiential Learning does enhance Work Readiness [H1], but this occurs primarily because Experiential Learning functions as an incubator for Digital Skill [H2], and it is this Digital Skill that ultimately becomes a crucial component evaluated as Work Readiness by employers [H3]. In other words, Digital Skill is the intervening mechanism that transforms "experience" into "readiness". This mediating role is consistent with recent empirical findings (Adegbite, 2024; Mabungela & Mtiki, 2024), which confirm Digital Skill/Literacy as an essential bridge in the work readiness model. Therefore:

H4: Digital Skill significantly mediates the relationship between Experiential Learning and Work Readiness.

The [X→M→Y] mediation path, as outlined in H1-H4, answers the question of "how" the process occurs. However, this model remains incomplete as it fails to answer the question of "when" (i.e., its boundary conditions). The effectiveness of Experiential Learning is not universal; its positive impact on Work Readiness likely depends on the individual characteristics of the student (Fromm et al., 2021). This awareness of boundary conditions was also acknowledged by (Adegbite, 2024), who attempted to test Life-Career Knowledge as a moderator. Prior work tested life-career knowledge as a potential moderator, but the effect was not supported. This non-significant finding leaves a an unresolved conceptual gap: the model remains incomplete because its true boundary conditions remain unidentified.

Prior research reported a non-significant moderation effect can be explained by our theoretical argument: Life-Career Knowledge is likely more appropriately conceptualized as an outcome (a result of learning) rather than as a condition (a moderator). Therefore, this study proposes a moderator that is theoretically and correctly positioned: Self-Efficacy.

Rooted in Social Cognitive Theory (Bandura, 1986), Self-Efficacy is defined as an individual's belief in their own capability to succeed in specific situations or tasks. In this context, Self-Efficacy is not a learned skill (like Digital Skill) but rather a psychological filter that students possess before and during their Experiential Learning. Bandura (1986) argued that self-efficacy is a primary determinant of whether

an individual will initiate action, how much effort they will expend, and how long they will persist in the face of difficulties.

The logic for the moderation of Self-Efficacy on the X→Y relationship is as follows: (a) Students with HIGH Self-Efficacy participating in Experiential Learning will tend to be more proactive, persistent, embrace challenging tasks, and view failure as a learning opportunity. For them, the impact of the experience will be maximized, potentially leading to higher Work Readiness. (b) Conversely, students with LOW Self-Efficacy in the same program may remain passive, avoid challenges, and give up easily. For them, the experience fails to deliver optimal impact, potentially weakening the X→Y relationship..

The X→Y relationship is, therefore, conditional upon the level of Self-Efficacy. Based on this strong theoretical argument addresses an unresolved conceptual gap identified in prior research we formulate the final hypothesis:

H5: Self-Efficacy significantly moderates (strengthens) the positive relationship between Experiential Learning and Work Readiness.

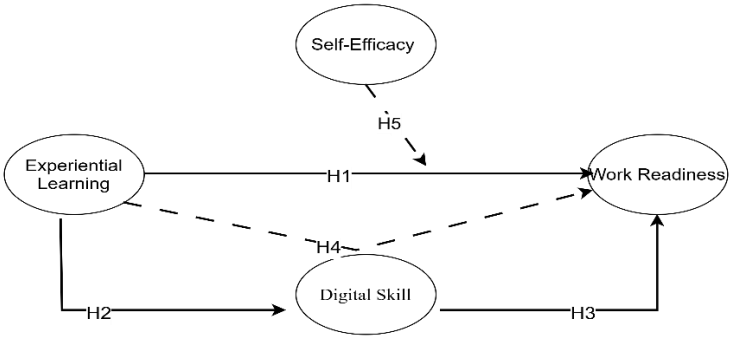

Figure 1. Theoretical Model Figure

RESEARCH METHODOLOGY

Research Design

This study employs a quantitative approach utilizing an explanatory correlational design. The primary objective is to explain and test the causal relationships hypothesized within the moderated mediation model (Hair et al., 2022). In line with this objective, data were collected using a cross-sectional survey method, wherein all data for the independent (Experiential Learning), dependent (Work Readiness), mediating (Digital Skill), and moderating (Self-Efficacy) variables were gathered from respondents at a single point in time (Sarstedt et al., 2021). This approach was selected for its efficiency in testing theoretical models and its alignment with standard methodologies used in this research domain.

Population and Sampling Technique

The target population for this study comprised active undergraduate students from various universities in Indonesia who possessed practical work experience. The research sample was drawn using a purposive sampling technique (Hair et al., 2022). Strict inclusion criteria were established to ensure respondent relevance: (1) Students who had completed an Experiential Learning program [such as an Internship, Field Work Practice, or similar program] within the last 12 months, and (2) Voluntary willingness to participate in the survey. Data collection was conducted online via a questionnaire distributed through social media platforms and academic networks to reach a broad and diverse audience. This

population was considered appropriate, as students who have recently completed an experiential learning program are in a transitional phase between education and employment, making them particularly relevant for assessing perceptions of work readiness and competency development.

Sample Size

The determination of the sample size was based on an a priori statistical power analysis using G*Power 3.1 (Faul & Lang, 2009), ensuring methodological rigor. This step was crucial as the research model includes a moderation test (H5), an effect that is theoretically often "small" and requires substantial statistical power for accurate detection (Hair et al., 2022). By setting stringent parameters ($\alpha = 0.05$, power $1-\beta = 0.95$) to detect a small-to-medium effect size ($f^2 = 0.05$), G*Power indicated that the minimum required sample size was n = 372.

The initial data collection process gathered approximately 500+ responses. After a meticulous data cleaning process (which included removing incomplete data, straight-lining, and extreme outliers), a final, clean sample suitable for analysis was obtained, totaling n = 469. This final sample size (n=469) substantially exceeds the minimal threshold required by G*Power (n=372). This confirms that the study possesses very strong and superior statistical power (well above the threshold), providing high confidence in the hypothesis testing results, particularly for H5 (moderation).

Variable Measurement (Operationalization)

All variables in this study were measured using classic and seminal instruments that have been extensively validated, ensuring the highest level of validity and reliability. Respondents were asked to provide their responses on a 7-point Likert scale (1=Strongly Disagree to 7=Strongly Agree).

(1) Experiential Learning was measured using 4 items adapted from the foundational scale of (Kolb, 1984), focusing on the learning cycle of concrete experience, reflective observation, active experimentation, and abstract conceptualization.

(2) Work Readiness, the dependent variable, was measured using 3 items from the seminal scale by (Fugate et al., 2004). This scale was chosen as it represents the "gold standard" definition of the employability construct, focusing on psycho-social attributes (e.g., adaptability, social capital, etc.).

(3) Digital Skill was measured using 3 items from the established scale by (Gui, 2011). This scale was intentionally chosen for its focus on foundational digital skills. (4) Self-Efficacy was measured using 4 items adapted directly from the scale construction guide pioneered by (Bandura, 1986). This scale was selected as it measures individual belief directly from its primary theoretical source, providing the strongest possible content validity.

We intentionally selected this combination of classic and seminal scales (Bandura, 1986; Fugate et al., 2004; Gui, 2011; Kolb, 1984) to ensure the highest measurement validity. This ensures that the hypothesis testing results (particularly for H5) are built upon a robust and defensible foundation.

Data Analysis Technique

To test the five hypotheses proposed in this moderated mediation model, the study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM). The analysis was conducted using the SmartPLS

4 software (Hair et al., 2022). The PLS-SEM approach was chosen for two primary reasons: (1) It aligns with the research objective, which is focused on prediction and variance explanation, and (2) Its robust capability in handling complex models (such as moderation and mediation) without the strict assumptions of normal data distribution (Hair et al., 2022). This technical choice is also consistent with methodologies commonly used in similar studies.

RESEARCH RESULTS

Respondent Characteristics

This study successfully collected a total of N = 469 clean and complete questionnaires from students at two universities in the Jabodetabek region. This sample exceeds the minimum threshold (n=372) required by the G*Power analysis. Respondent characteristics show a relatively balanced distribution, comprising 54% male and 46% female. The majority of respondents (over 99%) were within the productive age range of 21-24 years, which is the primary age group for final-year students who have completed an Experiential Learning (internship) program, thereby ensuring sample homogeneity and relevance.

Measurement Model Evaluation

The PLS-SEM analysis begins with the evaluation of the measurement model (outer model) to ensure instrument validity and reliability. Convergent Validity was evaluated via Outer Loadings and Average Variance Extracted (AVE). The majority of indicator outer loadings were above the ideal value of 0.70. While several indicators (DS1, DS2, DS5, EL4, WR2) had loadings between 0.60 and 0.70 (see Table 1), Hair et al (2022) state that these loadings are still acceptable as long as the AVE value of the respective construct is above 0.50.

Table 1 Constructs' reliability and validity

Construct	Item	Outer Loading	Cronbach's alpha	Composite reliability	Average variance extracted
Digital Skill	DS1	0.812	0.878	0.885	0.623
	DS2	0.804			
	DS3	0.704			
	DS4	0.848			
	DS5	0.806			
	DS6	0.752			
Experential Learning	EL1	0.729	0.882	0.882	0.547
	EL2	0.719			
	EL3	0.744			
	EL4	0.736			
	EL5	0.758			
	EL6	0.746			
	EL7	0.764			
	EL8	0.719			
Self-eficacy	SE1	0.779	0.851	0.877	0.521
	SE2	0.817			

	SE3	0.791			
	SE4	0.736			
	SE5	0.639			
	SE6	0.652			
	SE7	0.611			
Work Readiness	WR1	0.738	0.826	0.832	0.537
	WR2	0.774			
	WR3	0.671			
	WR4	0.716			
	WR5	0.804			
	WR6	0.683			

The results in Table 1 confirm the model's robustness. The Average Variance Extracted (AVE) values for all constructs were above the 0.50 threshold (Digital Skill=0.632; Experiential Learning=0.547; Self-Efficacy=0.521; Work Readiness=0.537). Furthermore, internal consistency reliability was also very strong, with all Cronbach's Alpha and Composite Reliability values well above the 0.70 threshold. Thus, the model's convergent validity and reliability have been convincingly met.

Structural model assessment

Finally, Discriminant Validity was tested using the Heterotrait-Monotrait Ratio (HTMT) criterion, which is the modern and more stringent standard (Henseler et al., 2015). The results in Table 2 show that all HTMT values between constructs were well below the 0.85 threshold. The highest value was only 0.82 (between DS and WR). This proves that the four constructs in this study (EL, DS, SE, WR) are distinct entities that do not overlap.

Table 2 Heterotrait-Monotrait Ratio HTMT

	DS	**EL**	**SE**	**WR**	**SE x EL**
DS					
EL	0.701				
SE	0.619	0.726			
WR	0.828	0.817	0.666		
SE x EL	0.329	0.363	0.441	0.346	

Furthermore, discriminant validity was also assessed using the classic Fornell & Larcker criterion, as presented in Table 3. This criterion stipulates that the square root of the Average Variance Extracted (AVE) for each construct (the diagonal value) must be greater than its correlation coefficients with all other constructs. The results Table 3 demonstrate that all values on the diagonal Digital Skill (0.789), Experiential Learning (0.740), Self-efficacy (0.722), and Work Readiness (0.732) were consistently higher than the off-diagonal correlation values in their respective columns and rows (e.g., the highest being 0.713, 0.700, and 0.651). Thus, discriminant validity for all constructs in this study was successfully established.

Table 3 Fornell-larcker criterion

	DS	**EL**	**SE**	**WR**

DS	0.789			
EL	0.622	0.740		
SE	0.563	0.651	0.722	
WR	0.713	0.700	0.594	0.732

Inner Model Evaluation - R^2 and Model Fit

Once the measurement model (outer model) was declared valid and reliable, the next step was to evaluate the structural model (inner model). First, we assessed the model's predictive power via the R-Square (R^2) value. The results show an R^2 for Digital Skill of 0.324 and for Work Readiness of 0.366. This means our model (EL, DS, SE) can explain 36.6% of the variance in Work Readiness, which is considered a moderate and substantial predictive power. Next, the Model Fit was evaluated using the SRMR (Standardized Root Mean Square Residual). This model achieved an SRMR = 0.057. As this value is below the 0.08 threshold, the research model is declared FIT and robust (Henseler et al., 2015).

Hypothesis Test Results (Direct Paths)

The subsequent evaluation involved hypothesis testing via bootstrapping (5,000 subsamples) to determine the significance of each path. The complete results for the path coefficients are presented in Table 4.

Table 4 Path Coefficients and Hypothesis Results

	Original sample	Sample mean	Standard deviation	T statistics	P values	F-square	Decision
H1: EL -> WR	0.356	0.354	0.045	7.859	0.000	0.162	Accepted
H2: EL -> DS	0.622	0.624	0.040	15.487	0.000	0.632	Accepted
H3: DS -> WR	0.420	0.421	0.040	10.445	0.000	0.266	Accepted
H4: EL -> DS -> WR	0.261	0.263	0.030	8.739	0.000		Accepted
H5: SE x EL -> WR	-0.006	-0.004	0.024	0.239	0.811	0.000	Rejected

H1 tested the influence of Experiential Learning on Work Readiness. The results indicated a positive and significant relationship (Beta = 0.356; T = 7.859; p = 0.000). The path exhibited a medium effect size ($f^2 = 0.162$). Thus, H1 was ACCEPTED.

H2 tested the influence of Experiential Learning on Digital Skill. The results indicated a positive and highly significant relationship (Beta = 0.622; T = 15.487; p = 0.000). This path showed a large effect size ($f^2 = 0.632$). Thus, H2 was ACCEPTED.

H3 tested the influence of Digital Skill on Work Readiness. The results indicated a positive and significant relationship (Beta = 0.420; T = 10.445; p = 0.000), with a medium-to-large effect size ($f^2 = 0.266$). Thus, H3 was ACCEPTED.

H4 proposed that Digital Skill mediates the relationship between Experiential Learning and Work Readiness. Using the results from Table 5 (Specific Indirect Effects), the analysis showed that the mediation path (X → M → Y) was positive and highly significant (Beta = 0.261; T = 8.739; p = 0.000). As the direct path (H1) was also found to be significant (as reported above), this finding confirms the presence of complementary partial mediation. Thus, H4 was ACCEPTED.

H5 was the study's primary contribution hypothesis, testing whether Self-Efficacy moderates the X-Y relationship. The bootstrapping results for the interaction path (SE x EL → WR) in Table 4 showed a highly non-significant coefficient (Beta = -0.006; T = 0.239; p = 0.811). This extremely high p-value, combined with a zero effect size (f^2 = 0.000), conclusively demonstrates that H5 was not statistically supported. Thus, H5 was REJECTED.

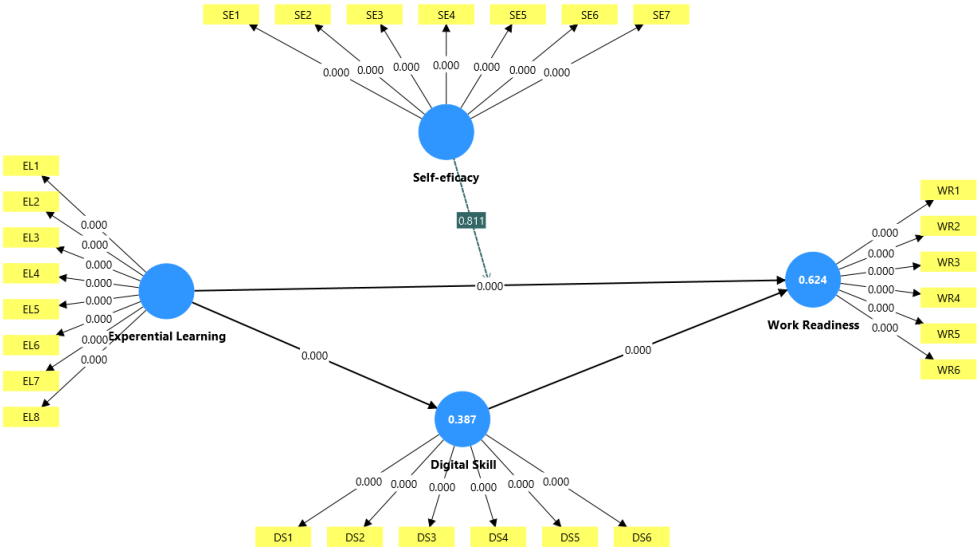

Figure 2. Path Coeficient

DISCUSSION AND CONCLUSION

Discussion of Findings

The findings of this study align with patterns reported in prior research, establishing that experiential learning is a significant predictor of student work readiness and consistently operates through the enhancement of digital skill as a key mediator. In this research, experiential learning was found to improve work readiness directly, while simultaneously enhancing digital skills, which in turn contributed significantly to work readiness (Kolb, 1984; Shore & Dinning, 2023).

The critical contribution of this study emerges from the moderation analysis. Similar to patterns observed in earlier studies, the moderation effect was not supported, this time using the construct of self-efficacy a fundamental psychological construct in Social Cognitive Theory (Bandura, 1986). This lack of significance indicates that the strength of experiential learning's influence on work readiness is not dependent on variations in student self-efficacy. In other words, even students with low self-efficacy still gain substantive benefits from engaging in experiential learning. The results indicate that variations in self-efficacy do not significantly alter the influence of experiential learning on work readiness in this study. This finding resonates with the reflective analysis by Sekhar, (2024), which suggests that transforming traditional pedagogy into more participatory and experiential models can effectively mitigate personal psychological barriers, such as lack of confidence and shyness, thereby providing universal benefits to student professional development.

In a competency model, tangible experience produces changes in technical skills, not in internal mental states (Ng, 2023; Van Laar et al., 2020). Digital skill, as a functional competency, is proven to play a central role because it is the type of skill directly applied when students confront modern digital work

contexts (Chonsalasin & Khampirat, 2022). This explains why the mediation effect of digital skill was robust and stable across two different studies, whereas the psychological moderators failed to function.

An alternative explanation that can be proposed is that experiential learning is inherently a highly structured learning environment. In such contexts, the experiences provided to students typically have clear instructions, mentor support, learning objectives, and standardized practical sequences. This type of environment diminishes the role of internal psychological variables like self-efficacy, as learning success becomes more determined by the quality of the experiential design rather than the individual's mental state (Sakitri et al., 2024). In other words, experiential learning "levels the playing field," allowing students with low self-efficacy to avoid significant hindrances because the learning structure itself helps them navigate initial uncertainty and anxiety.

This consistency in moderation failure also sends a methodological message: research designs seeking individual difference moderators on this pathway may be using a flawed theoretical assumption. Multiple studies in this domain have reported similar non-significant moderation results, suggesting that future research on psychological moderators should be grounded in stronger theoretical justification. Future research would be more relevant if directed toward context-based moderators, such as the intensity of the internship, the quality of industry supervision, or curriculum structure (Lan Lu, 2022; Malhotra et al., 2023) as these factors are theoretically closer to the operational character of experiential learning itself.

Thus, this study provides a sharper contribution than previous research. Beyond confirming the importance of digital skill as a primary mediator, this study also strengthens the evidence that the pathway from experiential learning to work readiness is robust, universal, and non-contingent on psychological conditions. This finding corrects the underlying assumption that educational interventions are effective only for students with specific psychological profiles. On the contrary, the results indicate that experiential learning is an inclusive pedagogical model that works in a relatively equitable manner for all students, regardless of their level of self-efficacy.

