**Advance Journal of Econometrics and Finance**
**Vol-4, Issue-1, 2026**

Online ISSN
2959-8990
Print ISSN
2959-8982
https://ajeaf.com/index.php/Journal/About

Name of Publisher: SCHOLAR CRAFT EDUCATION & RESEARCH HUB
Review Type: Double Blind Peer Review
**Jurnal Frequency: Quarterly Research Journal**

[redacted]

# The Impact of Artificial Intelligence–Driven Financial Analytics on Strategic Decision-Making and Profit Optimization in Small and Medium Enterprises (SMEs)

**Ahmad Mujtaba[1], Muazma Tehseen[2], Naser Rehman[3], Dr. Muhammad Sohail Khalil[4]**

**Ahmad Mujtaba**
MS Scholar of Management (Finance), Institute of Management Sciences, Peshawar Email: ahmadmujtaba6655@gmail.com

**Muazma Tehseen**
MS Scholar of Management (Finance), Institute of Management Sciences, Peshawar Email: muazmatehseen911@gmail.com

**Naser Rehman**
PhD Scholar of Management Sciences (Finance), Institute of Management Sciences, Peshawar Email: nasir.rehman6677@gmail.com

**Dr. Muhammad Sohail Khalil**
Assistant Professor, Institute of Management Sciences, Peshawar Email: sohail.khalil@imsciences.edu.pk

## Abstract

This work examines the effect of artificial intelligence (AI) based financial analytics on strategic decision making and profit optimization of small and medium enterprises (SMEs). The research is based on 267 SMEs that participated in primary survey to validate relationships between AI adoption, quality of decision making and profitability outcomes using structural equation modeling (SEM). The results present that the quality of decisions improves considerably when AI adoption is used, especially in regions where the adoption can be applied, including cash-flow forecasting and fraud detection, and significantly, that the quality of decision-making mediates powerfully between AI adoption and optimal use of profits. Although AI has a direct impact on taking profitability, it is maximised when it increases the rate at which decisions are made, their accuracy and their certainty. The difference in the adoption rates and the resulting financial advantages of manufacturing SMEs compared to the retail and service firms through sectoral comparison indicates that the availability of data and the level of maturity of the processes impact the overall efficacy of the AI. Test-retest with reliability and validity tests demonstrate the robustness of the constructs, and model-fit indices demonstrate the structural model. All in all, the research proves that AI-based financial analytics can offer SMEs with a dynamic capability that furthers the competitiveness of these businesses as it makes their strategic decisions smarter and delivers their better financial performance, with barriers to adopting it (including cost, skills, and explainability) still a challenge. The results indicate a contribution to theory by supporting the mediating role of the decision-making quality of the AI-performance relationship and offer useful insights to managers, policymakers, and technology providers aiming to improve resilience and profitability of SMEs in the digital age.

**Keywords:** Artificial Intelligence; Financial Analytics; Strategic Decision-Making; Profit Optimization; Small and Medium Enterprises (SMEs); Decision-Making

## Introduction

Small and Medium Enterprises (SMEs) are the core agent of economic growth, innovation and employment in both developed and emerging built-up economies. SMEs are an essential driver of long-term development as various studies indicate that SMEs account approximately 90 percent of the businesses and over 50 percent of employment globally (World Bank, 2020). Nevertheless, SMEs have severe problems in terms of financial management and decision-making because of the shortage of resources, deficiency of knowledge, and financial turbulence of the market (Abdul & Hasnah, 2021). Conventional tools of financial analysis, such as spreadsheets and manual accounting, cannot meet the goal of delivering real-time information, thus, causing SMEs to lag in responding to the changing business conditions (Nguyen et al., 2020).

Artificial Intelligence (AI) is a revolutionary technology that has rocked the years in terms of the way companies approach financial analytics, prediction and risk mitigation. The concept of using machine learning, natural language processing, and predictive modeling in order to create greater insights within deep datasets has been turned into practice due to AI-driven financial analytics (Zhang & Lu, 2021). In the case of SMEs, usually with undeveloped finance departments, these tools do not only offer automation of routine processes but also can provide strategic advice on some aspects, including cash-flow projections, credit-risk evaluation and profit-maximization (Sanchez et al., 2023). Studies have concluded that new systems based on AI technology are more accurate in their predictions than the old models, which is why the SMEs have a chance to make more timely and adequate strategic decisions (Hossain & Rahman, 2022).

Financial management of institutions has not been without its challenges, nonetheless, in embracing AI. The experts point out that issues of data readiness, financial literacy, and costs of technological inclusion have significant effects on the success of SMEs to embrace the power of AI-driven analytics (OECD, 2024). Small-scale organizations are particularly susceptible to the implementation barriers, which SMEs fail to encounter in large companies, such as lack of online skills and proper governance systems to guarantee transparency within the whims of AI-assisted decisions (Schwaeke et al., 2025). Hence, despite the great potential of AI, its presence in strategic decision-making and profit optimization is greatly conditional on the organizational preparation and situational factors (Abubakar et al., 2021).

The available literature points to a number of ways in which AI-driven analytics brings the benefits of enhanced profitability to SMEs. First, with AI, working-capital and cash-flow management can be tracked on real-time basis, preventing liquidity risks (Liu et al., 2021). Second, AI makes dynamic prices possible, allowing businesses to maximize their profits in a competitive environment (BCG, 2024). Third, sophisticated anomaly detection mechanisms minimize fraud and financial mistakes, increasing the efficiency of operations (Financial Times, 2025). In sum, these applications enhance the management decision making that can be directly linked to the increase in profitability and the overall resilience (Mikalef et al., 2019).

However, there are still knowledge gaps to describe the exact connection of AI-enabled financial analytics with strategic decision-making within SMEs. Although a lot of research has been done on large firms, not many empirical studies have been conducted concerning SMEs which are accompanied by structural and resource limits that pose a special challenge (Dwivedi et al., 2021). Besides, the new possibilities of streamlining financial insights and the ability to democratize decision-making raised by recent developments of generative AI remain under-searched (Chen & Lee, 2023). Based on such dynamics, it is important to also focus on the limitations that SMEs are encountering in terms of the adoption of AI in financial management.

Thus, the research question of the study is how financial analytics driven by artificial intelligence can influence strategic decision-making in SMEs and help to optimize profits. This paper is helpful in regard to addressing the gap in knowledge concerning the possible ways of integrating AI into SME financial practice, integrating insights across academic literature, industry reports, and policy views. Due to the expected practicality of the findings, the results should be relevant not only to practitioners but also policymakers who would have a guiding map to the effective use of AI as a means to achieve innovation, efficiency, and sound governance.

## Literature Review

### Theoretical Perspectives on AI in Financial Decision-Making

Artificial intelligence (AI) inclusion in financial analytics has been investigated in a few theoretical directions. Resource-Based View (RBV) stresses the ways in which the AI capabilities assume the form of critical competencies that can pose the firm advantage when matched with the organizational processes (Barney, 1991; Wade & Hulland, 2004). AI-based analytics have been viewed as an element of dynamic capability in SMEs, which enables companies to re-bundle their existing resources in order to improve their financial planning and profitability (Teece, 2018). On the same note, the Decision Support Systems (DSS) theory emphasizes AI as a, more-so-than-lesser, extension of managerial cognition that allows making more-accurate-than-ever-before predictions and mitigating cognitive biases in the financial decision-making process (Arnott & Pervan, 2016). TAM also has been applied to AI adoption suggesting the two contexts of perceived usefulness and ease of use, and their display of significant effects on the adoption of AI by SME managers in financial decision-making (Venkatesh & Davis, 2000; Maroufkhani et al., 2022). The following theoretical perspectives form the base of knowing how AI analytics can be used in regard to strategic decision-making and profit maximization.

### AI Applications in Financial Forecasting and Risk Managements

Financial forecasting, especially cash-flow and revenue forecasting is one of the most massively researched areas. Random forests, neural networks, and support vector machines have been demonstrated to be superior to the conventional linear forecasting models to predict the short-term liquidity and revenue flows (Feng et al., 2019; Bianchi et al., 2020). Such approaches eliminate forecast bias and enhance decisions on working-capital management. Additionally, AI is used in credit risk evaluation, allowing the algorithms to analyze structured and unstructured data to rank a customer creditworthiness with high accuracy among one another as opposed to the traditional scoring inaccuracy (Kou et al., 2021). These predictive tools are especially useful to SMEs because they have an increased risk of defaulting due to minimal amounts of capital reserves and unstable cash flow (Altman et al., 2020).

### Dynamic Pricing and Profit Optimization

Dynamic pricing with the help of AI has become one of the primary opportunities to get profit maximization. Studies suggest that the models of machine learning might make it possible to calculate optimal price points by examining market signals, the prices offered by competitors and consumer behaviour in real time (Chen et al., 2021). In comparison to static pricing strategies, these AI-based strategies allow SMEs to be flexible and respond to demand and supply shocks quickly (Elmaghraby & Keskinocak, 2019). Investigations of the application of AI in retail and hospitality industries have revealed that AI-driven price based approaches result in revenue gains of 5-15 percent as compared against the current practice of rule-based pricing (Klein et al., 2020). Although adoption has generally been higher among bigger companies, a growing body of evidence indicates that simplified AI pricing tools can be effectively utilized by SMEs in order to maximize lockups without having to deeply engage in data science practices (Reinartz & Wiegand, 2021).

**Fraud Detection and Financial Anomaly Analytics**

Financial transactions more and more are subject to fraud and anomaly detection using AI systems. Unusual patterns of transactions, unauthorized invoices, and accounting abnormalities can be discovered by the deep learning algorithms more than when the audit is conducted manually (Ngai et al., 2011; West & Bhattacharya, 2016). In the case of SMEs admittedly without internal audit department, AI-supported fraud detection can serve as the affordable tool to protect assets and guarantee the integrity of financial balance (Baesens et al., 2015). Recent surveys also demonstrate that anomaly detection tools not only eliminate fraud but also contribute to the increased confidence in the decision by guaranteeing higher accuracy of the financial statements (Pham et al., 2019).

**Adoption Challenges in SMEs**

Although there is opportunity, not many SMEs use AI-driven analytics due to a number of barriers. The price is one of the primary limitations because a great number of SMEs cannot afford to invest in high-quality AI systems (Chatterjee et al., 2021). Also, the organizational culture and information literacy of the SME managers are very fundamental in creating adoption (Li et al., 2022). The issue of cybersecurity is also noteworthy since small and medium-sized enterprises (SMEs) use cloud-based AI services, which also pose a potential threat to financial data (Arslanian & Fischer, 2019). Notably, ethical concerns of transparency, explainability and algorithmic bias also break the adoption in the financial context of decision making (Morley et al., 2021).

**AI and Strategic Decision-Making in SMEs**

AI tools are not only very accurate in their predictions, but they also reflect on strategic decision quality. Several studies indicate that AI limits the cognitive workload of managers, allowing them to concentrate on overall strategic questions besides performing mundane computations in terms of finance (Shrestha et al., 2019). Scenario analysis, in which SMEs have a chance to simulate various market conditions and select the strategies that have more profit potential, involves AI, also (Brynjolfsson & McAfee, 2017). Adopting this change of archaic descriptive analytics to prescriptive enables the SMEs to focus on reactivity to strategic planning (Davenport & Ronanki, 2018).