Theoretical Implications

The findings of this study provide several significant theoretical implications for the development of research on experiential learning, digital skill, and work readiness. First, this study confirms that the foundational mechanism of experiential learning operates primarily through a competency-based mechanism, rather than an individual psychological one. Consistent results across recent studies and the present research demonstrate that experiential learning generates changes in behavior and work readiness primarily because students acquire direct experience that enhances functional skills, particularly digital skills. This reinforces the literature that positions experiential learning as a means of competency transformation, as affirmed by Kolb (1984) and expanded by(Kolb and Kolb, 2018) .

Second, this study provides a conceptual correction to the assumption that the Experiential Learning → Work Readiness path is conditional. The non-significant moderation effect observed in this study, which utilized self-efficacy as a theoretically strong moderator, indicates that psychological variables do not play a role in strengthening or weakening the influence of EL on work readiness. This consistency provides a foundation for developing new theoretical models that treat this path as a stable and universal non-conditional pathway. Consequently, this research challenges prior approaches that sought to position psychological variables as moderators, affirming that such approaches may have a weak conceptual basis.

Third, this study enriches the understanding of digital skill as the primary mediation mechanism in the experiential learning - work readiness relationship. Digital skill is proven to be the nucleus of the competency-based transformation emerging from direct learning experiences. This finding aligns with

digital competency frameworks proposed by (Matriano, 2023; Yusof, 2022) which position digital skills as a foundational capability for work in the technology-based economy. This research thus solidifies the position of digital skill as a stable and essential mediator, while offering a clear theoretical basis for future research to develop more comprehensive competency models.

Fourth, this study contributes to the discussion on the theoretical boundaries of Social Cognitive Theory (Bandura, 1986) when applied to experience-based learning contexts. The failure of self-efficacy as a moderator suggests that self-belief does not always function as an amplifying factor in learning contexts that are structured, guided, and situational. This opens a new discourse for researchers to review the relevance and operational limits of the self-efficacy construct within the context of practical learning and the initial entry into the workforce.

Finally, this study offers a new direction for work readiness theory: shifting the focus from individual psychological factors to learning environment factors and the quality of the experience. By demonstrating that experiential learning works consistently without being influenced by student psychological conditions, this study provides a basis for formulating theoretical models that position instructional design, intensity of experience, and real-world exposure as key variables in building work readiness. This implication has the potential to strengthen educational theories that emphasize the function of the environment and tangible experience in shaping the work competencies of the younger generation.

Practical and Managerial Implications

The research findings offer several practical implications for higher education institutions, curriculum developers, and industry stakeholders. First, the results confirm that experiential learning is one of the most effective and inclusive pedagogical strategies for preparing students for the workplace. Because its influence is not contingent on psychological factors like self-efficacy, universities can implement experiential learning broadly without needing to segment or select students based on individual characteristics. This simplifies the institution's ability to design programs that can be equitably accessed by all students.

Second, the role of digital skill as the primary mediator signifies that digital skills must be a core component of every experiential learning program. Educational institutions must ensure that the learning experiences provided are not just practical, but also integrate the use of digital technologies relevant to workforce demands. Strengthening technological infrastructure, providing training on industry-standard software, and collaborating with digital-first companies are strategic steps that can enhance the program's effectiveness.

For example, universities can operationalize experiential learning by embedding mandatory digital task components within internship and work-integrated learning programs, such as requiring students to use project management platforms, data analysis tools, or collaborative digital systems commonly adopted in industry. Assessment should be based not only on participation but also on demonstrable outputs, such as digital reports, dashboards, or project deliverables that reflect real workplace practices.

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Third, the failure of psychological variables to moderate the experiential learning - work readiness relationship sends an important message to educational institutions: the focus for improving work readiness should be directed at providing high-quality direct experiences, not at individualized psychological reinforcement programs. In other words, the largest investment should be allocated to curriculum design, the quality of practical supervision, and industry partnerships. This approach is more realistic and operational than attempting to intervene in psychological aspects that have proven to be non-influential on this pathway.

Fourth, these findings provide a practical basis for companies or industry partners in designing internship programs. Programs that provide guided, real-world tasks will be more effective in enhancing student work readiness. Companies can strengthen the role of field supervisors and ensure that students are given opportunities to work on digital projects that reflect actual work conditions.

Limitations and Future Research

This study has several limitations that must be considered when interpreting the results and formulating the next research agenda. First, the study's cross-sectional design means causal relationships cannot be fully ascertained. Although the findings are consistent with existing literature and theoretical models, longitudinal or experimental research is still necessary to validate the causal direction between experiential learning, digital skill, and work readiness.

Second, although the moderation effect of self-efficacy was not supported, this study only examined one psychological construct. While this result is consistent with patterns reported in recent literature, it remains possible that other factors such as social support, learning styles, or career orientation may play a moderating role in more specific contexts. However, because two consecutive studies in this research domain have reported non-significant moderation effects, future investigations should ground the selection of psychological moderators in much stronger theoretical justification.

Third, this study utilized a student sample from a single institution, so the generalization of results must be done cautiously. Variations in academic culture, curriculum quality, and institutional context across universities could potentially influence the effectiveness of experiential learning. Future research could expand the sample scope to multiple universities or different national contexts to test the consistency of the findings.

Fourth, the measurement of variables using self-report instruments may introduce perceptual or social desirability bias. The use of objective instruments, supervisor assessments, or real-task performance could provide a more comprehensive picture of the actual returns from experiential learning and digital skills.

Finally, although this study confirmed the stability of the digital skill mediation path, variations in the design of the experiential learning programs were not measured directly. The depth of experience, duration, task intensity, and quality of field supervision may play important roles not captured in this study. Therefore, future research should integrate these variables as potential learning-environment-based moderators

Future Research Agenda

Future research is advised to employ longitudinal or experimental designs to more robustly validate the causal directionality between experiential learning, digital skill, and work readiness. Furthermore, variations in the experiential learning program design such as practice intensity, supervision quality, and task depth should be investigated as more relevant potential moderators than psychological variables. Subsequent research could also broaden the sample context to multiple universities to enhance the generalizability of the findings. Finally, the use of objective data or real-world performance assessments is recommended to complement self-report data and reduce potential perceptual bias.

CONCLUSION

This study reaffirms the critical role of experiential learning in enhancing student work readiness. Empirical results indicate that experiential learning has a direct influence on work readiness, while simultaneously enhancing digital skills, which in turn function as a strong mediator in this relationship. This pattern is consistent with literature asserting that real-world learning experiences are capable of building the functional competencies required in the modern workplace.

The other key finding is the non-significance of the self-efficacy moderation effect. This pattern is consistent with previous observations in the literature, provides a strong indication that the relationship between experiential learning and work readiness is stable and not contingent on student psychological conditions. Thus, the assumption that the effect of experiential learning is strengthened by individual psychological factors did not receive empirical support. This shifts the theoretical understanding towards a model that emphasizes a competency-based mechanism over a psychological one.

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A MACHINE-LEARNING APPROACH TO PREDICTING HIRING DECISION

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ABSTRACT

Making effective hiring decisions remains critical for organisational competitiveness, thus requiring the identification and signalling of reliable, qualified, and suitable candidates. Human capital theory (HCT) and matching theory provide the theoretical underpinnings for this procedure by stressing the monetary worth of education, experience, and skills and the degree to which candidate traits correlate with job needs. This research utilised a machine-learning methodology to analyse principal determinants of recruitment choices. More specifically, due to the limited availability of such research in the Global South, specifically South Africa, the study utilised a validated secondary dataset from Kaggle to model the influence of various predictors: recruitment strategy, educational level, personality score, skills score, interview score, and demographic variables. Moreover, a quantitative, positivist research approach was adopted, and three machine-learning algorithms—logistic regression, a decision tree, and XGBoost—were compared to determine the strongest predictor set and model performance. Consistent with the expectations of both theoretical lenses, the findings revealed that recruitment strategy, followed by educational level and personality score, are the most influential predictors of hiring decisions, indicating that both job–candidate fit and human capital attributes significantly shape outcomes. Additionally, XGBoost outperformed the other algorithms across all evaluation metrics, demonstrating superior predictive accuracy. This study advances theoretical understanding by demonstrating how matching theory and human capital theory can be operationalised through machine-learning techniques, and pragmatically by providing human resource management (HRM) professionals with data-driven insights that enhance fair, efficient, and strategic hiring.

Keywords: Educational level, hiring decision, personality score, recruitment strategy, XG-Boost

INTRODUCTION

In the modern people-analytics landscape, global businesses increasingly rely on advanced technologies, such as machine learning, to refine hiring processes and enhance evidence-based decision-making protocols (Sharari et al., 2025). Machine learning enables human resource manager (HRM) practitioners to analyse predictors such as age, experience, previous companies worked for, distance from the company, interview score, skills score, personality score, gender, educational level, and recruitment strategy—factors that are widely recognised as influencing hiring outcomes. These predictors form the conceptual basis of this study, as they directly relate to the theoretical frameworks guiding the research, namely, matching theory and HCT.

Matching theory explains how the alignment between candidate attributes and job requirements determines hiring outcomes; it has been used extensively in contexts where algorithms support decision-making processes (Tamunimiebi et al., 2023). Through this lens, machine-learning algorithms act as tools that operationalise the matching process by identifying patterns that reveal how candidate

characteristics align with organisational needs, often uncovering relationships that traditional hiring methods might overlook. On the other hand, HCT emphasises the economic value of education, skills, and experience, suggesting that individuals who invest in these attributes possess greater productive potential and organisational value. This establishes that variables, such as educational level, skills score, and experience, are central to understanding and enhancing hiring decisions (Becker, 1962).

Overall, the integration of these two theories is particularly salient for this study. Matching theory justifies the inclusion of predictors related to fit—such as personality score, interview performance, and recruitment strategy—as these reflect compatibility between candidates and roles. Accordingly, HCT complements matching theory by justifying predictors related to productivity and economic value, such as education, skills, and work experience (Becker, 1962). Together, these theories provide a holistic approach to understanding why certain predictors matter and how machine learning can quantify their influence in ways consistent with both theoretical frameworks.

Moreover, machine learning enhances hiring decisions by enabling global organisations to make equitable, faster, and more objective evaluations (Soundar, 2024). In order to enhance accuracy and reduce bias in the decision-making process, algorithms (e.g., logistic regression, decision trees, and XGBoost) can be utilised to identify meaningful relationships between predictors and hiring outcomes (Plonsky et al., 2025).

An observation in the literature discussed above is that research focusing on how people analytics practitioners use machine-learning algorithms is in the Global North; however, such research is sparse in the Global South, especially in South Africa. Notably, this was the motivation for the researchers to conduct the current study using secondary data from Kaggle. It is also envisaged that insights created in the current study will empower HRM or talent acquisition practitioners to use machine-learning algorithms in making effective hiring decisions. Moreover, the advantage of using machine-learning algorithms is that they provide organisations with insights that attract top talent and ensure that the hiring processes are equitable and efficient, while aligned with the organisation's strategic objectives (Koivunen et al., 2019). Additionally, machine-learning algorithms, used to predict hiring decisions, introduce a transformative approach for organisations to develop informed, data-driven decisions that enhance talent acquisition, management, and the required strategies to be implemented (Rai, 2024).
The study's objectives were:

- to identify major predictors with relevant hiring decision-making processes; and
- to identify the machine-learning algorithms that perform better in hiring decisions.

LITERATURE REVIEW

Matching Theory

Since it was vital to match the predictors of hiring decisions and machine-learning algorithms in global organisations, this study adopted matching theory. Laszlo Lovász and Michael Plummer wrote the theory, which was first published in 1986, and a reprint was made in 2009 by the American Mathematical Society (Lovász, 2009). The theory played a major role in mathematics and is now applied to algorithms, such as in machine learning, hence the adoption in this study (Denis et al., 2019). This theoretical framework significantly impacts the employment industry, while search activities in the labour market also influence the predictors of hiring decisions (Baum & Grace, 2020). This theory's role in hiring decisions helps to optimise hiring decisions, such as aligning job requirements with the candidate, thereby ensuring that the best candidate for the job is identified. Additionally, where machine-learning algorithms are used in hiring decisions, it is important to note that matching theory can be applied to evaluate the candidate's

characteristics. For example, the skills, personality traits, experience, and educational level should align with the specific needs of the organisation (Tamunimiebi et al., 2023).

Human Capital Theory

Developed by Becker and Schultz in 1960, HCT posits that the knowledge, experiences, and skills of employees are considered critical assets that influence an individual's contribution to institutional success (Becker, 1962). This assertion is compatible with the core of this current study, as it focuses on the importance of hiring predictors such as experience, age, gender, distance from company, interview score, skills score, personality score, age, educational level, and the recruitment strategy. Moreover, integrating machine learning with human capital theory allows companies to systematically assess the predictors based on data-driven plans (Wilson et al., 2025).

Furthermore, it is vital to acknowledge that machine-learning algorithms are capable of analysing extensive datasets and assisting in the identification of patterns correlating to human capital investment while enhancing job performance and employee retention. These organisations can determine which qualifications and skill sets are predictive of high performance in certain jobs, primarily by examining the historical hiring data. In this study, adopting HCT within the framework of machine learning in hiring decisions requires a deep understanding of how various aspects of a candidate's background may contribute to their organisation and become effective (Plonsky et al., 2025). Organisations, such as those in South Africa, can make informed decisions, using strategic hiring decisions for building a quality workforce, which drives long-term success by adopting the use of HCT through machine learning.

Predictors of hiring decisions

Recruitment Strategy

Recruitment strategy is defined as a plan for attracting, hiring, and retaining qualified employees who are aligned with the organisational values, goals, and objectives (Badouch & Boutaounte, 2025). This process includes identifying needs and effective sourcing using available alternatives, as per the matching theory and HCT. The recruitment strategy where machine learning is utilised can increase the usage of data, which may be analysed from various sources of recruitment, such as social media, employee referrals, or job boards (Shofiana et al., 2025). Machine learning can enhance this strategy by identifying the most effective sources for attracting top talent, thereby aligning with matching theory and HCT. Additionally, streamlining the recruitment strategies can be automated by using algorithms, tasking them to screen resumes and interview scheduling, allowing HRM professionals to focus on high-value activities that support the recruitment strategy.

Experience

Experience refers to the accumulated knowledge, competencies, and skills gained over time through hands-on experience in specific jobs. In the context of hiring decisions, this encompasses life experience and professional work history that contribute to a person's capacity to effectively execute a specific role (Yaswanth & Kumar, 2025). Machine learning can analyse a large quantity of data and identify the experiences available within the candidates and find those that correlate with the job performance as per matching theory and HCT. Additionally, machine learning can determine the years one worked in a particular role, positions held, and other projects completed by the individual candidate, and can predict the value for future role success within an organisation. Accordingly, by leveraging the use of machine-learning algorithms, organisations can move beyond the traditional evaluation of resumes or curriculum vitae (CVs).

Interview Score

This is an assessment of a candidate based on the job interview performance, typically reflecting the candidate's responses to the questions, checking the relevant skills and the candidate's fit for the purpose. This interview score constitutes a crucial factor in hiring decisions as a means of comparing the candidates. However, machine learning also enhances the effectiveness of intervention by analysing the historical data and identifying the prediction success of the job interviews. Moreover, using algorithms may evaluate various scores, such as problem solving, technical ability, and interpersonal skills, and determine if they correlate with job performance (Prajwal Vinayak Naik et al., 2025). In the context of this study, machine-learning algorithms can help mitigate biases by standardising the scoring process and provide some insights into how the candidates' evaluations were impacted by the interview questions.

Educational level and hiring decision

Educational level is another important aspect of hiring decisions, as it forms part of the recruitment process (Tshwane et al., 2023). Educational level is defined as the highest qualification a candidate holds, such as a master's degree or other professional qualifications. In short, education has been seen as a key predictor when considering the candidate's skills and knowledge relevant to the job. However, machine learning evaluates educational qualifications simply by analysing large datasets related to qualifications and can determine the correlation between educational qualifications and job performance.

Skills score

Another important predictor is the skills score. The skills score is defined as a quantitative measure used to evaluate the capabilities of a candidate for the vacancy position (Göğüş & Ertek, 2020). Furthermore, skills scores play an important role when conducting objective analyses to compare candidates. Thus, the skills score can be used by the organisation to identify candidates who are competent to successfully perform their roles. For example, a candidate with a higher skills score indicates a more suitable candidate.

Personality score and hiring decisions

Personality score can be referred to as a numerical score used to reflect a candidate's personal traits and behaviour, which are normally measured through personality tests during the hiring process (Sirasapalli & Malla, 2023). Additionally, hiring decisions can be enhanced by integrating machine learning into the personality score by using historical data to determine which traits can correlate with the success of the candidate on the job. By using such insights, organisations can define and refine the recruitment criteria, taking personality scores into account and choosing candidates with personality scores that align with the roles available.

Distance from a company

Research proffer that candidates who seem to be living closer to the workplace could be more reliable, since they have no relocation or transport costs (Badouch & Boutaounte, 2025). Interestingly, employers close to the workplace may have more knowledge about the market and cultural norms that are relevant to the organisation. Therefore, employers may need to give preferences to candidates close to the workplace and who can commute without hurdles, especially for roles that require in-person or immediate availability. Therefore, using machine learning in hiring decisions can help organisations make well-informed choices by relying on the benefits of a geographically diverse workforce.

METHODOLOGY

Paradigm and research design

To address the article's objectives, the most appropriate research paradigm was positivism. In this paradigm, new knowledge is created by measuring quantitative data (Maree, 2016). The research design was cross-sectional, since the researchers analysed data acquired at a single interval (Quinlan et al., 2015). A descriptive research design was selected since the sample distribution of 1500 employees was analysed. Additionally, a correctional research design was employed, since the researchers intended to measure how the predictors related to the outcome variable (Maree, 2016).

Sampling size and data collection

The sampling size of the study was 1500, as previous research revealed that this sample size is sufficient to use the machine learning (Maleka, 2023). The researchers used secondary data from Kaggle, which is an online platform where academicians and data analytics practitioners upload data and compete in hackathons. The benefits of using data from the source are that it is reliable and validated.

Statistical analysis

Divergent statistical techniques are utilised in this article. Firstly, the frequencies and descriptive statistics are discussed in the results section. The means (averages) and standard deviation, which measures the dispersion of the data away from the mean, were part of the descriptive statistics. Correlation, which measures the association between variables, was calculated using a statistical technique with scores ranging from 0 to 1; according to Cohen (1998), 0 means no correlation and 1 means perfect correlation. The same author opined that 0 to 0.29 means a small correlation, 0.30 to 0.49 means a medium correlation, and 0.5 to 1 represents a large correlation. Furthermore, a box plot was used to measure how the predictors (i.e., age, experience, distance from home, interview score) related to the outcome variable (hiring decision). A stacked bar plot was used to measure how another predictor (i.e., recruitment strategy) related to the predictor variable. Collectively, these statistical techniques in machine learning are known as exploratory data analysis.

The data were divided into training and test sets using the 80:20 ratio, as suggested by Gholamy et al. (2018), before the machine-learning algorithms (i.e., logistic regression, decision tree, and XGBoost) were used. Open-source and optimised for ensemble learning, XGBoost uses gradient boosting frameworks and decision trees as its basic learners. The decision trees are supervised machine-learning algorithms that utilise hierarchical tree structures, such as flow diagrams for making decisions and predictions. Logistic regression is a controlled machine-learning classification algorithm used to predict discrete or classified results based on an independent predictive variable set (Breiman et al., 1984; Maleka, 2023). Accordingly, various metrics were used to evaluate the algorithms; Table 1 depicts their mathematical formulae and descriptions.