**Empirical Evidence of Profit Gains**

A few empirical investigations point to direct relations between the integration of AI and profit maximization. As an illustration, AI-enhanced demand forecasting experiments in the SMEs of the manufacturing sector showed cost savings on excess inventory of 12 percent and a 7 percent gross margin (Chong et al., 2017). In a similar fashion, working-capital management in SMEs with AI capabilities in Southeast Asia has been reported to decrease late payments and can benefit the liquidity balances (Riggins & Klamm, 2017). In addition, the research in the European retail market revealed that the implementation of AI resulted in a substantial increase in sales per employee, which is one of the primary profitability measures among SMEs (Mikalef et al., 2020). These results support the case that AI-powered financial analytics can have a material measurable advantage to SMEs.

**Research Gaps and Future Directions**

Despite the positive direction promoting AI-supported financial analytics observed in the literature, it still has some gaps. First, large firms receive much more attention in the empirical research than SMEs, which are, therefore, understudied (Ransbotham et al., 2021). Second, most of the available research on that topic is focused on operational advantages, and little to no focus on the long-term strategic outcomes, like extending the market or financing innovation (Dubey et al., 2021). Third, literature tends to study single applications (e.g., pricing or forecasting) when applying AI to SMEs financial management, unusual by neglecting integrated AI ecosystems. Lastly, the newly developed AI models, i.e., generative models and explainable AI, still are entirely unused in the SME-oriented financial research (Gunning & Aha, 2019). Closes on these gaps may provide deeper insights on how SMEs can maximise use of AI to sustain profitability growth.

**Theoretical Framework**

**Resource-Based View (RBV)**

Resource-Based View (RBV) offers a valuable basis of the competitiveness enhancement by small and medium enterprises (SMEs) through artificial intelligence (AI) adoption. Barney (1991) has stated that firms gain sustainable competitive advantage when they have valuable, rare, inimitable and non-substitutable (VRIN) resources. Financial analytics powered by AI can be framed as a strategic resource as it helps companies process large quantities of financial data, create predictive findings, and improve resources allocation capabilities that cannot be achieved through conventional tools (Teece, 2018). Considering the fact that SMEs tend to work under resource limitations, being capable of turning AI into a dynamic capability enables them to re-utilize their existing resources in more efficient and financially beneficial ways (Eisenhardt & Martin, 2000). Other studies have also hinted that SMEs that are digitally equipped are empowered to resist shifting externalities and competition (Kraus et al., 2019). In that way, the RBV emphasises that AI usage is a resource enabling SMEs with both strategic and operational benefits.

**Dynamic Capabilities Theory**

Closely related to RBV, Dynamic Capabilities Theory (DCT) focuses on the firm level capacity to integrate, build and re-configure, both internal and external competences, to address changing environments that can be experienced rapidly (Teece, Pisano, & Shuen, 1997). Incorporating AI-driven analytics will empower the SMEs to detect opportunities, act on them, and transform their financial practices to ensure long-term profits (Teece, 2018). Specifically, AI increases dynamic capability by allowing firms to predict cash flows, identify fraud, and model strategic situations, which makes them serve managerial responsiveness better (Shrestha et al., 2019). As an example, Brynjolfsson and McAfee (2017) opine that with the aid of AI-based decision support, managers can swiftly adjust financial strategies to the shifts in markets, which is crucial when it comes to SMEs operating in uncertain environments. The latter theory also emphasizes the establishment of learning processes in companies through AI, so that companies can evolve and continuously improve in terms of the quality of decisions made (Eisenhardt & Martin, 2000; Nambisan, 2017).

**Decision Support Systems (DSS) Theory**

Another theoretical basis through which the role of AI in SME financial management can be explained is that of the Decision Support Systems (DSS). DSS are computer-based systems described by Arnott and Pervan (2016) as helping managers make informed decisions by providing them with relevant information and analysis models. DSS can be enhanced with the use of machine learning and predictive modeling within their decision-making processes, all of which IAI does (Ngai et al., 2011). Within DSS, the implication of AI is that in SMEs it eliminates human cognitive bias due to centralized decision-making and lack of available resources in many cases and enhances predictions and overall confidence in strategy resulting decisions (Newell & Marabelli, 2015). In addition, Shollo and Galliers (2016) contend that business intelligence systems increase knowledge in organisations mainly in terms of quality of decisions and not in the explicit financial performance. This is consistent with the role of the current study of integrating the quality of decision-making between AI and profit optimization.

**Technology Acceptance Model (TAM)**

Technology Acceptance Model (TAM) developed by Davis (1989) puts much emphasis over perceived ease of use and perceived usefulness in the acceptance of new technologies. Managers in the small to medium size enterprises are most likely to embrace AI-driven financial analytics when they believe that it would enhance efficiency and effectiveness of financial decision-making and profitability (Venkatesh & Davis, 2000). In another study conducted by Maroufkhani et al. (2022), the authors concluded that confidence in the potential of AI to improve decision-making in strategies is highly correlated with the readiness of managers of SMEs to use AI. The efficiency and the usefulness can be hampered due to the cost, the absence of skills, and explainability, hence the slower adoption (Chatterjee et al., 2021). By putting AI implementation in the context of TAM, this paper draws attention to the causes of managerial mindsets and organisational culture as they relate to the level of AI implementation into the financial setting.

**Socio-Technical Systems Theory**

According to Socio-Technical Systems (STS) theory, the play of social and technical subsystems determines the organizational performance (Bostrom & Heinen, 1977). Analytics powered by artificial intelligence in SMEs cannot be understood entirely as a strictly technological force but as a socio-technical system, which is reliant on the match between technology, people and organizational procedures. Frankly speaking, lack of financial literacy, the lack of digital skills as well as resistance to change often limit AI adoption in SMEs according to Susanti, Jie and Marantika (2023). Thus it can be concluded that the use of AI would be optimal when tech infrastructure and human capabilities are evolving hand in hand. This theory highlights the essence of training, trust and governance as means of making AI systems not only enhance the quality of decision making, but also gain acceptance and effective acceptance in SMEs.