Table 1: Evaluation metrics

Description	Mathematical formula
In the case of uneven class distribution, the F1 score is a harmonious mean of recall and precision, providing a balance between the two indicators.	$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$
Accuracy quantifies the ratio of accurately predicted observations to the total number of observations. It is useful if classes are balanced, but it can be misleading for the imbalanced data sets.	$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$
A recall, sometimes referred to as true positive or sensitivity rate, is the proportion of accurately anticipated positive observations relative to the total number of positive observations.	$\text{Recall} = \frac{TP}{TP + FN}$
The precision (also known as a positive prediction value) represents the ratio of accurately anticipated positive observations to the total number of predicted positive observations.	$\text{Precision} = \frac{TP}{TP + FP}$

Source: Powers (2011)

Ethical consideration

Since the article used secondary data, the researchers did not apply for ethical clearance at the academic institution with which they are affiliated. They ensured that they analysed the data honestly, and it can be made available upon request. In addition, the article is written in a tone that is not derogatory and demeaning, nor can it cause harm to the organisation. It also needs to be noted that since the organisation's name was not mentioned on Kaggle, this ensured that its identity is anonymised.

RESULTS

Sample distribution

There were 1500 respondents; 50.8% were females and 49.2% were males. Table 2 reflects the descriptive statistics (the scores are before the data was scaled or normalised).

Table 2: Descriptive statistics

	Age	Experience Years	Previous Companies	Distance From Company	Interview Score	Personality Score
Mean	35	7.69	3	25.51	50.56	51.12
Standard deviation	9	4.64	1.41	14.57	28.63	29.35
Minimum	20	0	1	1.03	0	0
25%	27	4	2	12.84	25	25.75
50%	35	8	3	25.5	52	53
75%	43	12	4	37.74	75	76
Maximum	50	15	5	50.99	100	100

Source: Authors

Bivariate analysis

The correlation results are presented in Figure 2. The data also showed a positive correlation of about 0.12, indicating a slight tendency for more experienced candidates to be hired. Also, there was a positive correlation of approximately 0.15, indicating that a higher interview score is somewhat associated with being hired. Skill Score had a positive correlation of around 0.20, suggesting that higher skill scores are moderately associated with a higher likelihood of being hired. Personality Score showed a positive correlation of about 0.20, indicating that a higher personality score is moderately associated with being hired. Recruitment Strategy had a strong negative correlation of around -0.50, which is the strongest correlation with Hiring Decision and suggests that different recruitment strategies have a significant impact on hiring outcomes. However, Age, Gender, and Distance from Company had very weak correlations with Hiring Decision, suggesting they have little impact on the hiring decision strategy.

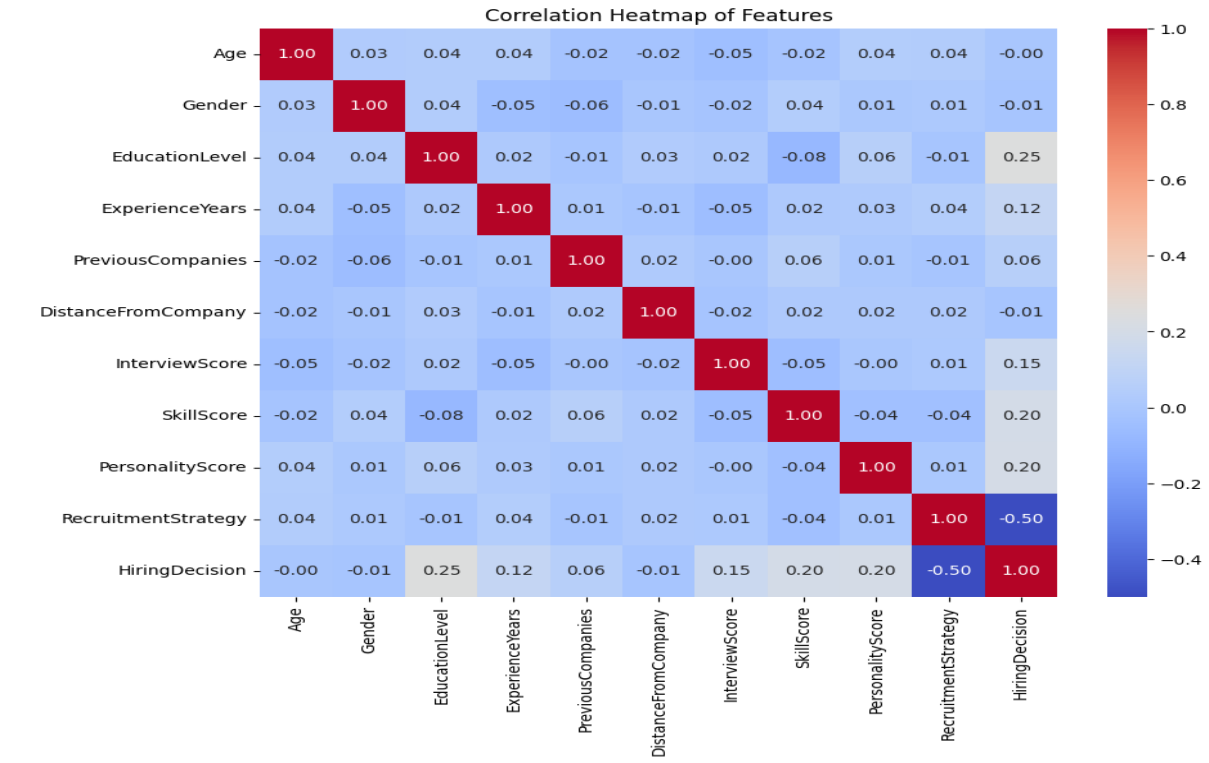

Figure 2: Correlation heatmap

Source: Authors

The relationship between the target variable is also depicted in Figure 2 through box plots. With regard to the age and decision to hire, the mean score of those who are not hired is slightly higher than that of those who are hired. The other box plots were interpreted similarly.

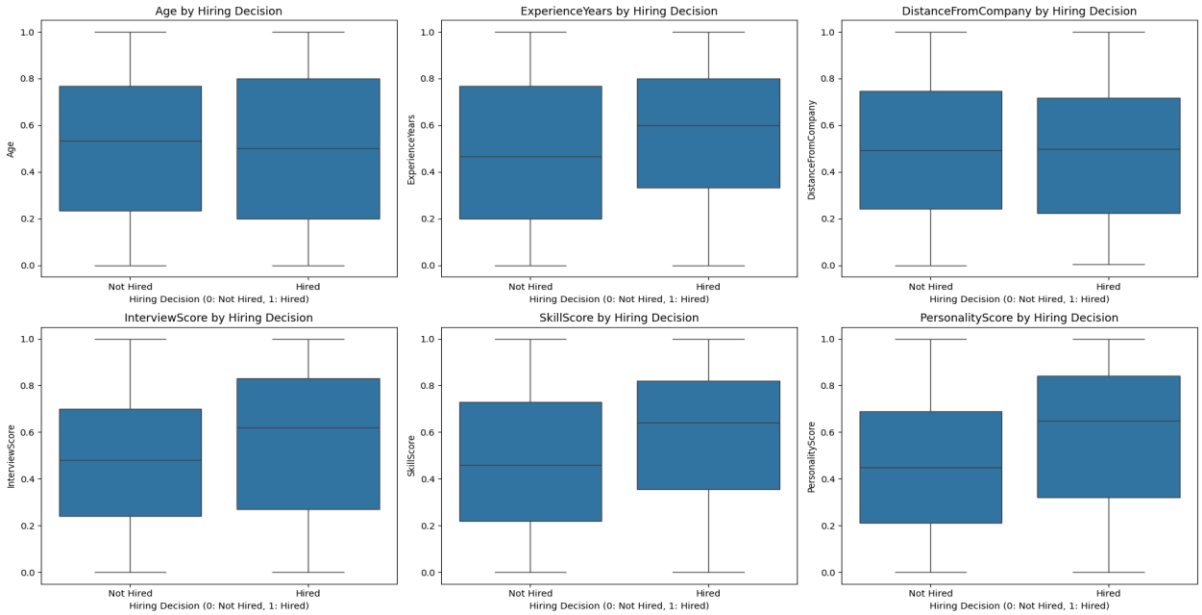

Figure 2: Numerical Predictors and Decision to Hire

Source: Authors

The proportions of those hired in relation to the recruitment strategies are depicted in Figure 3. These data can be interpreted as reflecting that recruitment strategy 0.0 is strongly associated with a high likelihood of a positive hiring decision. Importantly, a large proportion of candidates who went through this strategy were ultimately hired. The other results were interpreted similarly.

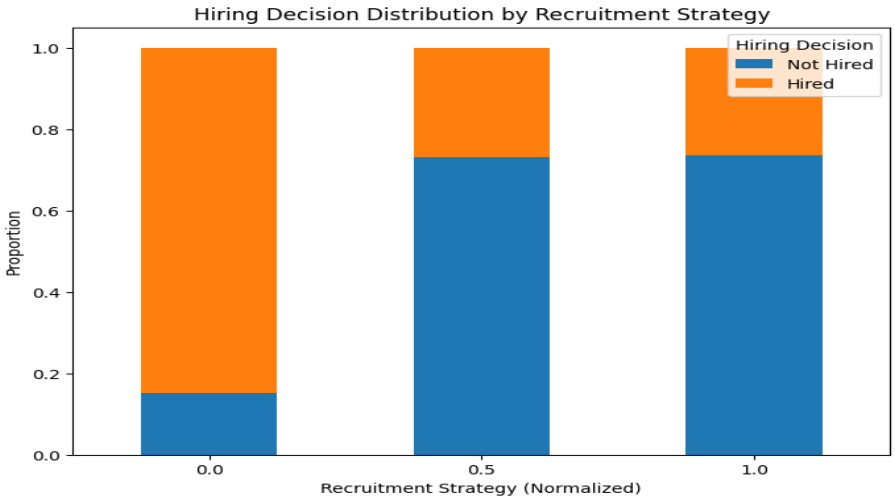

Figure 3: Hiring Decision by Recruitment Strategy

Source: Authors

Model selection

Before splitting the data, the researchers normalised the data, as the target variable was imbalanced (Refer to Figure 4).

Figure 4: Hiring Decision Imbalanced Data

Source: Authors

The comparison showed that both Decision Tree and XGBoost significantly outperformed Logistic Regression (Table 3). XGBoost achieved the highest scores across most metrics, indicating it is the most efficacious model among the three for forecasting hiring decisions on this balanced dataset.

Table 3: Model Comparison Results

Training results				
Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
Logistic Regression	0.824275	0.815511	0.838164	0.826683
Decision Tree	1	1	1	1
XGBoost	1	1	1	1
Test results				
Model	**Accuracy**	**Precision**	**Recall**	**F1-score**
Logistic Regression	0.823671	0.825243	0.821256	0.823245
Decision Tree	0.968599	0.961905	0.975845	0.968825
XGBoost	0.983092	0.985437	0.980676	0.983051

Source: Researchers

Hyperparameter-tuning the XGBoost model

Hyperparameter optimisation was performed utilising Randomized Search CV with a defined search space for parameters such as:

- the max_depth, learning_rate, n_estimators, subsample, colsample_bytree, reg_alpha, and reg_lambda. Cross-validation was set up using StratifiedKFold with 5 splits. The tuned XGBoost model attained performance metrics on the test set as follows: Accuracy: 0.9807, Precision: 0.9761, Recall: 0.9855, F1-score: 0.9808, and ROC AUC Score: 0.9863. The tuned model still demonstrated a perfect performance on the training set (all evaluation metrics are 1.0).

Table 4: XGBoost Hyperparameter Tuning

XGBoost	**Accuracy**	**Precision**	**Recall**	**F1-score**	**ROC AUC Score**
Original XGBoost (Test)	0.983092	0.985437	0.980676	0.983051	0.98476
Tuned XGBoost (Test)	0.980676	0.976077	0.985507	0.980769	0.986254

Source: Authors

Confusion Matrix

Figure 5 depicts the confusion matrix. There were 202 True Negatives (Top-Left). These are the instances where the model correctly predicted that the hiring decision was 'Not Hired' (Actual = 0, Predicted = 0). In addition, the matrix showed 204 True Positives (Bottom-Right). These are the instances where the model correctly predicted that the hiring decision was 'Hired' (Actual = 1, Predicted = 1). There were 5 False Positives (Top-Right), which are instances where the model incorrectly predicted that the hiring decision was 'Hired' (Actual = 0, Predicted = 1). These are Type I errors. Lastly, there were 3 False Negatives (Bottom-Left), which represent instances where the model incorrectly predicted that the hiring decision was 'Not Hired' (Actual = 1, Predicted = 0). These are Type II errors. Based on the results, it can be inferred that the confusion matrix indicates that the tuned XGBoost model performed very well on the test set, as it correctly identified many both 'Not Hired' (202 True Negatives) and 'Hired' (204 True Positives) candidates. The number of misclassifications (False Positives and False Negatives) was very low (5 and 3, respectively). This low number of false positives and false negatives, coupled with the high number of true positives and true negatives, aligns with the high accuracy, precision, and recall values we observed earlier for the tuned XGBoost model. It further confirms that the model is effectively distinguishing between candidates who are hired and those who are not.

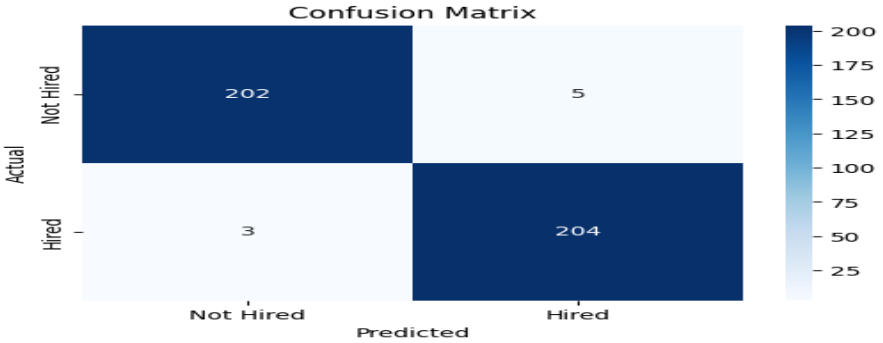

Figure 5: Confusion matrix

Source: Authors

Feature importance

The XGBoost *feature importance* is shown in Figure 6. Recruitment Strategy had the highest importance score (~0.549). This means that Recruitment Strategy was the most influential feature in the XGBoost model's decisions for predicting hiring outcomes. The model relied heavily on this feature, which resulted in a higher feature importance score, indicating that a feature had a greater impact on the XGBoost model's predictions. In this dataset, Recruitment Strategy was the most significant aspect affecting the hiring choice according to the model, followed by Education Level, Personality Score, Skill Score, and Interview Score. Features with lower scores had less influence.

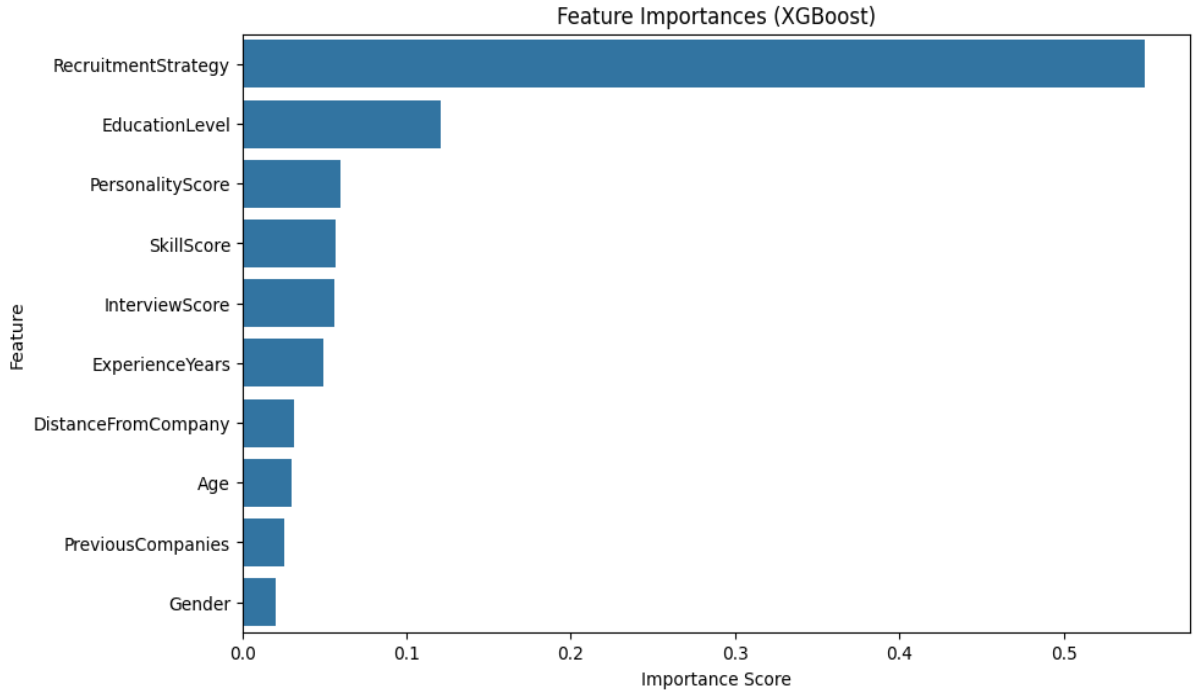

Figure 6: Feature Importance

Source: Authors

DISCUSSION

This research endeavoured to identify the predictors of hiring decisions and assess the performance of three machine-learning algorithms—logistic regression, decision tree, and XGBoost—in modelling these outcomes. An innovative addition to the South African recruitment literature is the use of machine learning, whereas past studies have largely relied on qualitative methods (Townes et al., 2025). By grounding the analysis in matching theory and HCT, this study provides a theoretically informed interpretation of the predictors that influence hiring outcomes.

Moreover, a key finding was that recruitment strategy emerged as the strongest predictor of hiring decisions, with a feature-importance score of approximately 0.549 in the XGBoost model. This finding strongly aligns with matching theory, which posits that the mechanisms of sourcing and screening candidates influence the quality of the match between applicants and organisational requirements. Recruitment strategies, such as employee referrals, employer branding, and online recruitment, are also known to shape candidate pools and ultimately influence selection outcomes. Consistent with literature, strategies such as employer branding and referrals decrease time-to-hire and reduce costs while improving candidate—job alignment (Verlinden, 2025). Thus, the machine-learning results quantitatively validate the theoretical expectation that recruitment strategies help shape the quality and fit of candidates considered for selection.

The second and third strongest predictors—educational level and personality score—also reflect the combined influence of HCT and matching theory. For example, educational level, which contributes significantly to hiring decisions in this study, aligns with HCT's assertion that education enhances individual productivity and economic value. Education is the variable that is associated with HCT, which

states that such employees should receive higher remuneration than employees with lower qualifications (Becker, 1962). Similarly, prior research supports the importance of education in recruitment, demonstrating that hiring highly educated employees provides organisations with a competitive edge. On the other hand, the personality score aligns more closely with matching theory. The fact that the personality score ranked higher than the skills or interview scores further suggests that behavioural predictors may play a more significant role than is traditionally assumed.