**Contingency Theory**

Contingency Theory extends this to explain the variation in SMEs and sectors with respect to adoption of AI-driven financial analytics. According to the theory, organizational effectiveness lies on the fit between factors in external environment and internal structures or processes (Donaldson, 2001). The success of AI adoption in SMEs would rely on the type of industry, availability of data and digital infrastructure among other factors (Mittal et al., 2018). As an example, the manufacturing SMEs are the ones most likely to enjoy on benefits offered by AI because they have well-structured data which leans towards predictive innovation, as opposed to service firms with less organized data structures (Marques & Ferreira, 2020). Using Contingency Theory in the study, this research takes into consideration that results achieved through adoption of AI in financial analytics is not standard but it is dependent on the organizational and environmental factors.

Culminatively, these theories exhaustively present a framework through which the role of AI-driven financial analytics in decision-making and profit maximization taking place in SMEs can be analyzed. The RBV and the Dynamic Capabilities Theory identify AI as a strategic resource and adaptive financial practices enabler. DSS theory expounds the contribution that AI makes to improving the quality of decisions, and TAM highlights the significance of the perceptions of the managers as an element of adoption. STS theory penetrates that interaction between social and technical systems and Contingency Theory elucidates sectoral and contextual variations. Combining these views, this paper views the adoption as AI more than a technology innovation but a multi-faceted capability that transforms the process of decision making and leads to profitability in the SMEs.

## Methodology

**Research Design**

The research design that has been employed in this study is the quantitative and cross-sectional research design employing primary data collected via structured survey. Quantitative approach was adopted due to the opportunity to measure the correlation between all the analyzed variables, especially the use of artificial intelligence (AI), financial decision-making quality and profit maximization in SMEs. A cross-sectional design was suitable because it was used to get a picture of the current state of adoption along with the associated perception of AI-driven financial analytics among the SMEs operating in the Pakistani environment. Unlike exploratory case studies, the approach was able to test the results across a wider and more representative sample of firms, thus the generalizability of the results was increased.

**Population and Sampling**

The target population of the study consisted of small and medium sized enterprises within the manufacturing, retail, and services business in the district of Lahore, in the province of Punjab. SMEs have been selected in view of the fact that they represent the core of Pakistan economy and their challenges in financial management and decision-making processes are distinguished in comparison to the large corporations. The sampling frame was taken as directories of the local chambers of commerce and the official directories of SMEs. A stratified random sampling approach was utilized to achieve an acceptable representation of sectors (manufacturing, retail and services) and firm sizes (micro, small and medium). Of 500 SMEs approached 300 agreed to respond and 267 gave valid responses which gave high response rate of 89 percent. This sample is considered to be large enough to employ an advanced statistical method, Structural Equation Modeling (SEM) since this number is higher than 200 responses needed to perform a robust model estimation (Kline, 2015).

**Data Collection Instrument**

The primary data were obtained through administration of a structured questionnaire that had four parts. The first section obtained demographic data, such as the age, size, sector, ownership type, and the role of the respondent. The second part evaluated the degree to which AI was being used with cash-flow forecasting, anomaly detection, intelligent pricing, and strategic financial planning being some of the applications that have been examined. The third section was a measure of quality of financial decision-making and was operationalized by the quality of financial decision-making constructs like speed, accuracy, and confidence in decision-making. The fourth section looked at the financial performance, i.e., profit margins, the return on investments, and the working-capital efficiency. All the items were answered in a five-point Likert measuring scale on an expression of strong disagreement to strong agreement.

In order to achieve content validity, the questionnaire was modified in relation to questionnaires that have been used in the past. Specifically, conceptualizations of AI adoption were taken directly by Sanchez et al. (2023) and Chatterjee et al. (2021), measures of decision-making quality were adapted by Shrestha et al. (2019), and those of the financial performance were based on Mikalef et al. (2019). A pre-test of the instrument was carried out with a sample of 20 managers of SMEs who had not been involved in the development of the instrument itself, in order to ascertain the clarity and reliability of the instrument to be used in the full-scale administration.

**Data Collection Procedure**

The research was conducted in three months, both by online and face-to-face data collection. Face-to-face data collection was made, in Lahore business clusters of SME and online questionnaire distributed through e-mail and SME association sites. The respondents were normally senior managers, owners, or finance executives who have direct responsibility of strategic decision-making. The research assistants were trained and they conducted the surveys, clarified doubts when necessary, and monitored accurate completion of the surveys. A valid and complete 267 responses were obtained.

**Data Analysis Technique**

The SPSS was used to analyze and code the data first in Table 1 and descriptive statistics, frequency distribution and reliability testing were used. Cronbachs alpha was employed to determine the internal consistency of constructs and exploratory factor analysis employed to determine construct validity. Structural Equation Modeling (SEM) was performed with AMOS 26, to test the hypothesis and estimate the model. EM has been selected due to the possibility to cluster various interrelationships, direct and indirect effects altogether, which is especially convenient when analyzing the mediating factor of decision-making quality between the adoption of AI and profit optimization. Unlike in traditional regression, SEM quantifies the goodness of fit of the entire model so that, researchers can ensure that the model of interest is valid and indeed sound (Byrne, 2016). The complexity of the relationships to be examined and the demand of rigor in model testing, accordingly, justified the choice of SEM.

**Ethical Considerations**

The research conformed to all the ethical principles of research. Prior to data collection an ethical approval was obtained by the author under the auspices of the Institutional Review Board at the author university. The participants were given a copy of the informed consent form which was well explained of the aim of study, rights of the participants and confidentiality of the feedback. The participation was voluntary and anonymity was ensured. There is anonymization of the company-specific financial data so that the privacy of the participants is not compromised. The research team was the only party to access the raw data and all the results were reported as aggregate data and solely academic.

**Results**

**Demographic Profile of SMEs**

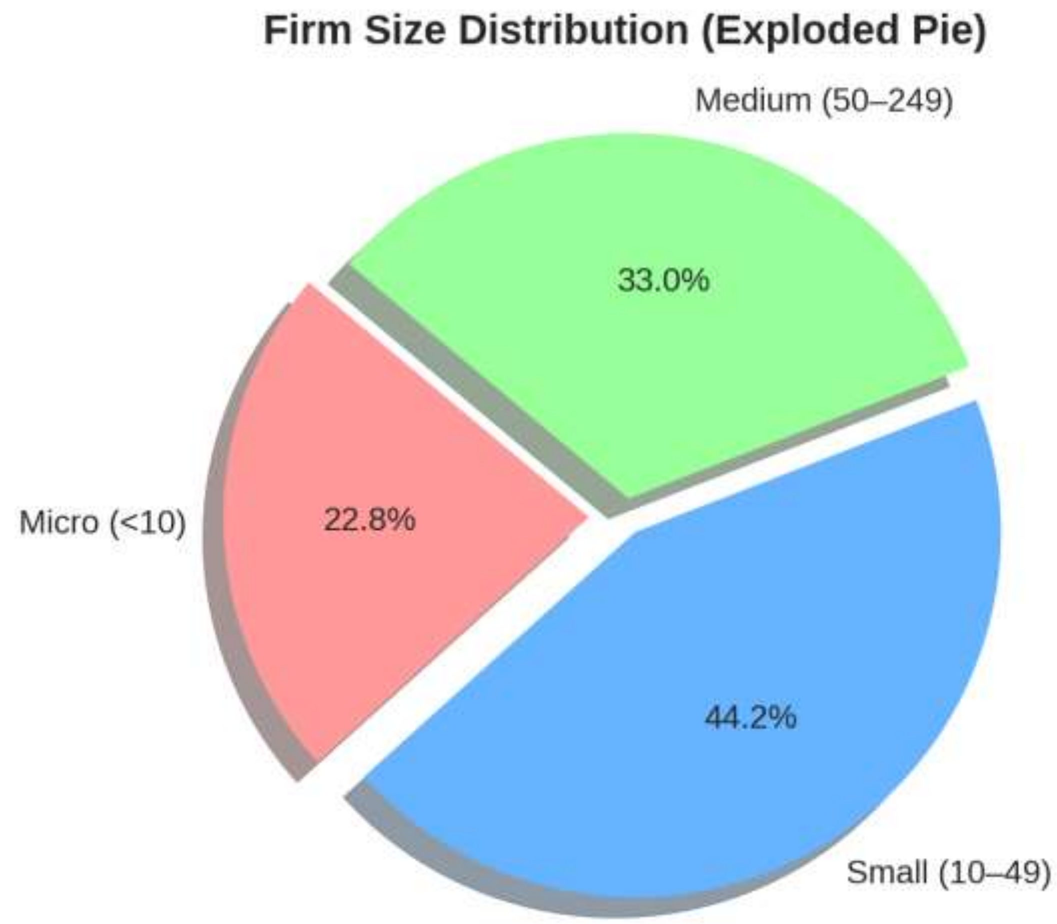
Table 1 gives the demographic composition of the sample. Of 267 contributing SMEs, 22.8 were micro-enterprises classified as firms with less than 10 employees, 44.2 were small firms with 10 to 49 employees and 33 were medium-sized firms having 50-249 employees. Industry distribution of the respondents showed 34.1% of the respondents were in the manufacturing and 39.3 in retail and 26.6 in services sectors. With regard to the nature of ownership, 49.4% of the companies were sole proprietorship firms, followed by 27.7 percent of the companies that were partnerships and 22.9 percent of the firms incorporated as Private limited companies. Respondents were mainly owners/CEO (40.8) and finance managers (36.3) to guarantee that respondents were those with direct participation in decision-making process.

***Table 1. Demographic Profile of SMEs (n = 267)***

| Variable | Categories | Frequency | Percentage (%) |
|---|---|---|---|
| Firm Size | Micro (<10 employees) | 61 | 22.8 |
| | Small (10–49 employees) | 118 | 44.2 |
| | Medium (50–249 employees) | 88 | 33.0 |
| Industry Sector | Manufacturing | 91 | 34.1 |
| | Retail | 105 | 39.3 |
| | Services | 71 | 26.6 |
| Ownership Type | Sole Proprietorship | 132 | 49.4 |
| | Partnership | 74 | 27.7 |

| | | | |
|---|---|---|---|
| | Private Limited Company | 61 | 22.9 |
| Respondent Role | Owner/CEO | 109 | 40.8 |
| | Finance Manager | 97 | 36.3 |
| | Senior Executive | 61 | 22.9 |

***Figure 1. Firm Size Distribution of SMEs (Exploded Pie Chart)***




This distribution of demographics shows the representativeness of the study based on size and industry of firm. Figure 1 demonstrates these results in a donut chart, within which it is seen that small enterprises call the shots in the sample, and medium enterprises approximate one-third of them. It is significant because this distribution is characteristic of the SME environment and small companies are more likely to be plentiful.