Regarding algorithm performance (across both training and test sets), XGBoost significantly outperformed logistic regression and decision tree models, achieving the highest recall, precision, accuracy, and F1-scores. Moreover, the hyperparameter-tuned version of XGBoost achieved similarly strong results, confirming the robustness of the model's predictive capability. The confusion matrix further demonstrated that the tuned XGBoost model exhibited minimal errors related to misclassification, with high true-negative and true-positive and rates. Importantly, these findings indicate that XGBoost is highly effective for classification problems involving complex, multidimensional recruitment datasets. The results reinforce literature showing that XGBoost is one of the most accurate ensemble algorithms for predictive analytics in HRM (Prajwal Vinayak Naik et al., 2025).

Collectively, the findings confirm that both matching theory and HCT remain salient frameworks for understanding modern hiring practices—even in a machine-learning context. However, machine-learning algorithms do not replace these theories; rather, they quantify and operationalise them. Recruitment strategy, personality score, and interview performance reflect the principles of matching theory by identifying predictors linked to job–candidate fit. Meanwhile, education, skills, and experience embody the HCT assertion that investment in human capital enhances future productivity. Thus, this study demonstrates that integrating these theories with machine learning yields a more holistic, empirically grounded understanding of hiring determinants.

IMPLICATIONS OF THE STUDY

This study also made a practical contribution related to the machine learning approach when it comes to predicting hiring decisions. For example, it empowers HRM professionals with knowledge that they must use recruitment strategies, including leveraging the use of machine-learning algorithms to streamline hiring decisions. These kinds of recruitment strategies reduce hiring costs and make the process efficient. Thus, in accordance with the study's findings, it is advised that employers be encouraged to strive for creating diversity within the workplace. In the South African context, through employment equity, it is also recommended that managers must ensure that the personality tests are valid, reliable, and not biased based on race, gender, or ethnicity when they hire employees. Furthermore, the equity legislation states that when applicants have not acquired enough experience, but have an appropriate qualification, they should be placed on an accelerated development programme and mentored after they have been hired (Maleka & Siziba, 2019). Based on the study model, the managers should ensure that when they hire employees based on meritocracy, they also adopt online recruitment and other strategies that enhance efficiency. In addition, they should ensure that they mitigate ethical issues associated with an online recruitment strategy. However, in the South African context, online application platforms are limited to a few applicants, which represents one of the ethical issues, and tend to exclude applicants in rural areas where Internet coverage does not exist.

LIMITATIONS OF THE STUDY, FUTURE RESEARCH, AND MANAGERIAL RECOMMENDATIONS

This study has several limitations that should be acknowledged, despite offering both theoretical and practical contributions to the recruitment body of knowledge. First, the cross-sectional research design provides only a single snapshot of hiring patterns at one point in time. Thus, as a result, causal inferences about how predictors influence hiring decisions over time cannot be adequately established. Therefore, longitudinal studies would be valuable in assessing how predictors of hiring decisions evolve and how machine-learning-based models perform across different organisational cycles.

Second, although Recruitment Strategy emerged as the strongest predictor, the dataset did not contain information specifying the types of recruitment strategies implemented. This limited the study's ability to interpret *why* recruitment strategy exerted such a strong influence. Understanding whether certain strategies (e.g., referrals, online platforms, or traditional advertising) drive this effect remains a gap. Future studies should incorporate more granular measurements involving 'recruitment strategy', enabling more precise theoretical and practical insights.

Third, since this study used a quantitative machine-learning approach**,** it could not uncover the deeper motivations, perceptions, or organisational processes underlying why education, personality, and recruitment strategy emerged as dominant predictors. Qualitative approaches, such as interviews with HRM professionals, candidate evaluations, or organisational case studies, could complement machine-learning findings by providing richer explanations grounded in lived experiences.

Finally, the study emphasised predictors aligned with matching theory and HCT; however, these theories were operationalised only through quantitative features. Hence, future research may consider expanding the theoretical lens by exploring additional recruitment theories or integrating qualitative data that captures organisational culture, candidate expectations, and recruiter cognition—all of which may offer deeper insights into how candidate–job fit and human capital value are assessed in practice.

Below are managerial recommendations:

- Managers should prioritise data-driven and well-structured recruitment strategies, as recruitment strategy was the strongest predictor of hiring decisions;
- Educational qualifications should be central to selection decisions because education demonstrated a strong predictive influence aligned with HCT; and
- Managers must incorporate valid and unbiased personality assessments since the personality score significantly influences hiring outcomes and supports the person–job fit principle.

CONCLUSION

Key determinants of hiring decisions were identified by applying machine-learning algorithms in this study, offering an evidence-based alternative to traditional recruitment approaches. Accordingly, unlike qualitative or purely statistical techniques, the value of machine learning was demonstrated in the study by examining the multivariate and complex factors that shape hiring outcomes. The analysis focused on predictors such as age, gender, previous companies, distance from the company, experience in years, interview scores, skill scores, educational level, personality traits, and recruitment strategy.

Grounded in matching theory and HCT, this study established a theoretically informed foundation for selecting and interpreting these predictors. Matching theory helped explain how variables related to job–candidate fit—such as recruitment strategy, personality score, and interview performance—influence hiring

decisions. In contrast, HCT clarified why human-capital-related attributes, such as educational level, skills, and experience, remain central to organisational decision-making. Together, these theories offered a holistic lens for interpreting machine-learning model outputs, confirming their salience in modern, data-driven recruitment contexts.

The empirical results showed that recruitment strategy is the strongest predictor of hiring decisions, followed by educational level and personality score, thus reinforcing the theoretical expectation that both job–candidate fit and human capital attributes shape hiring outcomes. Furthermore, among the machine-learning algorithms tested, XGBoost consistently outperformed logistic regression and a decision tree, demonstrating the highest precision, accuracy, recall, and F1-scores. This further confirms that algorithms which are ensemble-based are particularly effective in modelling complex HRM datasets.

In summary, this study concludes that XGBoost is the most suitable algorithm for supporting data-driven hiring decisions, and that recruitment strategy is the most influential predictor in determining hiring outcomes. By integrating machine learning with matching theory and HCT, the study contributes both theoretically and practically to the recruitment literature, offering significant insights that can enhance fairness, efficiency, and strategic alignment in organisational hiring practices.

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AI AND ENTREPRENEURIAL INNOVATION: A SYSTEMATIC ANALYSIS AND RESEARCH AGENDA

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ABSTRACT

Artificial Intelligence (AI) is increasingly recognized as a powerful force for change in entrepreneurship, enabling innovation through improved decision-making, greater operational effectiveness, and the creation of new business models. This study uses data from Scopus, Web of Science, and ScienceDirect, along with a systematic analysis of 78 academic articles published between 2013 and 2024. The review identifies four main thematic clusters: platform-based scaling strategies, customer integration, AI-driven entrepreneurial cognition, and innovation process efficiency. This study introduces the AI-Enabled Innovation Capabilities framework, which highlights four key dimensions: cognitive augmentation, operational intelligence, customer-centric accuracy, and scalability with ecosystem leverage. This framework shows how AI facilitates several kinds of innovation, such as strategic, product, process, and business model innovations, by offering a capability-based viewpoint that goes beyond conventional linear innovation models. By emphasizing both the revolutionary potential and the contextual challenges of AI adoption, the study adds to the literature on entrepreneurship and advocates for more investigation into the responsible and inclusive integration of AI.

Keywords: Artificial Intelligence, AI Adoption, Business Model, Entrepreneurship, Innovation, Strategic Decision-Making

INTRODUCTION

Entrepreneurial innovation is at the forefront of social change, economic expansion, and technological advancement. By tackling complex societal and commercial issues, entrepreneurs promote competitiveness and job development while also serving as systemic change agents. Entrepreneurial success in today's fast-paced, globalized, and unstable environment, often characterized as volatile, uncertain, complicated, and ambiguous, depends on ongoing innovation, flexibility, and strategic foresight (Usman et al., 2024). Entrepreneurs are increasingly relying on cutting-edge technology to boost their ability to innovate, compete, and meet these demands. AI has become an unprecedented force, changing governance, business, and society. AI enables business owners to uncover new market trends, automate procedures, customize services, and rethink items. AI becomes a key partner in the entrepreneurial process thanks to these qualities, which enable quicker, smarter, and more adaptable invention (Paramesha et al., 2024).

AI has become a potent and disruptive force within this range of technologies, transforming the fundamentals of how companies function, innovate, and expand. AI has transcended big businesses and tech behemoths in the context of entrepreneurship. Startups and small businesses use AI to improve consumer interaction, product creation, opportunity recognition, and strategic decision-making. These

advancements present AI as a digital tool and a strategic innovation enabler, a resource that radically changes how entrepreneurs view, assess, and respond to new opportunities. AI is commonly defined as the capacity of machines to mimic or outperform human intelligence in tasks such as learning, reasoning, pattern recognition, and problem-solving. John McCarthy first defined AI as "the science and engineering of making intelligent machines" in 1958. Since then, the field has grown to encompass a wide range of subfields, such as computer vision, machine learning, natural language processing (NLP), and deep learning (Chalmers et al., 2021; McCarthy, 1960; Obschonka & Audretsch, 2020). With these technologies, business owners can automate complex processes, extract valuable insights from large databases, and scale innovations with previously unheard-of accuracy and speed.

However, using AI in business endeavors is more than just a technical advancement. It entails significant organizational and strategic change. According to Pai et al. (2022), integrating AI requires aligning business models with data-driven reasoning, reconfiguring processes, and developing new leadership mindsets. Additionally, by automating routine jobs and freeing up human capital for higher-order cognitive and creative capabilities, AI can rehumanize labor (Daugherty & Wilson, 2024). Accordingly, AI serves as both a driver for human-centered innovation and an enhancer of efficiency. The widespread use of AI also poses significant challenges. Scholars caution that unregulated or uneven adoption of AI could exacerbate already-existing socioeconomic disparities, lead to job displacement, and upend established industries (Chalmers et al., 2021). In developing nations with inadequate institutional support and digital infrastructure, these dangers are more noticeable. Thus, using AI for entrepreneurship necessitates striking a careful balance between the application of inclusive, moral technology governance and innovation-driven growth.

Although scholars and practitioners are paying more attention to AI, its role in entrepreneurial innovation remains theoretically underdeveloped and empirically scattered. A sizable amount of research focuses on the application of AI in large, resource-rich companies or specific high-tech industries, offering little insight into how AI operates in the unstable, resource-constrained contexts typical of entrepreneurship. This focus has led to an oversimplified perception of AI as a general-purpose technology, often conflated with broader digital transformation initiatives. According to current perspectives, AI fosters innovation in several ways, such as boosting creativity and thinking (cognitive augmentation), increasing operational effectiveness, customizing goods for consumers, and promoting expansion via digital channels. These roles demonstrate how AI can aid in planning, testing ideas, designing user-focused products, and scaling business models. However, there is limited research on how startups and small businesses use these AI tools and how this relates to well-established concepts such as identifying opportunities, innovating, and creating value (Anzola-Román et al., 2018; Truong & Papagiannidis, 2022).

Furthermore, despite their crucial significance in emerging and transitional economies, important contextual elements, including digital literacy, regulatory environment, and institutional preparation, are still sporadically discussed in the literature. While some researchers focus on external characteristics such as network embeddedness and ecosystem engagement (Panetti et al., 2020; Yam et al., 2011), others highlight internal drivers, such as R&D intensity, as predictors of innovation outcomes (Anzola-Román et al., 2018). Nevertheless, real insights into how AI technologies are integrated into entrepreneurial processes have not yet been harmonized with these theoretical viewpoints. An integrated, multifaceted perspective that explains how startups and small businesses use AI to innovate while navigating uncertainty, resource constraints, and changing market conditions is conspicuously lacking.

By investigating how AI supports entrepreneurial innovation in four crucial areas: improving operations (operational intelligence), improving thinking and creativity (cognitive augmentation), personalizing customer experiences (customer-centric precision), and enabling businesses to grow through digital platforms (ecosystem scalability), this study seeks to close a sizable gap. By analyzing AI as a multidimensional tool, the study provides a more accurate and thorough understanding of how AI promotes

entrepreneurship. It also emphasizes that AI operates differently across networks, businesses, and environments. Consequently, the study facilitates the development of a more thorough and realistic understanding of AI-driven innovation in entrepreneurship by offering a helpful framework and new evidence to connect diverse research.

THE EMERGENCE AND CONCEPTUAL FOUNDATIONS OF AI

AI is still conceptually ambiguous and lacks a single, widely recognized definition, yet it is a field of study with roots dating back more than 60 years. It embraces several computing methodologies rather than a single technology or a particular class of technologies. These include NLP, computer vision, machine learning, deep learning, and other algorithmic systems that mimic various facets of human cognitive function. Academics have presented divergent interpretations of what AI is. Haenlein and Kaplan (2019), for example, emphasize the algorithmic aspect of AI, highlighting its capacity to learn from data and execute predefined tasks. On the other hand, more general definitions of AI include any computing system that mimics human intelligence to perform tasks (Dellermann et al., 2019; Goodfellow et al., 2020; Kühl et al., 2022). We use a pragmatic definition for this discussion: AI is a set of technologies inspired by human cognition and intended to perform tasks commonly associated with intelligent behavior. Three fundamental components form the basis of this viewpoint: (1) algorithms; (2) the ability to learn from data; and (3) the capacity to carry out activities ranging from limited and precise to those requiring minimal human supervision or larger adaptability.

Three interrelated trends have spurred the recent revival of AI. First, the amount of data available has skyrocketed due to the digital transformation of businesses and societies. Second, improvements in computing power have enabled more effective analysis of vast amounts of data. Third, the efficacy of AI technology has significantly increased due to advances in deep learning and neural network design (National Academies of Sciences, et al., 2020).

AI is now positioned to impact almost every industry thanks to these convergent developments. It frequently outperforms humans in processing large, complex datasets and automating repetitive, precision-driven, or cognitively demanding tasks (Ashrafi & Kabir, 2023). For instance, AI has outperformed radiologists in the early detection of breast cancer (McKinney et al., 2020). It is more effective than human designers at producing optimum semiconductor layouts in engineering (Khan et al., 2021). In dynamic contexts like real-time traffic monitoring, AI also performs better than humans (Perumallaplli, 2011). According to Baruffaldi et al. (2020), AI applications are numerous and expanding, offering substantial opportunities for increased productivity and innovation across a variety of fields.

AI AND ENTREPRENEURIAL INNOVATION

The development and use of creative solutions in the form of goods, services, or models that address unmet market needs is known as entrepreneurial innovation, and it is a significant force behind economic advancement. Traditionally, the entrepreneur's inventiveness, intuition, and capacity to handle ambiguity have propelled this process of invention. Opportunity discovery and idea generation, idea screening, experimentation, and commercialization are the four processes that are usually included (Kijkuit & Van Den Ende, 2007). The degree to which each step depends on human judgment and cognitive abilities changes, with the initial stages requiring very high levels of creativity and contextual awareness (Amabile, 2020). This environment is changing as AI use grows, bringing new tools and capabilities that are revolutionizing entrepreneurs' creativity. Machine learning, natural language processing, and predictive analytics are just a few of the many technologies that make up artificial intelligence (AI). These technologies enable machines to learn from data, identify trends, and assist or automate decision-making

(Paramesha et al., 2024). AI's strategic role in entrepreneurship is attracting attention, especially as a driver of innovation under constraints, even though its ability to supplement human effort is recognized across a variety of industries (Cockburn et al., 2018).

This paper's main contention is that entrepreneurial innovation and artificial intelligence are growing more intertwined. Innovation in entrepreneurial endeavors is both facilitated and amplified by AI. In today's data-rich, rapidly evolving world, where business owners must swiftly evaluate vast volumes of information to recognize and seize new opportunities, this relationship is significant. By enabling data-driven idea evaluation, automating repetitive testing, and refining go-to-market tactics, artificial intelligence (AI) fosters entrepreneurial innovation. In this way, AI reduces the time and resource constraints that impede innovation in startups and early-stage businesses (Haefner et al., 2021). AI and entrepreneurial innovation have a reciprocal relationship. Additionally, entrepreneurs are crucial in determining how AI is used, understood, and incorporated into innovation processes. Entrepreneurs frequently need to take a hands-on approach to tailoring AI solutions to their specific environments, unlike large organizations with specialized data science teams. This interaction points to a co-evolutionary dynamic in which AI improves the ability to create, test, and scale innovations while entrepreneurial thinking propels the creative application of AI (Gentsch, 2018).

Despite its potential, AI's use in early phases of innovation, such as idea generation and opportunity recognition, remains constrained by its inability to mimic human creativity, emotional intelligence, and domain-specific intuition (Amabile, 2020). Even so, AI can foster creativity by revealing hidden patterns, producing parallels, and proposing novel cross-domain linkages. Therefore, AI enhances and informs entrepreneurial judgment rather than replacing it, particularly in cognitively demanding activities that require processing vast amounts of unstructured data.

In summary, entrepreneurial innovation and AI are revolutionary and complementary. As AI technologies advance, they become more than just automation tools; they become strategic facilitators that transform how business owners find opportunities, resolve issues, and scale solutions. Future research and valuable insights can benefit significantly from an understanding of this dynamic, especially when creating hybrid human-AI systems that balance automation with entrepreneurial agility and vision.

METHODOLOGY

The methodological approach put forward by Tranfield et al. (2003), well known for ensuring rigor, transparency, and replicability in evidence-based reviews, was followed in conducting a systematic literature review (SLR). This method was used to thoroughly compile empirical studies on the relationships among innovation, entrepreneurship, and artificial intelligence (AI). The main goal was to find, assess, and integrate empirical data that clarifies how AI affects entrepreneurial innovation across organizational and contextual contexts.

To ensure the scope and applicability of the literature, an organized, iterative search approach was used. "Artificial Intelligence AND Entrepreneurship," "AI AND Innovation," "AI Adoption AND Organizations," and "AI AND Entrepreneurial Strategy" are just a few of the meticulously crafted keyword combinations and Boolean operators that were employed. To capture recent, methodologically sound empirical investigations in this rapidly developing field, the review was restricted to peer-reviewed English-language journal publications published between 2013 and 2024. Because of their extensive coverage and intellectual reputation, three significant academic databases, Scopus, Web of Science, and ScienceDirect, were chosen.

Study Selection and Screening Process

The inclusion criteria were that studies: (1) empirically evaluate the use or impact of AI in entrepreneurial or organizational contexts; (2) address innovation-related outcomes; (3) be published in English; and (4) use either quantitative or qualitative empirical research approaches. The initial search found 554 items (327 from Scopus, 139 from Web of Science, and 88 from ScienceDirect). After deleting 142 duplicate records, 412 unique articles remained.

To evaluate relevance and empirical rigor, a second screening process included a thorough examination of abstracts and methodological details. 338 articles were eliminated at this phase: 86 did not specifically address AI, 65 had nothing to do with entrepreneurship, 57 did not explicitly focus on innovation, 28 were not empirical research, and 102 did not show a significant connection between AI, entrepreneurship, and innovation. 74 empirical publications that met the inclusion criteria comprised the final sample (see Figure 1).

Evaluation of Data Analysis and Research Methods

Because the final sample was entirely empirical, special attention was paid to determining if the research methods used were appropriate, pertinent, and conducted correctly. Of the 74 studies, 15 used qualitative approaches, while 59 used quantitative research strategies.