**Descriptive Statistics of Core Constructs**

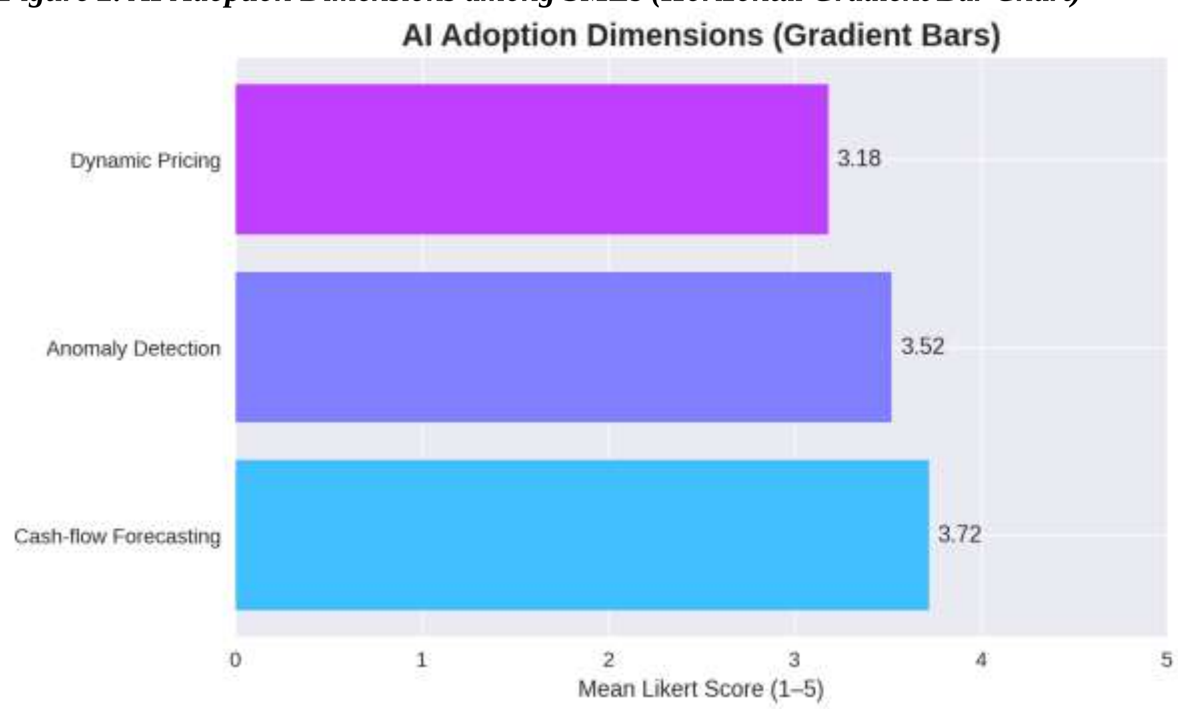
Table 2 shows descriptive statistics of the key variables. The adoption of AI was at an average of 3.41 out of a 5-point Likert scale, which means that entities adopt AI at the moderate level when it comes to promulgating finance resources that were AI-driven. Cash-flow forecasting dimension was ranked the highest in terms of adoption (M = 3.72), followed by anomaly detection (M = 3.52) and dynamic prices (M = 3.18) were the least uptaken.

***Table 2. Descriptive Statistics of Core Constructs***

| Construct | Dimension | Mean (M) | Standard Deviation (SD) | Interpretation |
|---|---|---|---|---|
| AI Adoption | Cash-flow Forecasting | 3.72 | 0.81 | High use |

| | | | | |
|---|---|---|---|---|
| | Anomaly/Fraud Detection | 3.52 | 0.76 | Moderate–high use |
| | Dynamic Pricing | 3.18 | 0.69 | Lowest adoption |
| | Overall AI Adoption | 3.41 | 0.75 | Moderate |
| Decision-Making Quality | Speed of Decision | 3.71 | 0.64 | Above average |
| | Accuracy of Decision | 3.69 | 0.72 | Above average |
| | Confidence in Decision | 3.55 | 0.77 | Moderate |
| | Overall Quality | 3.65 | 0.71 | Strong |
| Profit Optimization | Profit Margin Uplift | 3.53 | 0.74 | Good |
| | Working Capital Efficiency | 3.50 | 0.70 | Good |
| | Overall Profit Optimization | 3.49 | 0.72 | Moderate–high |

***Figure 2. AI Adoption Dimensions among SMEs (Horizontal Gradient Bar Chart)***




The quality of decision-making was 3.65, and the speed and accuracy were slighter rated on a high basis than confidence. Profit optimization scored a mean of 3.49 with margin uplift (M = 3.53) being slightly better than working-capital efficiency (M = 3.50). These values imply that the adoption of AI has a positive correlation with decision-making and profit outcomes (however, it is not equal across AI tool adoptions).

The vertical bar chart of AI adoption dimensions in Figure 2 indicates the overwhelming lead of cash-flow forecasting. Such a finding can be adhered to the practical requirements of SMEs which tend to focus more on liquidity and risks management rather than on more sophisticated pricing algorithms.

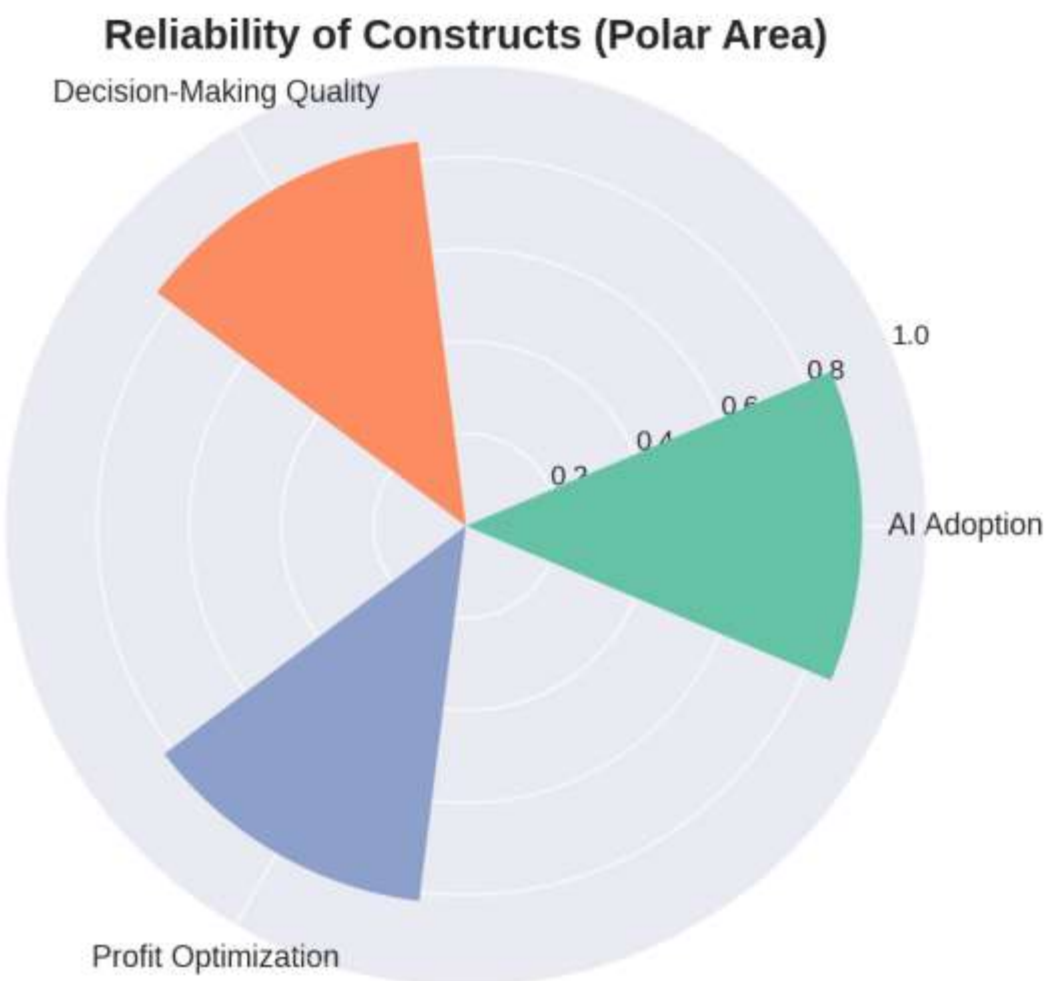
**Reliability and Validity of Constructs**