Research designs, sample plans, measurement models, and analytical methods were all methodically investigated for the quantitative studies. Multiple regression analysis, structural equation modeling (SEM), partial least squares SEM (PLS-SEM), panel data analysis, and machine learning-based analytical techniques were among the frequently employed data analysis techniques. The alignment of these approaches with research aims, construct operationalization, sample size sufficiency, and statistical validity and reliability procedures was used to evaluate their methodological suitability. All things considered, the quantitative studies employed appropriate, well-established analytical approaches consistent with accepted scientific norms.

The methodological approaches used in the qualitative studies, including case study designs, interviews, ethnographic methodologies, and mixed-methods strategies, were assessed for their applicability and transparency. Thematic analysis, content analysis, and grounded theory are examples of data analysis techniques evaluated for systematic coding procedures, analytical depth, triangulation, and credibility checks. In general, the qualitative investigations showed methodological rigor, with well-documented analytical procedures and clearly stated research designs.

The reliability and robustness of the synthesis findings were improved by the methodologically sound and well-administered research designs and data analysis procedures found throughout the empirical literature evaluation. This methodical evaluation provides a strong basis for identifying trends, theoretical understandings, and research gaps regarding how AI influences entrepreneurial innovation and for guiding future empirical studies in the area.

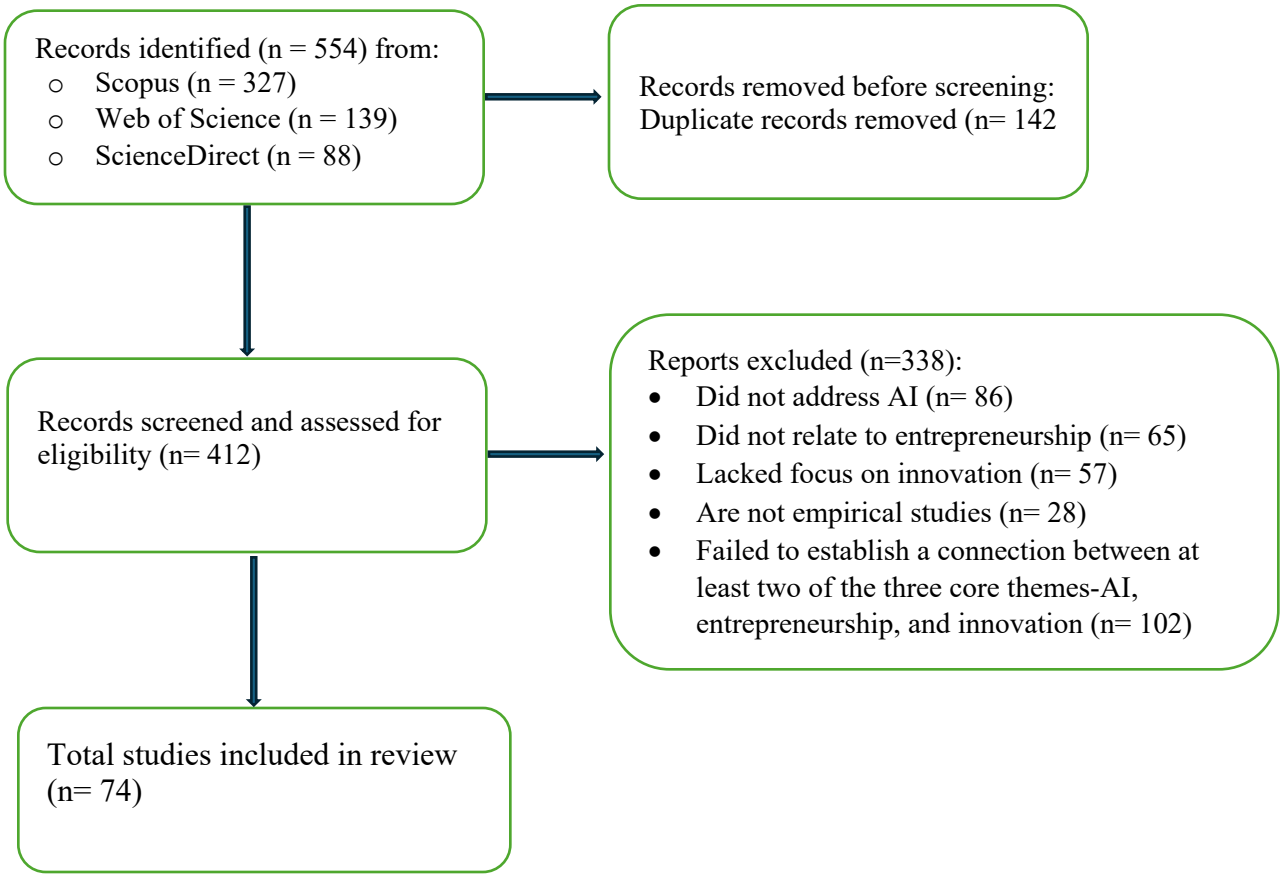

Figure 1. The PRISMA 2020 flow diagram template for systematic reviews was adapted from Page et al (2021).

FINDINGS AND THEMATIC ANALYSIS

The growing use of AI in entrepreneurial settings has led academics to recognize it as a strategic enabler of innovation rather than merely an automation tool. Four major themes are identified in this analysis based on an examination of 74 scholarly articles published between 2013 and 2024 (see Table 1): AI-Powered Customer Integration, AI-Driven Entrepreneurial Cognition, AI and Innovation Process Efficiency, and AI and Platform-Based Scaling Strategies. These themes serve as the foundation for the suggested framework and are connected to a variety of innovation categories, such as business model, process, product, and strategic innovation.

The study presents a novel conceptual lens, AI-Enabled Innovation Capabilities, that builds on these discoveries. This paradigm takes a capability-based approach, highlighting how AI fosters innovation across strategic functions at all stages, in contrast to current models that connect AI functions to linear stages of entrepreneurship (e.g., Chalmers et al., 2021). The framework identifies four key enabling elements: (1) cognitive augmentation; (2) operational intelligence; (3) customer-centric precision; and (4) scalability and ecosystem leverage (see Table 2). These dimensions, which represent unique ways in which AI fosters entrepreneurial creativity across a variety of circumstances, are inductively derived from the theme clusters.

Table 1. Thematic clusters derived from the systematic literature review.

Cluster Name	**Key Focus**	**Representative Studies**
1. AI-Driven Entrepreneurial Cognition	How AI tools influence ideation, strategic thinking, and decision-making.	Conceptual and quantitative studies (n = 18)(Ahmad et al., 2021; Carillo et al., 2019; Celestin & Vanitha, 2018; Chalmers et al., 2021; Csaszar et al., 2024; Davidsson & Sufyan, 2023; Gheorghiu et al., 2016; Houser, 2019; Jarrahi et al., 2023; Kreuzer et al., 2022; Lee, 2018; Roundy, 2022; Sedkaoui, 2018; Shepherd & Majchrzak, 2022; Nuseir et al., 2020; Townsend & Hunt, 2019; Upadhyay et al., 2022; Usman, Eyo-Udo, et al., 2024).
2. AI and Innovation Process Efficiency	Use of AI for agile experimentation, resource optimization, and lean operations.	Quantitative empirical studies (n = 21)(Achumie et al., 2022; Ali et al., 2024; Allam, 2016; Blackburn et al., 2017; Brem et al., 2021; Deb et al., 2014; Denning, 2013; Hutchinson, 2020; Jin et al., 2013; Jin et al., 2016; Kakatkar et al., 2020; Karunathilake et al., 2023; Khan et al., 2023; Ogunwole et al., 2022; Raneri et al., 2023; Saßmannshausen et al., 2021; Silva et al., 2020; Srinivas et al., 2020; Tang et al., 2020; Verganti et al., 2020; Weber et al., 2022).
3. AI-Powered Customer Integration	Real-time customization, behavioral analytics, and product-market alignment.	Qualitative empirical studies (n = 15) (Awasthi & S Sangle, 2013; Chatterjee et al., 2019; Egbuhuzor et al., 2021; Kamthania et al., 2018; Kasem et al., 2024; Kedi et al., 2024; Kitchens et al., 2018; Kohler, 2016; Margetis et al., 2021; Mingione & Abratt, 2020; Okeke et al., 2024; Polas et al., 2022; Rajagopal et al., 2022; Saura et al., 2019; Wan et al., 2020).
4. AI and Platform-Based Scaling Strategies	Scaling business models through AI-enabled networks and digital platforms.	Quantitative and strategic studies (n = 20) (Abisoye & Akerele, 2022; Arsénio et al., 2013; Autio et al., 2018; Cautela et al., 2019; Fosso Wamba et al., 2022; Fountaine et al., 2019; Hammad & Abu-Zaid, 2024; Kaggwa et al., 2024; Kasem et al., 2024; Li, 2020; Moro-Visconti et al., 2023; Nambisan et al., 2018; Rai et al., 2019; Shaik et al., 2024; Shepherd & Majchrzak, 2022; Sjödin et al., 2021; Soni et al., 2019; Thomas, 2014; Xu et al., 2019; Zeng et al., 2023).

Table 2. AI-Enabled Innovation Capabilities Framework.

Enabler Dimension	**Definition**	**AI-Enabling Mechanisms**	**Type of Innovation Supported**
Cognitive Augmentation	AI supports entrepreneurs in ideation, foresight, and opportunity framing	Generative AI, trend prediction, scenario simulation	Strategic & Product Innovation

Enabler Dimension	Definition	AI-Enabling Mechanisms	Type of Innovation Supported
Operational Intelligence	AI enables process efficiency, experimentation, and adaptive execution	Workflow automation, digital twins, decision-support systems	Process Innovation
Customer-Centric Precision	AI enables hyper-personalization and real-time market feedback loops	NLP, recommender systems, customer analytics	Product & UX Innovation
Scalability & Ecosystem Leverage	AI facilitates rapid growth, platform participation, and partner orchestration.	API-based scaling, partner matching, and multi-sided platform optimization	Business Model Innovation

Temporal Emergence and Evolution of Themes

When the publication schedules for the four themes are examined, it becomes evident how the concept and research on AI's role in entrepreneurial innovation have developed over time.

The first and most important idea is AI-Driven Entrepreneurial Cognition. Research in this field began to appear in the middle of the 2010s (e.g., Gheorghiu et al., 2016; Lee, 2018), initially focusing on human-AI interaction in management contexts and decision support systems. Scholarly interest in AI as a cognitive augmenter, as opposed to merely an analytical tool, increased after 2019, especially between 2021 and 2024. Recent studies (e.g., Chalmers et al., 2021; Shepherd & Majchrzak, 2022) show a shift toward capability-based and cognition-centered approaches that emphasize strategic sense-making, ideation, and judgment under uncertainty.

Between 2013 and 2016, there were early conceptual and practical conversations about efficiency (e.g., Denning, 2013; Jin et al., 2013). Later, AI and Innovation Process Efficiency gained popularity. However, after 2020, as automation, machine learning, and agile innovation advanced, this subject gained significant traction. As AI applications inside innovation workflows matured, empirical research on AI-enabled experimentation, lean operations, and resource optimization became more common beginning in 2020 (e.g., Weber et al., 2022).

AI-Powered Customer Integration gained popularity in the late 2010s, building on earlier research on marketing analytics and customer relationship management (e.g., Moon et al., 2015; Kohler, 2016). The majority of contributions appeared after 2018 due to the expansion of big data, real-time analytics, and customization technologies. Post-2020 research has increasingly concentrated on behavioral analytics, customer co-creation, and product–market alignment (e.g., Manser Payne et al., 2021; Polas et al., 2022; Kasem et al., 2024), indicating a trend toward dynamic, data-driven customer integration in entrepreneurial contexts.

AI and Platform-Based Scaling Strategies is the newest and most strategically oriented theme. The explicit integration of AI into platform strategies and scaling gained popularity around 2018, despite early research on platforms and digital ecosystems beginning in the mid-2010s (e.g., Arsénio et al., 2013; Vardakas et al., 2014). Research in this area increased between 2019 and 2023, focusing on AI-enabled network effects, ecosystem orchestration, and scalable business models (e.g., Nambisan et al., 2018; Fountaine et al., 2019; Haefner et al., 2023). This historical pattern suggests that AI-based scaling is a higher-order capability that builds upon earlier cognitive, process, and customer-focused applications.

The chronological analysis thus shows an evolutionary trajectory: early research focused primarily on cognitive and decision-support capabilities, followed by efficiency and process optimization, customer integration, platform-based scaling, and ecosystem strategies. Both the advances in AI technology and the growing intricacy of entrepreneurial applications over time are reflected in this evolution.

Cognitive Augmentation: AI as a Strategic Thinking Partner

Cognitive augmentation is the application of AI to improve entrepreneurial creativity and decision-making. Cognitive augmentation enables entrepreneurs to work in more iterative and nonlinear ways than traditional models, which view innovation as a linear, stage-based process. For instance, generative AI makes it easier to prototype concepts and quickly reframe issues, allowing business owners to investigate more expansive opportunities (Jin et al., 2013; Sedkaoui, 2018). Environmental scanning and trend-spotting activities essential to early-stage innovation are further supported by the real-time synthesis of many data sources, from market trends to social media sentiment (Roundy, 2022). AI-based forecasting and scenario simulations help entrepreneurs think more clearly by providing structured support. They enable entrepreneurs to explore various "what-if" scenarios and predict potential outcomes before making costly decisions (Csaszar et al., 2024).

In high-uncertainty situations where heuristics might not adequately represent dynamic complexity, this function is invaluable. The literature on entrepreneurial cognition highlights the importance of pattern detection and judgment under uncertainty (Celestin & Vanitha, 2018). AI can improve these abilities by detecting latent patterns that are invisible to humans. The degree to which entrepreneurs believe or disregard AI recommendations, cognitive reliance, and decision bias from AI-generated output are all significant issues raised by this. These issues necessitate more investigation into learning curves while using AI tools, entrepreneurial cognitive styles, and human-AI interaction (Usman et al., 2024).

Operational Intelligence: Process Innovation through Intelligent Execution

One essential AI feature that enables business owners to restructure internal processes for increased flexibility, effectiveness, and scalability is operational intelligence. By their very nature, startups frequently lack the established procedures and structures found in larger businesses. As a result, using AI for process mapping, experimentation, and dynamic resource allocation becomes a source of competitive advantage. AI-enabled workflow automation frees entrepreneurs to focus on strategic growth initiatives by minimizing bottlenecks and reducing the cognitive load associated with repetitive tasks (Deb et al., 2014; Tang et al., 2020). In line with the lean startup technique of validated learning, digital twins enable risk-free experimentation with business models or service delivery structures by modeling outcomes before actual implementation (Raneri et al., 2023).

Additionally, AI-powered decision-support systems can improve decision speed and accuracy, especially in complex, rapidly changing contexts where data is ambiguous. Real-time analytics enabled by these systems improve managerial responsiveness and foresight, which are essential in volatile, rapidly changing markets (Matyushenko et al., 2022; Weber et al., 2022). Despite these advantages, research indicates that entrepreneurial enterprises frequently underutilize AI's full operational potential due to skill shortages, implementation costs, and resistance to digitalization (Kakatkar et al., 2020). To achieve successful AI-enabled operational transformation, future research should focus on how startups create organizational learning processes, enhance absorptive capacity, and strengthen dynamic capabilities.

Customer-Centric Precision: Facilitating Ultra-Customized User Experience Innovation

The ability of AI to personalize offerings and interactions at scale is known as "customer-centric precision," which enables highly responsive innovation that responds to user behavior, feedback, and changing needs. In today's experience economy, personalization has evolved from a competitive advantage to a necessity for innovation. AI helps business owners gain a detailed understanding of consumer preferences, behavior patterns, and unfulfilled needs through recommender systems and customer analytics (Kedi et al., 2024; Moon et al., 2015). By enabling more accurate consumer segment targeting and informing iterative product development, these insights lower market-entry risks and improve product-market fit (Wan et al., 2020).

Additionally, NLP enables sentiment analysis and direct user interaction, creating an ongoing feedback loop between the client and the business (Okeke et al., 2024). This improves the client experience and provides business owners with the information they need to dynamically modify services (Kitchens et al., 2018; Wahab et al., 2023). Additionally, AI enables "mass customization," providing individualized experiences without compromising scalability, which is especially advantageous for digital-native businesses up against more established firms (Mingione & Abratt, 2020). However, there are growing worries about algorithmic transparency, consumer data ethics, and digital trust, particularly in markets with less developed privacy laws or lower levels of digital literacy (Aldboush & Ferdous, 2023). These conflicts highlight the need for a more thorough analysis of how consumers view and entrepreneurial enterprises govern AI-driven personalization.

Scalability and Ecosystem Leverage: AI in Networked Business Model Innovation

AI's potential to unlock platform-based business model innovation is demonstrated by its scalability and ecosystem leverage, which enable firms to expand by boosting internal capacity and coordinating value across networks. AI enables startups to operate as "micro-multinationals," gaining access to international markets and resources through cloud platforms, Application Programming Interface (API), and algorithmic coordination (Autio et al., 2018). While partner-matching algorithms facilitate ecosystem collaboration by cleverly finding synergistic players, API-based designs enable modular integration with partner enterprises (Sussan & Acs, 2017). AI thus allows for "orchestration-led" innovation and reshapes the firm's boundaries.

Additionally, by dynamically allocating attention, resources, and incentives across user groups, AI enables real-time governance of multi-sided platforms. According to Parker et al. (2016), platforms acquire value through interaction optimization rather than just size, and AI is essential to enabling this. This AI-enabled orchestration can increase network participation and reduce entry barriers in entrepreneurship ecosystems, especially in areas with poor traditional infrastructure and limited internet access. However, institutional backing, interoperability standards, and stakeholder confidence are necessary for the benefits of ecosystem leverage (Fosso et al., 2022). Consequently, more investigation is required into the contextual factors that influence the effectiveness of AI-enabled ecosystem engagement and scaling initiatives, especially in developing nations with burgeoning digital infrastructures.

AI-Enabled Innovation Capabilities: A Layered Capability Framework for Entrepreneurial Innovation

The adoption of AI in entrepreneurship has evolved from an efficiency-driven tool to a dynamic capability enabler that augments how ventures ideate, operate, connect with customers, and scale. This study presents a layered framework of AI-enabled innovation capabilities, grounded in insights from a systematic literature review and existing theory (Sarasvathy, 2001; Teece, 2007). Unlike step-by-step models that link AI to fixed stages of entrepreneurship (like idea → development → launch), this

framework shows how different AI capabilities work together simultaneously. They support innovation across strategy, operations, customer experience, and business growth by continuously building on and strengthening each other. Each capability layer makes a unique contribution to entrepreneurial innovation. Still, the synergistic interactions among them deliver adaptive value creation, especially under conditions of uncertainty and constraints typical of startups and emerging-market ventures.

Layer 1: Cognitive Augmentation – Ideation, Insight, and Strategic Framing

The foundational layer is built on cognitive augmentation, which enhances entrepreneurs' ability to identify opportunities, predict trends, and model potential outcomes. Large language models, generative AI, and predictive analytics are examples of AI technologies that help entrepreneurs go beyond intuition-based decisions by offering structured foresight and quick ideation (Roundy, 2022). Additionally, these tools enable opportunity recombination, which connects many information sources to provide innovative company concepts (Townsend & Hunt, 2019). Cognitive augmentation is a strategic capability that enables the creation of high-quality, forward-thinking innovation prospects and cultivates entrepreneurial alertness (Tang et al., 2020). This layer is crucial because, without profound cognitive framing, operational execution, market adaptation, and scalable growth might not be strategically coherent.