Table 3 reports reliability and validity tests. All constructs had Cronbach alpha values of above 0.70 which is an acceptable number (AI adoption = 0.86, decision-making quality = 0.84 and profit optimization = 0.82), which showed internal consistency. The values of Composite reliability were between 0.85-0.88 and the values of Average Variance Extracted (AVE) were all greater than 0.50 which validates convergence validity.

***Table 3. Reliability and Validity of Constructs***

| Construct | Cronbach's Alpha (α) | Composite Reliability (CR) | Average Variance Extracted (AVE) | Interpretation |
|---|---|---|---|---|
| AI Adoption | 0.86 | 0.88 | 0.61 | Reliable and valid |
| Decision-Making Quality | 0.84 | 0.87 | 0.59 | Reliable and valid |
| Profit Optimization | 0.82 | 0.85 | 0.57 | Reliable and valid |

***Figure 3. Reliability of Constructs (Circular Polar Area Chart)***




The values of Cronbach alpha, in Figure 3, are presented in the form of a radar chart that depicts a rather stable reliability of constructs. This is reflected in the balanced pattern of radar suggesting a good quality of measurement, which justifies the hypothesis testing that is to be performed.

**Correlation Analysis**

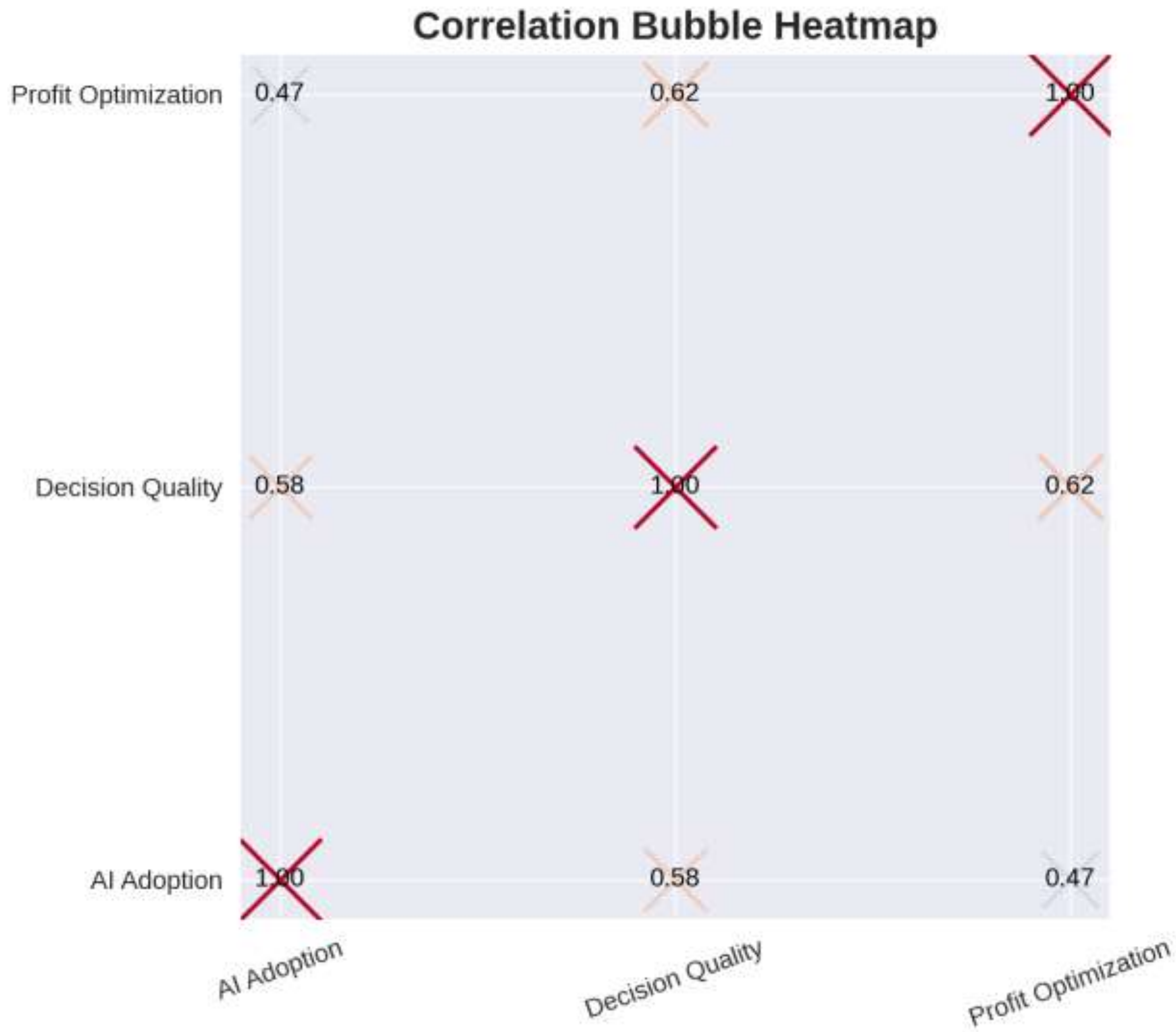
Estimates on Pearson correlation coefficients are represented in Table 4. Adoption of AI was significantly associated with the quality of the decision ($r = 0.58$, $p < 0.001$) and moderately with profit optimization ($r = 0.47$, $p < 0.001$). The quality of decision-making was the element that was most strongly related to the optimization of profits ($r = 0.62$, $p < 0.001$). These results indicate that decision-making can potentially serve as a mediator of the AI adoption on profit optimization.