Layer 2: Operational Intelligence – Execution, Efficiency, and Adaptive Action

Operational intelligence, or how AI helps businesses turn strategic insights into action through effective, flexible, and data-driven operations, sits atop the cognitive layer. Digital twins for real-time process simulation, AI-driven automation, and intelligent decision-support systems are examples of these capabilities (Ali et al., 2024). AI is helpful because it encourages experimentation and agility, allowing business owners to test and improve business procedures, reduce resource waste, and dynamically reorganize operations in response to shifting demands (Raneri et al., 2023). Cognitive augmentation serves as an operational intelligence layer, feeding outcomes to guide strategic improvement. AI becomes a catalyst for ongoing operational improvement by fostering process innovation.

Layer 3: Customer-Centric Precision – Personalization, Market Sensing, and user experience–driven Innovation

Customer-centric precision, which uses AI to hyper-personalize offerings and establish real-time feedback loops with consumers, builds on cognitive and operational skills. Startups can quickly customize their products and services and co-create value with users by leveraging techniques such as natural language processing (NLP), recommender systems, and customer sentiment analysis (Huang & Rust, 2021). This skill aligns with practical thinking, which finds product-market fit through continuous stakeholder interaction rather than forecasting (Kitchens et al., 2018). Additionally, customer-centric precision functions as a reflexive mechanism that informs strategy (through cognitive tools) and process (through operational adaptations), allowing entrepreneurs to consistently align their offerings with changing market expectations and deliver innovation driven by both product and user experience (Egbuhuzor et al., 2021).

Layer 4: Scalability & Ecosystem Leverage – Networked Growth and Platform Orchestration

By enabling network-level orchestration, platform-based commercial models, and quick scaling, the top layer, scalability, and ecosystem leverage improve the efficacy of the lower capabilities. In digital ecosystems, AI technologies such as partner-matching algorithms, API-based modularization, and multisided platform analytics enable startups to collaborate on resource development across firm boundaries (Autio et al., 2018; Cautela et al., 2019). This layer is essential for facilitating business model innovation, especially for companies looking to expand via dispersed innovation networks or platform

participation. Importantly, the robustness and maturity of the underlying layers determine scalability. Without operational stability, market congruence, and strategy clarity, ecosystem growth may be brittle or unsustainable.

These four skills are layered in a synergistic manner rather than as separate stages (see Figure 2). A company may think strategically (cognitively), respond interactively (customer-centrically), act adaptively (operationally), and scale successfully (ecosystemically) thanks to these interconnected levels. This layering facilitates nonlinear, recursive innovation processes that mirror how startups operate in uncertain real-world environments, where ideation, testing, and scaling often occur simultaneously. The framework supports AI maturity models that contend layered integration rather than sequential adoption is essential for long-term performance (Mikalef et al., 2020; Vial, 2021) and is consistent with dynamic capabilities theory (Teece, 2007), which highlights the significance of sensing, seizing, and reconfiguring in turbulent environments.

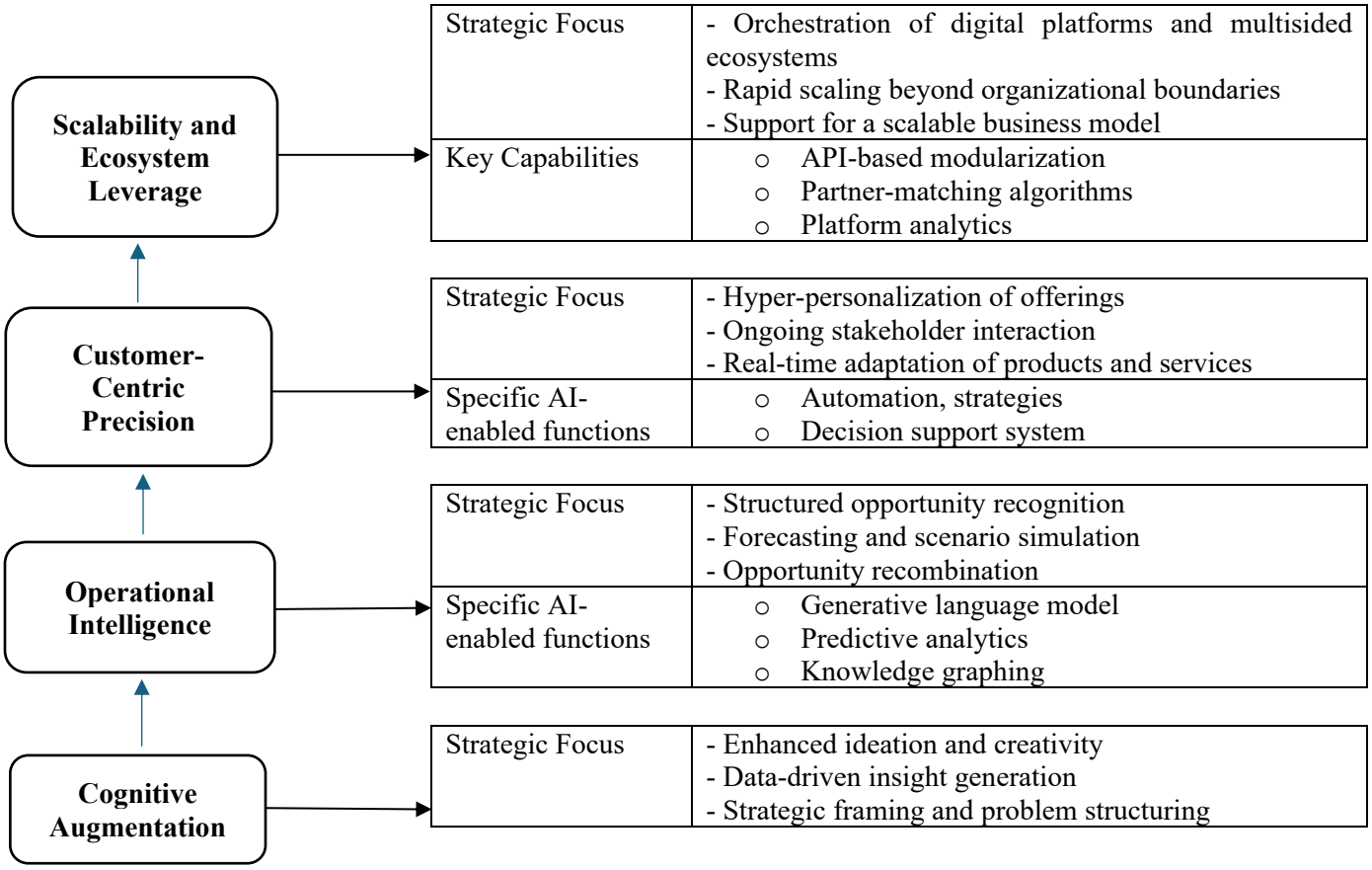

Figure 2. A layered capability framework for entrepreneurial innovation enabled by AI.

DISCUSSION

The results of this systematic review provide strong evidence that implementing AI in entrepreneurial contexts radically alters the innovation ecosystem. This change recognizes AI as a strategic enabler of multifaceted innovation, moving beyond the conventional view of AI as a simple automation tool. The increasing sophistication with which AI is used to promote innovation at the strategic, operational, experiential, and ecosystem levels is reflected in the emergence of four thematic clusters: AI-driven

entrepreneurial cognition, innovation process efficiency, customer integration, and platform-based scaling strategies.

The concept of cognitive augmentation highlights how AI might improve entrepreneurial cognition, a field that has historically relied on human intuition, heuristics, and judgment in the face of uncertainty. AI promotes a more flexible, iterative, and expanding ideation process than linear innovation models, which map entrepreneurial activity in fixed steps. The opportunity canvas is expanded beyond human cognitive limitations by generative AI, enabling entrepreneurs to prototype concepts and explore various problem framings quickly (Jin et al., 2013; Sedkaoui, 2018). Furthermore, more precise environmental scanning and proactive strategic thinking are made possible by AI's capacity to combine diverse data sources, from macroeconomic patterns to social media sentiment (Roundy, 2022). Before allocating limited resources, entrepreneurs can assess potential outcomes and reduce risk by using scenario modeling and forecasting, thereby facilitating "what-if" analyses (Csaszar et al., 2024). This marks a significant advance in decision support, particularly in high-uncertainty entrepreneurial contexts where conventional heuristics often fail to capture complexity (Celestin & Vanitha, 2018).

However, this augmentation raises new behavioral and epistemological issues. There is still much to learn about how entrepreneurs combine algorithmic recommendations with their own judgment and how much they become cognitively dependent on AI outputs. It encourages critical investigation into cognitive styles, trust calibration in AI-augmented decision-making processes, and the dynamics of human-AI interaction (Usman et al., 2024). To fully utilize AI's potential without compromising entrepreneurial liberty or innovation, these issues must be addressed.

The operational intelligence component emphasizes how AI may transform internal entrepreneurial processes by promoting efficiency, adaptability, and agility. AI-powered workflow automation reduces operational bottlenecks and cognitive stress for companies with informal routines and limited resources, allowing entrepreneurs to refocus on strategic growth activities (Deb et al., 2014; Tang et al., 2020). Digital twin technologies, which closely correspond with lean startup concepts of validated learning, are a prime example of AI's involvement in enabling risk-free experimentation with business models and service delivery (Raneri et al., 2023). Furthermore, AI-enabled decision-support systems improve managerial responsiveness in turbulent markets by offering real-time analytics and foresight (Weber et al., 2022). Given these benefits, empirical research indicates that many entrepreneurial businesses underuse AI's operational capabilities because of cultural opposition, high implementation costs, and a lack of digital skills (Kakatkar et al., 2020). To properly leverage AI for operational change, startups must have effective organizational learning mechanisms, absorptive capacity, and dynamic skills. This gap underscores the need for additional study. Researchers should examine how ecosystem support, leadership, and training contribute to the development of this capacity.

The customer-centric precision theme highlights AI's vital role in enabling hyper-personalized innovation sensitive to changing consumer needs in an increasingly experience-driven economy. Entrepreneurs can obtain detailed insights into customer preferences and behavioral patterns through AI-powered recommender systems, customer analytics, and natural language processing, which facilitates iterative product refinement and better market fit (Kedi et al., 2024; Wan et al., 2020). By aligning offerings more closely with changing user expectations, this precision reduces market-entry risks and improves targeting accuracy. By using continuous feedback loops, startups can attain competitive parity with larger incumbents through mass customization and agile adaptation (Mingione & Abratt, 2020). However, this raises important ethical and governance issues related to algorithmic transparency, data privacy, and digital trust. These concerns are especially salient in contexts with limited regulatory oversight or lower digital literacy (Aldboush & Ferdous, 2023). Future research should focus on how entrepreneurial firms can design responsible AI personalization strategies that balance innovation with ethical considerations, and on how customers perceive and respond to AI-driven customization.

The networked, platform-centric business models that support modern entrepreneurial growth strategies are enabled by AI, as demonstrated by the scalability and ecosystem-leverage dimensions. AI enables companies to effectively access international markets and orchestrate value across ecosystems by facilitating modular integration through APIs, intelligent partner matching, and multi-sided platform governance (Autio et al., 2018; Sussan & Acs, 2017). Instead of just scaling transactions, AI's dynamic resource allocation inside multi-sided platforms improves interactions, generating new sources of competitive advantage (Parker et al., 2016). This orchestration capability is critical in emerging or digitally underdeveloped markets where growth is limited by traditional infrastructure restrictions (Fosso et al., 2022). However, stakeholder trust, interoperability standards, and institutional frameworks are necessary for leveraging the ecosystem. The efficacy of AI-enabled scaling and collaboration is mediated by these socio-technical settings, underscoring the significance of contextualized research, particularly in emerging economies. Researchers should investigate how entrepreneurial network architecture, platform governance, and policy interact to support or impede AI-powered ecosystem innovation.

The argument highlights AI's revolutionary position as a strategic partner in entrepreneurial innovation, shifting from stage-based, linear models to capability-driven ones. A key way that AI improves scenario planning, environmental scanning, and entrepreneurial ideation, especially in unpredictable times, is through cognitive augmentation. However, this highlights the need for more research on human-AI interaction and cognitive trust, raising serious questions about how to strike a balance between human judgment and AI dependence. Operational intelligence shows how AI-driven simulation and automation increase resource efficiency and process adaptability. However, many startups encounter adoption and capability challenges, underscoring the importance of organizational learning and dynamic skills for unlocking the operational value of AI.

Customer-centric precision highlights the need for hyper-personalization and ongoing feedback loops enabled by AI, which enhance product-market fit but also raise moral dilemmas around data governance and transparency, calling for cautious management and supervision. Lastly, scalability and ecosystem leverage demonstrate how AI can support platform orchestration and cross-organizational collaboration, especially in underserved areas. However, achieving these advantages largely depends on institutional frameworks and stakeholder confidence. To successfully integrate AI while maintaining creativity, entrepreneurs must manage cognitive, organizational, ethical, and institutional challenges. This requires a deeper empirical and theoretical investigation.

CONCLUSION

This study shows that the significance of AI in entrepreneurial contexts has evolved, moving from a narrow focus on automation to its recognition as a complex strategic enabler of innovation. A thorough review of 74 scholarly articles revealed four main topic clusters: platform-based scaling techniques, customer integration, innovation process efficiency, and AI-driven entrepreneurial cognition. The four interrelated pillars of the AI-Enabled Innovation Capabilities framework, cognitive augmentation, operational intelligence, customer-centric precision, and scalability with ecosystem leverage, are built upon these clusters. Various types of innovation, such as strategic, product, process, user experience, and business model innovations, are driven by these aspects. By facilitating AI-powered ideation, foresight, and opportunity recognition, cognitive augmentation improves entrepreneurial decision-making. Operational intelligence uses digital twins and workflow automation to increase efficiency and agility. By utilizing behavioral analytics and real-time feedback, customer-centric precision enables hyper-personalized user experiences. Lastly, platform-based growth and value orchestration through networked relationships are enabled by scalability and ecosystem leverage. Despite the revolutionary potential of these capabilities, entrepreneurs continue to encounter obstacles, including over-reliance on AI in cognitive processes, organizational capability gaps, ethical concerns about data protection, and institutional limitations that

prevent ecosystem engagement. To fully realize AI's promise of facilitating innovation, these challenges must be addressed. To foster sustainable and inclusive entrepreneurial innovation, future research should focus on understanding human-AI collaboration, developing dynamic capabilities, encouraging ethical personalization practices, and investigating the contextual factors that define AI-enabled ecosystem strategies.

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MEDIATION OF COMPETITIVE ADVANTAGE, DIGITAL INNOVATION, AND CAPABILITY IN SUPPLY CHAIN RESILIENCE–PERFORMANCE

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ABSTRACT

This study investigates the relationship between supply chain resilience and firm performance in food and beverage companies operating in West Java, Indonesia, in the midst of the COVID-19 pandemic and the acceleration of technological disruptions. Using a quantitative research approach, data were collected from 193 respondents representing various business scales and analyzed through a second-order conceptual model withl of likert scale questionaires forms and occured by using SMART PLS 4. The sampling method for this research was carried out using a random sampling approach. The empirical results demonstrate that supply chain resilience alone does not directly and significantly enhance firm performance. Instead, mediating variables play an essential role in linking resilience to business outcomes. Specifically, competitive advantage and digital capability emerge as significant mediators, exhibiting high and medium mediation effects, respectively. Conversely, digital innovation shows no significant influence, either directly or indirectly, on performance improvement. These findings suggest that resilient supply chains must be supported by strategic differentiation and digital competence to generate sustainable value. The study contributes to the growing body of knowledge in supply chain and strategic management by integrating resilience, competitiveness, and digital transformation within a unified framework. From a managerial perspective, the findings offer valuable insights for business leaders and policymakers to strengthen adaptive capabilities, enhance innovation readiness, and design proactive strategies to maintain competitiveness and achieve long-term business sustainability amid uncertainty and technological change.

Keywords: Supply chain resilience, competitive advantage, digital innovation and digital capabilities.

INTRODUCTION

The food and beverage industry in Indonesia, especially in West Java, plays a very vital role in producing nutritious food and beverage goods. The process and distribution of nutritious food and drinks throughout the archipelago will be able to boost nutritional resilience and improve the quality of life of the Indonesian people in general. in order for the government to keep working to support and enhance Indonesia's manufacturing sector's capabilities by boosting digital capabilities and making Indonesia 4.0 (Kemenperin, 2019). The endeavor demonstrates the government's and the corporate sector's dedication in tackling the world's pressing issues. The government is working to make sure that the enormous influx of imported goods can be met by the competitiveness of domestic food and drink products. Increasing digital capabilities has become part of the government's plan in carrying out digital transformation in the industrial business, especially food and beverage products (Ministry of Finance Republic of Indonesia., 2020).

Alongside Indonesia's population boom, the country's food and beverage industry has seen a considerable boost in performance. Even so, growth has significantly slowed as a result of the epidemic and has rebounded in tandem with its recovery. However, given the competitive environment and the highly

uncertain Volatility, Uncertainty, Complexity, Ambiguity (VUCA) future, the food and beverage industry's performance need to be continuously enhanced. The corporate world is developing at an accelerating rate, which is characterized by the emergence of fiercer rivalry (Abdalla & Nakagawa, 2021). This is inextricably linked to the enormous and quick advancement of technology, which is only going to get much worse in the years to come. Rapid technological advancement is compared to a knife's edge, which can have both positive and negative effects on corporate and societal development. If a business can adjust to change, it will have a beneficial effect on its operations; if it cannot, the opposite will happen. Utilizing current resources and investigating the creation of new opportunities as the company's dynamic capability will enable this adaption.

In the manufacturing sector, the supply chain is crucial, particularly in sectors of the food and beverage industry where spoilage occurs rapidly (Alfarsi et al., 2019). However, lengthy supply chains are particularly susceptible to supply and demand-side disturbances (Baghersad & Zobel, 2021). Disruptions can have both immediate and long-term negative effects on a company's performance. Therefore, it necessitates dependable supply chain capabilities, also known as supply chain resilience.

Because a stronger and more resilient supply network will further boost the company's potential to raise sales, earnings, and market share, the supply chain has a significant impact on enhancing the performance of the business (Stephens et al., 2022; Chowdhury et al., 2019). Therefore, the supply chain's resilience is a crucial component in helping the business succeed and win the competition. It is still unclear, though, how supply chain resilience may enhance the company's success. How the supply chain may be made more resilient to enhance the performance of the company, even when supply chain disruptions are increasing in frequency these days.

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Supply chain resilience is crucial for enhancing business performance, but it's not always simple to put into practice. Research from a number of nations, including Australia and India, highlights the challenges of supply chain resilience in terms of practical application (Bak et al., 2020; Ali et al., 2017). Because supply chain resilience is tied to a firm's ability to predict and minimize supply chain disruptions, it necessitates company capabilities that are not simple or inexpensive, and will be challenging for businesses with minimal resources to create. Expensive resources are needed for this skill, particularly when it comes to how businesses build dynamic supply chain capabilities. However, the way supply chain resilience is implemented differs from nation to nation based on the kind and degree of disruption encountered as well as the company's internal resource capabilities. In other words, it has to do with how the company builds dynamic capabilities by setting up and coordinating resources to overcome supply chain disruption and uncertainty.

In actuality, it is more difficult to establish a robust supply chain in Indonesia's industrial sector, particularly in the food and beverage (F&B) sector, than in other sectors. Technical constraints and stringent production process standards, such as GMP and CIP (Clean in Place) when altering products or specific tastes, are root reason cause of the high degree of complexity. Strict rules governing the production process undoubtedly limit the ability of manufacturers to adapt to shifts in consumer demand. Then, it has to do with managing the flow of materials and final goods, which are still limited by the capacity of skilled and organized suppliers, making it challenging to move more rapidly between them. Deliveries to customers at the FG level are therefore less flexible than in the non-F&B sector since final goods are shipped based on the fleet type—frozen, chilled, or dry. The strength of supply chain resilience in confronting and mitigating unforeseen events is determined by the next practical restriction pertaining to each company's digital technology capabilities (Ali et al., 2017).

In the Indonesian sector, particularly in the West Java region, it is crucial to understand how supply chain resilience and other elements relate to enhancing business success. There must be a company's dynamic capability, in this case the ambidexterity capability, to fill the relationship, according to Pertheban

& Arokiasamy, (2019). Can its implementation directly improve the company's performance capabilities, or are there other factors that actually mediate the relationship? According to the findings of empirical study, there is still contradiction in the findings of the impact of supply chain resilience on business performance, both in favor of and against it. Other factors can mediate direct relationships through competitive advantage variables, risk management performance by (Liu et al., 2018), and product innovativeness and innovation magnitude (I. Ali & Gölgeci, 2019), according to research indicating that supply chain resilience does not support such as (Abeysekara et al., 2019).

In theory, there are still a lot of differing perspectives on supply chain resilience, particularly the resilience metrics that are employed. The topic of supply chain resilience is highly dynamic since different scholars and nations have different understandings of resilience adaptation and different metrics. Each researcher uses these many resilience markers according to the relevant practical approach. Four resilience indicators flexibility, agility, redundancy, and collaboration were employed in this study and were modified from research by Shekhar et al., (2019). Thus, based on the aforementioned phenomenon, supply chain resilience implementation is crucial in Indonesia today, but it does not always directly enhance business performance; instead, other factors must be involved as mediating factors to enhance business performance. Digital capability, digital innovation, and competitive advantage are other variables in this study that act as mediating factors. It is anticipated that these factors would be able to resolve the ambiguous connection between supply chain resilience and business performance.

Competitiveness is a powerful motivator for raising the performance of the business. Through enhancements to business procedures across the supply chain, supply chain performance must be able to raise the company's competitiveness. Supply chain resilience plays a critical function in raising competitiveness metrics. Competitive competitiveness can be measured by a number of metrics that show how well the company can outperform its rivals. Price, delivery, quality, innovation, and time to market are some of these factors (Azizi et al., 2016). Numerous earlier studies have empirically demonstrated how the supply chain can enhance a business's competitiveness (Afraz et al., 2021*;* Jiwa et al., 2021). Therefore, before enhancing the performance of the company, the food and beverage industry should be able to boost competitiveness through the application of supply chain resilience.

LITERATURE REVIEW

This literature review aims to synthesize various theoretical perspectives addressing supply chain resilience. It will explore the various definitions, constituent elements, and measurement metrics that have developed within this field. In doing so, this literature review seeks to map the evolving research landscape.

Supply Chain Resilience

Through the integration of numerous agents from upstream to downstream, the supply chain plays a crucial role in enhancing the company's capabilities. Network theory or system theory, which is concerned with the integration approach amongst different agents in the supply chain, and the RBV (Resource Base View) method, which was created by (Barney, 2015) and (Teece, 2018), are two theoretical perspectives on the supply chain. Today's supply chain management differs greatly from that of a few decades ago, when it was still relatively simple and less sophisticated. The complexity and dynamics of the external environment's incredibly rapid changes make the supply chain vulnerable. Business actors must be able to swiftly adapt to changes in corporate and community behavior brought about by rapid technological improvements. The supply chain must be made more resilient in order to manage the uncertainty that results from the disruption.

Supply chain resilience has been shown to improve business performance in prior empirical studies (Chowdhury & Quaddus, 2017; Asamoah et al., 2020; Wieland & Wallenburg, 2013; Stephens et al., 2023; Mashaphu et al. 2024) Through its capacity to manage changes brought on by supply chain interruptions, supply chain resilience capability can enhance business performance. In unpredictable circumstances, supply chain resilience can nevertheless preserve customer satisfaction by ensuring on-time delivery and quantity. At every stage of the supply chain, dependable flexibility and cooperation mechanisms enable prompt and appropriate handling of demand changes that occur very downstream. For instance, when demand forecasting changes, the prior level is promptly modified. This includes alterations to inventory levels and production volume at the focal manufacturing level, which are based on changes in the demand for raw materials and packaging. The adaptive capability in the supply chain causes the company's performance to be maintained, thus building the following hypothesis:

H1: Supply chain resilience has a positive effect on company performance

Competitive Advantage

Competitive advantage refers to a company's strength in comparison to other firms of a similar sort. Businesses can gain a competitive edge by utilizing existing resources to create things that are valuable, unique, and difficult for competitors to imitate (Barney, 2015). A corporation can gain a competitive advantage by using its organizational skills and available resources, both tangible and immaterial (Collis & Anand, 2019; Teece, 2018). Numerous empirical studies have found a strong positive correlation between supply chain resilience and competitive advantage; however, the specific factors that determine competitive advantage have not been fully explored in these studies. Azizi et al., (2016) conducted indicators of competitive advantage in this study, focusing on cost, quality, delivery, product innovation, and time to market. The capacity of supply chain resilience to consistently maintain timely delivery capabilities and the quantity and speed of market penetration both increase competitive advantage, allowing the following hypothesis to be constructed:

H2: Supply Chain Resilience has a positive effect on competitive advantage.

Digital Innovation

One essential element of supply chain resilience is the capacity to overcome supply chain uncertainty. This competence necessitates the utilization of supplementary resources, specifically the existing digital technologies and infrastructure. Using technology and digital infrastructure can increase the company's ability to innovate (Ivanov et al., 2021). Businesses today need to innovate their processes, goods, and digital marketing through the use of digital technology (Nambisan et al., 2017). According to a number of empirical studies, resilience can increase an organization's ability to innovate (Akgün & Keskin, 2014). In order to improve corporate performance through excellent service and satisfaction through digital engagement, digital innovation helps to strengthen the supply chain's resilience through the implementation and development of digital marketing innovation (Varadarajan et al., 2022; Matyushenko et al., 2022). The ability of the company to create innovations that complement the practices, values, and operations of each supply chain participant can be improved by cooperation and integration at all supply chain levels (Freije et al., 2021). In order to construct the following hypothesis:

H3: Supply Chain Resilience has a positive effect on digital innovation

Digital Capabilities

The supply chain is associated with effective management of the information and material flow at all stages of the supply chain, from upstream to downstream, whereas resilience is associated with the

supply chain's ability to withstand changes. Collaboration and cooperation from upstream to downstream are stronger and more stable in supply chains that are more robust. In order to create greater and mutually beneficial value, close communication and collaboration can enhance the willingness to adopt digital technology in the supply chain (Yang et al., 2021). Businesses can expand their digital capabilities thanks to digital infrastructure and technology. Zhu et al., (2020) demonstrate how digital skills help to bridge engagement and collaboration at the supply chain level by enhancing online management capabilities.

The degree of digital technology utilized in communication media amongst supply chain members is also influenced by the degree of cooperation within the supply chain (Yang et al., 2021). In order to improve coordination, delivery, and product speed to market, digital capability refers to the company's capacity to develop the ability to mitigate supply chain risks by coordinating its human capital and current information technology (Raut et al., 2021). Supply chains can become more resilient with digital technology, which can enhance their digital capabilities to reduce supply chain problems. Digital capabilities that can be utilized to reduce supply chain risks can be enhanced by resilience and its interaction with digital technology (Zhu et al., 2020; Ivanov et al., 2021). These empirical investigations allow for the construction of the following hypothesis:

H4: Supply Chain Resilience has a positive effect on Digital Capability.

Competitive Advantage and Company Performance

One type of competitive advantage is the capacity of the business to create a collection of distinctive resources that rivals cannot copy. Each business must constantly improve its competitive edge to meet the shifting needs of the market and its ever-evolving clientele due to fierce competition. Gaining a competitive advantage can help a business boost sales, market share, and profitability. Some studies on the connection between competitive advantages are carried out by Lee & Yoo (2021) and Hidayat et al. (2022). The superiority that is built can be emphasized on several specific aspects, both in terms of product innovation, very competitive prices or the ability to develop quality and delivery that is very difficult for competitors to imitate (Barney, 2015; Azizi et al., 2016). Competitive advantage causes the company's ability to always win very fierce competition and has an impact on the company's performance which is always increasing so that the following hypothesis can be built:

H5: Competitive advantage has a positive effect on company performance.

Digital Capabilities and Digital Innovation

The ability of a business to integrate digital capabilities into its operations in the face of swift technological change is referred to as digital capability. The ability of the business to implement the technology change is correlated with its digital capabilities. This competence relates to the organization's capacity to coordinate IT resources and IT human capital in order to dynamically confront the uncertainty that arises (Khin & Ho, 2019; Wang et al., 2022). Businesses can digitize their business processes more effectively than their rivals thanks to digital capabilities. Exceptionally strong digital skills that serve as a catalyst for innovation across all industries. Today, digital innovation is essential to overcoming extremely fast changes in both product quality and product changes. The following hypothesis can be developed since it is undeniable that digital competence has a significant impact on the company's capacity for digital innovation:

H6: Digital capability has a positive influence on Digital Innovation

Digital Innovation and Firm Performance

Innovation is a way for businesses to meet the ever-increasing needs of their clientele (López & Oliver, 2023) The development of digital activities and technology that enable innovation to be carried out more quickly is another factor that is driving innovation, which is also the solution to the needs of fierce and highly dynamic competition among competitors. Accordingly, the focus of innovation has changed from traditional to digital (Nambisan et al., 2017). Digital innovation can be implemented both upstream and downstream in the supply chain. Digital innovation in the material procurement process and supplier and vendor relationships can be used to digitalize business operations at the upstream level. Digital innovation or digitizing the production process are two ways to innovate at the focal level. Digitalizing marketing through a shift from traditional to digital marketing methods, either through multichannel or omnichannel, is how innovation is accomplished at the downstream level.

Digital innovation has the potential to boost value for all parties involved, particularly for consumers; the more advanced the innovation, the more value is created (Varadarajan et al., 2022). Because digital innovation incorporates client feedback with current digital technologies, it enables innovation to be executed more quickly and effectively. Many empirical studies have demonstrated the role of digital innovation in enhancing business success, including (Annarelli et al., 2021; Hamidi & Shams Gharneh, 2017; Cuevas-Vargas et al., 2021). Thus, the following hypothesis can be developed from these studies:

H7: Digital Innovation has a positive effect on Company Performance

Digital Capabilities and Firm Performance

Digital resource capabilities that can overcome disruptions to business processes are necessary for a company's effectiveness in the face of rapid technological change (Annarelli et al., 2021). Today, traditional business procedures are incredibly antiquated. People's and businesses' activities have drastically changed from being based on time and location to being able to do anything they want online. Without a company's digital transformation, key business processes cannot be digitalized. According to numerous studies, digital capabilities play a significant influence in enhancing a company's capacity to turn a profit and expand (Wang et al., 2022; Heredia et al., 2022; Martínez-Caro et al., 2020). Thus, the following hypothesis can be developed from these studies:

H8: Digital capability has a positive effect on company performance.

Following a theoretical and empirical assessment of the literature from a variety of sources, Figure 1 below can be used to describe a conceptual model. Figure 1 shows how competitive advantage, digital innovation, and digital capabilities moderate the relationship between supply chain resilience factors and business performance. The conceptual model is based on empirical supply chain resilience relationships that have been developed thus far, but the results are still erratic and require a more thorough explanation. This study's innovation is the addition of mediating variables.

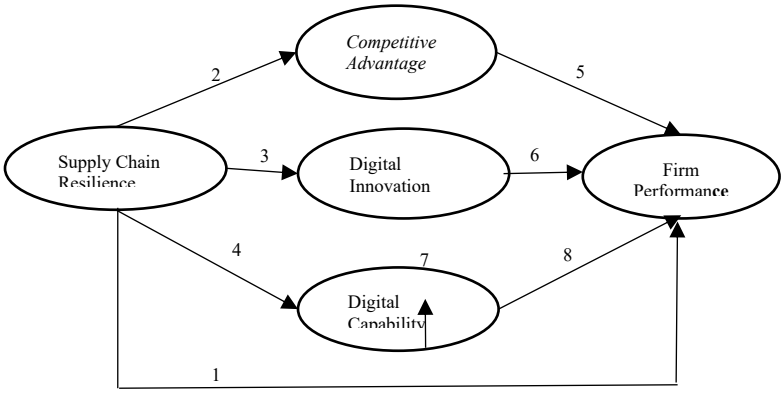

Figure 1. Conceptual Model

Mediation Effect

The relationship between supply chain resilience and business performance is mediated in large part by competitive advantage, digital innovation, and digital capacity. According to a number of earlier studies, supply chain resilience has a significant impact on competitive advantage (Hadi & Herianingrum, 2020), and competitive advantage affects business performance (Lee & Yoo, 2021). As a result, supply chain resilience can enhance business performance by leveraging competitive advantage.

Currently, digital technology is a key factor in increasing the speed and efficiency of business operations. Supply chain participants can work together more firmly thanks to digital technology. The cooperation and participation of suppliers in the supply chain, as stated by Zhu et al. (2020), Raut et al. (2021) and Zeynali et al. (2024), further reinforce the use of digital technology as a means to accomplish more effective and efficient goals. As a result, the supply chain's resilience further improves the company's capacity to develop its digital capabilities, including innovation.

The relationship between supply chain resilience and business performance can be mediated by competitive advantage, digital innovation, and digital capabilities.

H9: Competitive Advantage Mediates the Relationship Between Supply Chain Resilience and Business Performance

H10: Digital innovation acts as a mediator in the relationship between business performance and supply chain resilience.

H11: Digital capability acts as a mediator in the relationship between supply chain resilience and business performance.

RESEARCH METHODOLOGY

The food and beverage sector in West Java, both inside and outside of the Industrial Area, was the subject of this study. The only industries covered by this research category are those in the food and beverage sector and those that have integrated digital technology into their business processes. Examples include developing the company's operational system through the use of ERP (Enterprise Resource Planning) and improving the current warehouse system through the use of ASRS (Automated Storage and Retrieval System) or WMS (Warehouse Management System). In the meantime, the production process has adopted digitalization through the use of real-time data recording. The withdrawal, analysis, and assessment of system performance can be completed more rapidly and effectively with the help of this method.

West Java was chosen as the research region because it is home to nearly all of the food and beverage sectors, whether they are small, medium, or large-scale. The medium to big food and beverage industry, which uses digital technology in its business processes, was the subject of this study. Due to the high implementation expenses, which include the requirement for dependable IT resources, the employment of digital technology is not simple or inexpensive. It is therefore not surprising that 34% of people working in the food and beverage manufacturing sector still use digital technology at a medium to high level; the remaining employees still rely on basic technological systems for their business operations, such as Excel, email, and Zoomet.

Research Approach

This study focused on a population of 375 food and beverage companies in West Java that have undergone technological transformation. Using the Slovin method, a sample of 193 respondents from various job levels in the manufacturing sector was selected through random sampling. Data analysis was conducted using Partial Least Squares (PLS) 4 and structural equation modeling, complemented by a mediation test using the Sobel test calculator. Data collection was conducted online through the Google Forms platform and distributed via email to respondents.

Population and Samples

The study's population consisted of 375 food and beverage enterprises in West Java that have implemented technology transformation in their business processes. The Slovin method (Bosteley & Peters, 2023) was used to determine the sample size, which came out to be 193. 193 respondents with a range of manufacturing job levels, including the respondent's educational attainment, were sampled. Emails were used for sampling, and responder data was gathered via the Google form platform. The simple random sampling technique was chosen to provide an equal opportunity for each member of the population to be selected, allowing research results to be generalized to the entire population. This approach is considered the most effective for minimizing selection bias and ensuring a representative sample. However, the basic random sampling approach was used to determine the number of samples. Partial least squares (PLS) 4 software tools and structural equation modeling analysis are used in the analysis process. The Sobel test calculator tool is used for mediation testing (Hair et al., 2019).

Data Collection

The data collection process for this study was conducted online using the Google Forms platform. Questionnaires were distributed via email to 193 respondents, employees of various levels at a food and beverage manufacturing company in West Java. The questionnaires were distributed directly by the researcher to ensure accountability and allow for follow-up if necessary. The selection of Google Forms as the survey tool was based on several key considerations: cost and time efficiency, broad reach without geographical limitations, and ease of real-time data processing. Compared with other methods such as interviews (which are time-consuming) or paper-based surveys (which are less practical), Google Forms was deemed more suitable for quickly reaching geographically dispersed target respondents.

The questionnaire used in this study was developed by the researcher, adapting validated instruments from previous studies. The instrument is divided into four main sections measuring research variables, with a total of 25 questions. Most questions use a 1-5 Likert scale to gauge respondents' perceptions, supplemented by several multiple-choice questions for demographic data. This adaptation of a tested questionnaire was chosen to ensure construct validity and reliability of the instrument, while also allowing for contextual adjustments to make it relevant to the food and beverage industry setting in Indonesia (Hair et al. 2019; lachowicz et al. 2028; Ogbeibu et al. 2021)

RESULT

Result and analysis

The distribution of samples taken from the population of the food and beverage industry that has implemented digital technology in its business processes is as follows:

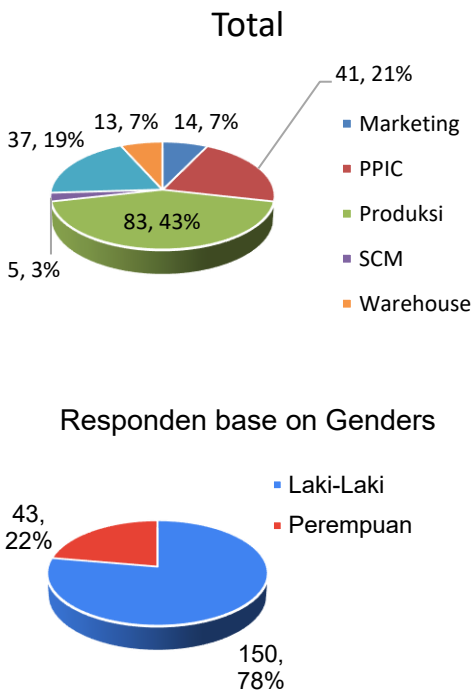

Figure 2. Category of respondents in department (a), category based on gender (b)

The respondents in this study consisted of 19% of the Marketing Department, 21% of the PPIC Department, 43% of the Production Department, 3% of the SCM Department, and 7% of the Warehouse Department. Based on gender, 22% were female and 78% were male.

Measurement model analysis

The measurement model analysis was created using the steps that Smart Pls v 4 initially performed. These steps included reliability, discriminant validity, and convergent validity. The measurement model's analysis was conducted using parameters and value limits provided by Hair et al., (2019). This study's measurement model was implemented in two steps. The first stage involved measuring first- and second-order variables. Assessing the validity and reliability of the indicator items is the first step in the measurement process. Measurements are conducted on the second order, both validity and reliability, using SmartPLS version 4 once the findings of the measurement are confirmed to be valid.

First-order validity and reliability test

Measure the validity of the indicator by comparing it to the question items or by comparing the variables to the measurement indicators using convergent validity. Since the following table shows that each measurement item's value is over the necessary threshold, it may be concluded that the indicators meet convergent validity. The limit of convergent validity is 0.7, meaning that the loading factor's minimum value is 0.7. The second-order model used in this study measures latent variables by using indicators of each variable rather than directly measuring them.

Cronbach alpha and composite reliability values for each dimension are calculated to determine first-order reliability, and the findings are displayed in table 2 below. Redundancy, agility, adaptability, and teamwork are the components of resilience. Time to market, pricing, quality, delivery, and product innovation are the components that make up competitive advantage. Digital product, digital process, and digital marketing innovation are the aspects of digital innovation, while online activities, digital technology acquisition, and digital analysis are the elements of digital capacity. Table 1 shows that all indicators have good convergent validity, as evidenced by all indicator items having values above the threshold of 0.7 and the AVE value for each item being above the standard of 0.5. This first-order measurement is to determine how the indicators in the dimensions of each variable are against the specified standards (Hair et al., 2019).

Table 1. Outer loading of each measurement item

VARIABEL	DIMENSI	ITEM	OUTER LOADING	KET
Supply Chain Resilience (RRP)	Flexibility	FLEX 3	0.849	VALID
		FLEX 4	0.927	VALID
		FLEX 5	0.889	VALID
	Agility	AGI 1	0.855	VALID
		AGI 3	0.889	VALID
	Collaboration	COL 1	0.849	VALID
		COL 2	0.780	VALID
		COL 3	0.876	VALID
		COL 4	0.841	VALID
	Redundancy	RED 2	0.871	VALID
		RED 3	0.893	VALID
Competitive Advantage (CA)	Cost	SA 1.1	0.915	VALID
		SA 1.2	0.916	VALID
	Delivery	SA2. 1	0.957	VALID
		SA2.2	0.958	VALID
	Quality	SA3.1	0.927	VALID
		SA3.2	0.904	VALID
	Product Innovation	SA4.1	0.959	VALID
		SA4.2	0.958	VALID
	Time to Market	SA5.1	0.912	VALID
		SA5.2	0.884	VALID
Digital Capability (KD)	Digital Technology Acquisition	KD1.1	0.919	VALID
		KD1.2	0.896	VALID
		KD1.3	0.887	VALID
	Digital Analysis	KD2.1	0.864	VALID
		KD2.2	0.917	VALID
		KD3.3	0.950	VALID
	Online Activity	KD3.1	0.885	VALID
		KD3.2	0.876	VALID
		KD3.3	0.812	VALID

Digital Innovation	Digital Product Innovation	ID1.2	0.802	VALID
		ID1.3	0.924	VALID
	Digital Process Innovation	ID2.1	0.892	VALID
		ID2.2	0.855	VALID
		ID2.3	0.908	VALID
	Digital Marketing Innovation	ID3.1	0.961	VALID
		ID3.2	0.982	VALID
		ID3.3	0.961	VALID
Firm Performance	Market Growth	KP1	0.897	VALID
	Sales Growth	KP2	0.907	VALID
	Margin Proft	KP3	0.864	VALID
	ROI	KP4	0.872	VALID

The Cronbach alpha value and composite reliability are then displayed in Table 2. This parameter is used to make sure that every indicator item in the study is dependable, and it is evident that the indicator items are highly dependable when they fall inside the parameter threshold.

Table 2. First Order Reliability

Indicator	Cronbach Alpha	(rho.a)	AVE
Flexibility	0.703	0.716	0.77
Agility	0.857	0.866	0.70
Redundancy	0.868	0.880	0.791
Collaboration	0.715	0.719	0.778
Digital Product Innovation	0.678	0.771	0.748
Digital Process Innovation	0.862	0.866	0.783
Digital Marketing Innovation	0.967	0.967	0.938
Digital technology acquisition	0.884	0.885	0.811
Digital Analysis	0.897	0.897	0.83
Online Activity	0.821	0.829	0.737
Cost	0.807	0.807	0.838
Quality	0.909	0.909	0.917
Delivery	0.807	0.817	0.838
Product Innovation	0.911	0.911	0.918
Time to Market	0.760	0.769	0.806
Firm Performance	0.908	0.908	0.783

Second order Validity and Reliability Test

The table format can be in colour or greyscale in the best quality. Text in the table must be readable with font type Times New Roman, font size 10 (9). Tables are located directly into the text and centred [1,3,11,12]. All tables must be numbered in the order in which they appear on the paper

Following the completion of the first order calculation, which yields valid and trustworthy findings, the validity and reliability of the second order calculation are determined. In a technical sense, the Smart Pls system replicates the identical data from the first order computation results. The findings of the first measurement pertaining to measuring dimensions cannot be used to measure the validity and reliability of variables. Therefore, the 2-stage PLS stage can be used to convert the dimensions into indicators in order to measure new variables. According to table 3 below, which shows the findings of the second stage's computation, the dimensions in this study have satisfied convergent validity as the outer loading value of the current dimensions is higher than the 0.7 criterion. It may be concluded that the second stage's calculation satisfies the validity and reliability of the measurement model since the Cronbach alpha and composite reliability values are over the threshold, indicating the variables' dependability to the dimensions.

Table 3. Validity and Reliability of Second Order

Variabels	Indicators	Outer Loading	Cronbach alpha	Rho.a	AVE
	Flexibilty	0.774			
Supply Chain Resilience	Agility	0.889	0.885	0.902	0.774
	Redundancy	0.908			
	Collaboration	0.872			
	Cost	0.874			
	Quality	0.861			
	Delivery	0.862			
Competitive Advantage	Product Inovation	0.862	0.926	0.926	0.771
	Time to Market	0.911			
	Digital Product Innovation	0.911			
	Digital Process Innovation	0.904			
Digital Innovation	Digital Marketing Innovation	0.912	0.894	0.900	0.825
	Digital technology acquisition	0.936			
	Digital Analysis	0.890			
Digital Capability	Online Activity	0.950	0.897	0.899	0.829
	Market Growth	0.898			
Firm Performance	Sales Growth	0.908	0.908	0.908	0.783
	Profit Margin	0.863			
	ROI	0.871			

Structural model measurement

A number of metrics are employed in the measurement of the structural model utilizing Smart Pls, including direct and indirect hypothesis testing, F Square and R Square, multicollinearity tests, and the GoF index and SMRS to determine the robustness of the model constructed. Based on the results of structural model testing with Smart PLS, all direct hypotheses were proven significant at the α level < 0.05, while two of the three indirect hypotheses also showed a significant mediation effect. The R-Square value for the endogenous constructs was in the moderate to substantive category, namely between 0.45 and 0.67, which indicated that the model had adequate predictive power. The multicollinearity test seen from the VIF value was below the threshold of 5, thus confirming the absence of distortion in the regression coefficients. The f-Square value for each exogenous-endogenous relationship was generally in the small to medium effect category (0.10 - 0.25). In addition, the overall model also showed good robustness, as indicated by the Goodness of Fit (GoF) value of 0.45 and the Standardized Root Mean Square Residual (SRMR) of 0.065, which is still below the recommended limit of 0.08.

Multicollinearity Test

This test is performed to examine if the VIF (Variance Inflation Factor) value indicates that the model has a high correlation between variables. This study use a threshold of 5 from (Hair et al., 2019). The foundation for determining whether or not there is a high connection. There is substantial multicollinearity if the value is greater than 5, and no significant correlation between the variables if it is less than 5 (Chan et al., 2022). The VIF values of the variables constructed are shown in Table 4. Based on the computations, it is evident that there is no strong link between the same variables that are currently in use, with an indicator of the VIF value between variables falling below the designated threshold.

Table 4. Variance Inflation Factor

	RRP	CA	ID	KD
RRP				
CA	1.00			
ID	2.371			
KD	1.00		2.371	
KP	3.393	3.724	3.286	4.997

F Square Measurement

To ascertain the degree to which exogenous variables impact endogenous variables, the F Square test is used. In order to give a general explanation of the exogenous factors' influence, this parameter gives a summary of how strongly they influence things. F square aids in elucidating the significance of the independent variable, giving researchers a clearer understanding of its meaning that they may utilize to further explain the relationship between the variables that occur. According to Hair et al., (2019), the F square limits are as follows: 0.02 is low, 0.15 is medium, and 0.35 is high. The F Square value of the exogenous factors on the endogenous variables is displayed in Table 5. RRP to KP and ID to KP are examples of low-quality links, whereas RRP to CA, KD to ID, and CA to KP are examples of high-quality relationships.

Table 5. F Square

Variables	F Square
RRP->KP	0.040

Variables	F Square
RRP->CA	1.690
RRP->ID	0.031
RRP->KD	1.287
CA->KP	0.482
ID->KP	0.014
KD->KP	0.102

R Square Measurement

The goal of using R Square to assess the coefficient of determination is to ascertain the extent to which the exogenous factors can account for the endogenous variable. The greater the exogenous variable's ability to explain the endogenous variable, the higher the R square value. As a reference for its category based on (Hair et al., 2019), the R-adjusted value of the computations using smart PLs can be seen, with a value limit of 0.75 considerable, 0.50 medium category, and 0.25 weak category. Table 6 shows that the adjusted R value of company performance is 0.758, indicating that it falls into the substantial category. In other words, 75% of the company performance can be explained by exogenous variables, with the remaining portion being explained by variables not included in this research model.

Table 6. R Square

	Original Sampoe (O)	Mean	STDEV	T stat	P values
CA	0.628	0.630	0.081	7.751	0.000
ID	0.721	0.723	0.058	12.383	0.000
KD	0.563	0.576	0.098	5.67	0.000
KP	0.768	0.778	0.042	18.006	0.000

Model Fit Test

Using the model fit test, one can ascertain whether or not the model developed for this study is part of a robust model based on its parameters. SRMR, NFI, and GoF are among the parameters that are employed. The results of the GoF calculation in this study were 0.696, which indicates very good more than the threshold limit. The other parameters are shown in Table 7 below, which displays each parameter in accordance with the specified standards. The maximum SRMR parameter limit is 0.110, while the index for GoF is 0.36 and for NFI it is near 0.950 (Hair et al., 2019). Based on established standards, these findings indicate that the tested model meets acceptable model fit criteria. The SRMR value of 0.110, which is right at the maximum limit, along with the NFI approaching the threshold, indicates that while the model is quite good, there is still room for improvement to achieve a more ideal fit.

Table 7. Fit of Goodness Test

	Saturated Model	Estimated Model
SRMR	0.066	0.090
d_ULS	0.817	1.532
d_G	1.105	1.197
NFI	0.753	0.750

Hypothesis Testing

To ascertain the significance of the impact of exogenous variables on endogenous variables, hypothesis testing is carried out. Eight hypotheses were tested directly in this study, while three mediating factors were used for indirect hypothesis testing. Depending on the amount of samples utilized, bootstrapping was done for 193 samples following the validity and reliability phases. Direct testing results are displayed in Table 7, and indirect testing (mediation) findings are displayed in Table 8. Table 7 illustrates how the P value of each hypothesis is used to test the impact of exogenous variables on endogenous variables. Three hypotheses—the impact of supply chain resilience on company performance, the impact of supply chain resilience on digital innovation, and the impact of digital innovation on company performance—are deemed not significant because the P value is higher than 0.05. The efforts to strengthen supply chain resilience have not directly contributed to improved company performance or driven digital innovation. Consequently, management needs to reevaluate its strategy and seek more effective mediating factors or variables, such as leadership quality or the adoption of specific technologies, that can bridge these relationships.

Table 8. Direct Testing

Path Analysis		Original Sample (O)	Mean	Std Dev	T stat	P Value
From	To					
RRP	FP	- 0.170	- 0.161	0.081	2.113	0.036
RRP	CA	0.793	0.792	0.051	15.64	0.000
RRP	DI	0.140	0.149	0.082	1.712	0.088
RRP	KD	0.750	0.756	0.065	11.543	0.000
CA	FP	0.628	0.630	0.079	7.921	0.000
DI	FP	0.107	0.107	0.987	0.839	0.325
KD	ID	0.739	0.728	0.083	8.902	0.000
KD	KP	0.346	0.336	0.110	3.140	0.000

Through indirect testing, the direct relationship between supply chain resilience and business performance may be examined in relation to the mediating factors of competitive advantage, digital innovation, and capability. Table 9 shows the P value for each mediating variable, indicating the mediating role. While digital innovation cannot mediate supply chain resilience and corporate performance, the mediating variables competitive advantage and digital competence have a substantial impact because their respective P values are below 0.05 at 0.000 and 0.004. Using the word upsilon (Ʊ), (Lachowicz et al., 2018) calculated the degree of influence of the mediating variables. Using the criteria of 0.175 large effect, 0.075 medium effect, and 0.01 small impact, the upsilon calculation is used to ascertain the degree of influence that the mediating variables have (Ogbeibu et al., 2021). According to the media competitive advantage estimate using the Upsilon formula, mediation has a significant impact (0.261), but digital capacity has a medium impact (0.7) and digital innovation has no effect at all.

Table 9. Indirect Testing

Indirect Effect					
Path Analysis	**Path Coef**	**Mean**	**STD.DEV**	**T stat**	**P value**

From	Med	To					
RRP	CA	FP	0.510	0.508	0.072	7.078	0.000
RRP	DI	FP	0.014	0.015	0.021	0.659	0.0511
RRP	KD	FP	0.271	0.267	0.093	2.095	0.004

Graphically, it can be explained in Figure 2 below regarding the 2 stages of analysis of the research model conducted in the food and beverage industry in West Java.

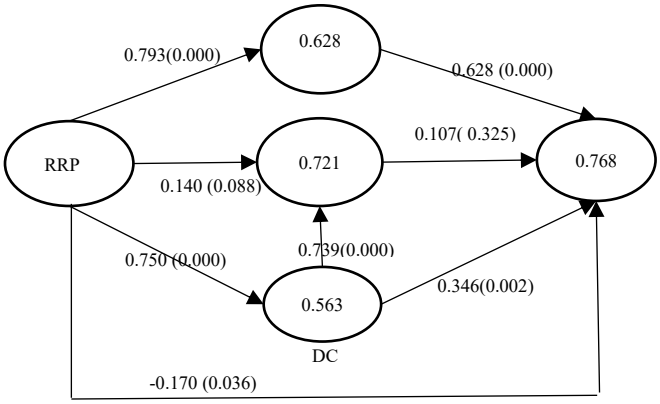

Figure 3. Final results of the 2-stage analysis

DISCUSSION

The use of supply chain resilience in West Java's food and beverage sector is the subject of this study. The findings of earlier research on the function of supply chain resilience remain erratic. The results' inconsistency suggests that there is potential for improvement in the relationship between supply chain resilience and business performance, which has not been adequately addressed. This is particularly true as the disruption brought on by uncertainty and the impact of rapidly evolving and massive technology increases (Huang et al., 2023). In order to better understand how supply chain resilience affects business performance, this study includes mediating variables for competitive advantage, digital innovation, and digital skills.

According to the research findings, the first hypothesis (H1) was unable to allay the study's initial suspicions since it was discovered that the supply chain's implementation had no beneficial impact on the performance of businesses in West Java's food and beverage sector. The p value was 0.036 and the negative path coefficient was -0.170, indicating that its application in the food and beverage sector has the opposite effect and may lower business performance due to the industry's distinct features from those of the non-food and beverage sector. Collaboration, flexibility, agility, and redundancy are all aspects of supply chain resilience that, when implemented, come at a high cost and do not instantly boost business performance. One instance of process flexibility involves extremely high expenses, particularly when setting up multiple flavors and goods. This significant expense is associated with the use of chemical sanitation materials during CIP (Clean in Place) and COP (Clean Out Place) procedures. Resilient supply chains that have no effect on business performance are consistent with studies by (Abeysekara et al., 2019), (Liu et al., 2018) and (Akgün & Keskin, 2014)

Resilient supply chains can boost competitive advantage (H2), as this study's introduction states. A company's capacity to gain a competitive edge through competitive pricing, timely delivery, and well-

maintained quantity and quality can be enhanced by a robust supply chain capability. This theory aligns with other research on the contribution of supply chain resilience to competitive advantage (Hadi & Herianingrum, 2020); (Liu & Lee, 2018). With a P value of 0.088 and a path coefficient of 0.140, supply chain resilience, on the other hand, is unable to boost digital innovation (H3). This lack of impact is linked to the incomplete cooperation that takes place at every stage of the supply chain in order to increase value through digital space. But according to the study's p value of 0.000 and path coefficient of 0.750, supply chain resilience can actually boost digital capabilities (H4). Put another way, if one looks at the model's concept, digital innovation cannot be realized directly from supply chain resilience; instead, businesses must first develop digital capabilities. According to earlier research, supply chain resilience to digital capabilities is important ((Zhu et al., 2020);(Raut et al., 2021);(Freije et al., 2021).

With a path coefficient of 0.628 and a P value of 0.000, the study's parameters show that competitive advantage significantly improves business performance (H5). Its importance is demonstrated by the company's capacity to create advantages in terms of cost, quality, delivery, product innovation, and the rate of market penetration and research in accordance with. However, as evidenced by its p value of 0.325, it turns out that digital innovation has no effect on company performance (H6). This insignificance is related to the complexity and fragmentation of digital innovation, which necessitates that human resource capabilities (employees) be in line with the technological transformation while digital capabilities itself can boost digital innovation (H7) and enhance business success (H8),

In order to support the role of supply chain resilience in enhancing business performance, mediating variables play a critical role. Although digital innovation (H10) did not have a mediating effect in this study, it can be concluded that competitive advantage (H9) and digital capability (H11) fully mediate, as the study's findings indicate that supply chain resilience has no effect on company performance (Hair et al., 2019). When supply chain resilience is implemented without taking costs into account, business performance actually suffers. Therefore, it is necessary to transform supply chain resilience into a competitive advantage first. For instance, the systemic orientation of flexibility, agility, redundancy, and collaboration is necessary to build and enhance competitive advantage through cost, quality, delivery, product innovation, and quicker market penetration. Collaboration and integration at all supply chain levels, from upstream to downstream, grow with supply chain resilience. The development of a well-digitized system fosters mutual symbiosis and value creation, both of which can be enhanced by strong collaboration.

CONCLUSION

The study finds that in West Java's food and beverage sector, supply chain resilience does not directly improve company performance in terms of profit margin, market share, sales growth, or return on investment. This is due to the industry's unique manufacturing standards and regulatory requirements, which differ from non-food sectors. For resilience to enhance performance, it must first strengthen competitive advantage by optimizing costs, ensuring fast and reliable delivery, supporting product innovation, and reducing time to market and improve digital capability to manage supply chain uncertainty in the face of rapid technological change. Both competitive advantage and digital capability are key to maintaining performance under intense competition. Meanwhile, digital innovation fails to positively impact performance due to several barriers: partial adoption, limited cross-departmental involvement, misalignment between technological benefits and employee competencies, and system complexity that does not match existing workflows, leading to suboptimal implementation.

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