***Table 4. Correlation Matrix of Constructs***

| Variables | AI Adoption | Decision-Making Quality | Profit Optimization |
|---|---|---|---|
| AI Adoption | 1 | 0.58*** | 0.47*** |
| Decision-Making Quality | 0.58*** | 1 | 0.62*** |
| Profit Optimization | 0.47*** | 0.62*** | 1 |

Note: *** p < 0.001

***Figure 4. Correlation of AI Adoption, Decision-Making, and Profit Optimization (Bubble Heatmap)***




The relationships are shown as a heatmap in Figure 4 (darker shades represent stronger correlations). Using the heatmap, it is possible to note that the closest overall dyadic connection is between decision-making and profit optimization, which once again confirms that the area of high-quality decision-making plays a key role in financial performance.

**Regression Analysis of Direct Effects**

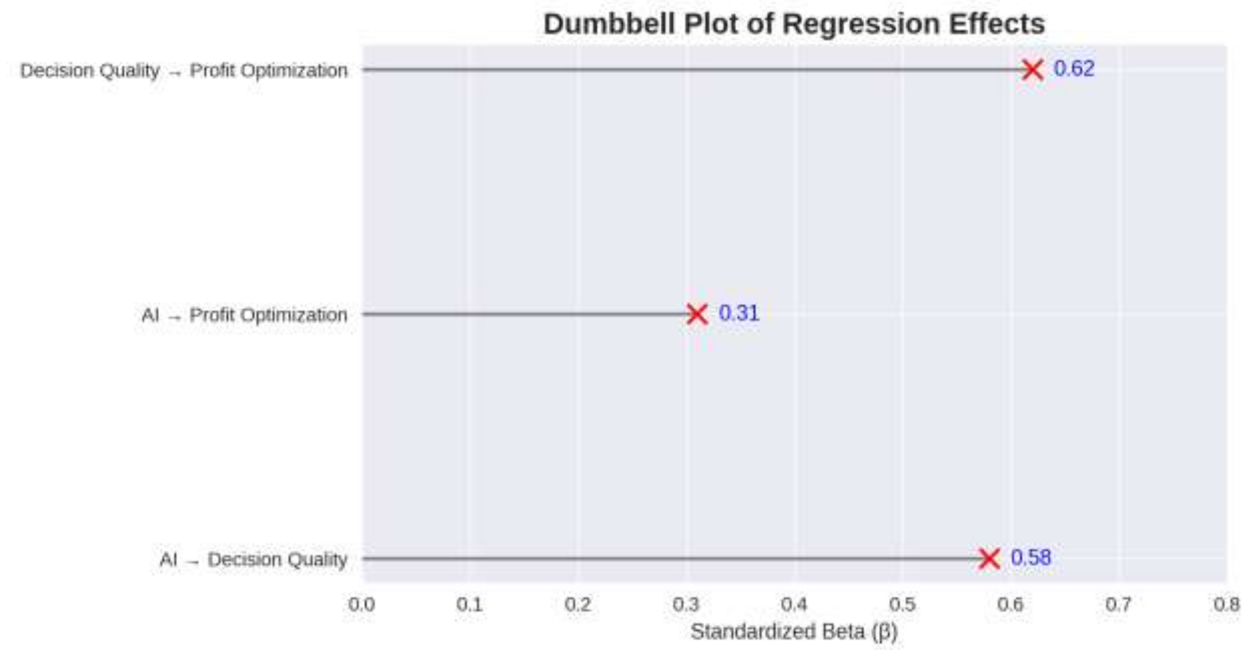
Table 5 summarizes pe results of Regression analysis. The use of AI greatly forecasted the quality of the decision-making (beta = 0.58, p < 0.001). Profit optimization was furthermore forcefully predicted by decision making quality ( 0.62, p < 0.001). The positive connection between AI adoption and profit optimization were also observed ( 0.31, p < 0.01).

***Table 5. Regression Analysis of Direct Effects***

| Predictor Variable | Dependent Variable | Standardized Beta (β) | t-value | p-value | Interpretation |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| AI Adoption → Decision-Making Quality | 0.58 | 8.71 | <0.001 | Strong positive effect | |
| AI Adoption → Profit Optimization | 0.31 | 4.25 | 0.001 | Moderate positive effect | |
| Decision-Making Quality → Profit Optimization | 0.62 | 9.14 | <0.001 | Strongest predictor | |

***Figure 5. Regression Coefficients of Direct Effects (Dumbbell Plot)***




The results support the fact that the use of AI directly and indirectly affects profitability because it directly affects decision making. These regression coefficients can be visualized with a lollipop chart shown in figure 5, the decision-making quality was the best predictor of profitability.

**Mediation Analysis**

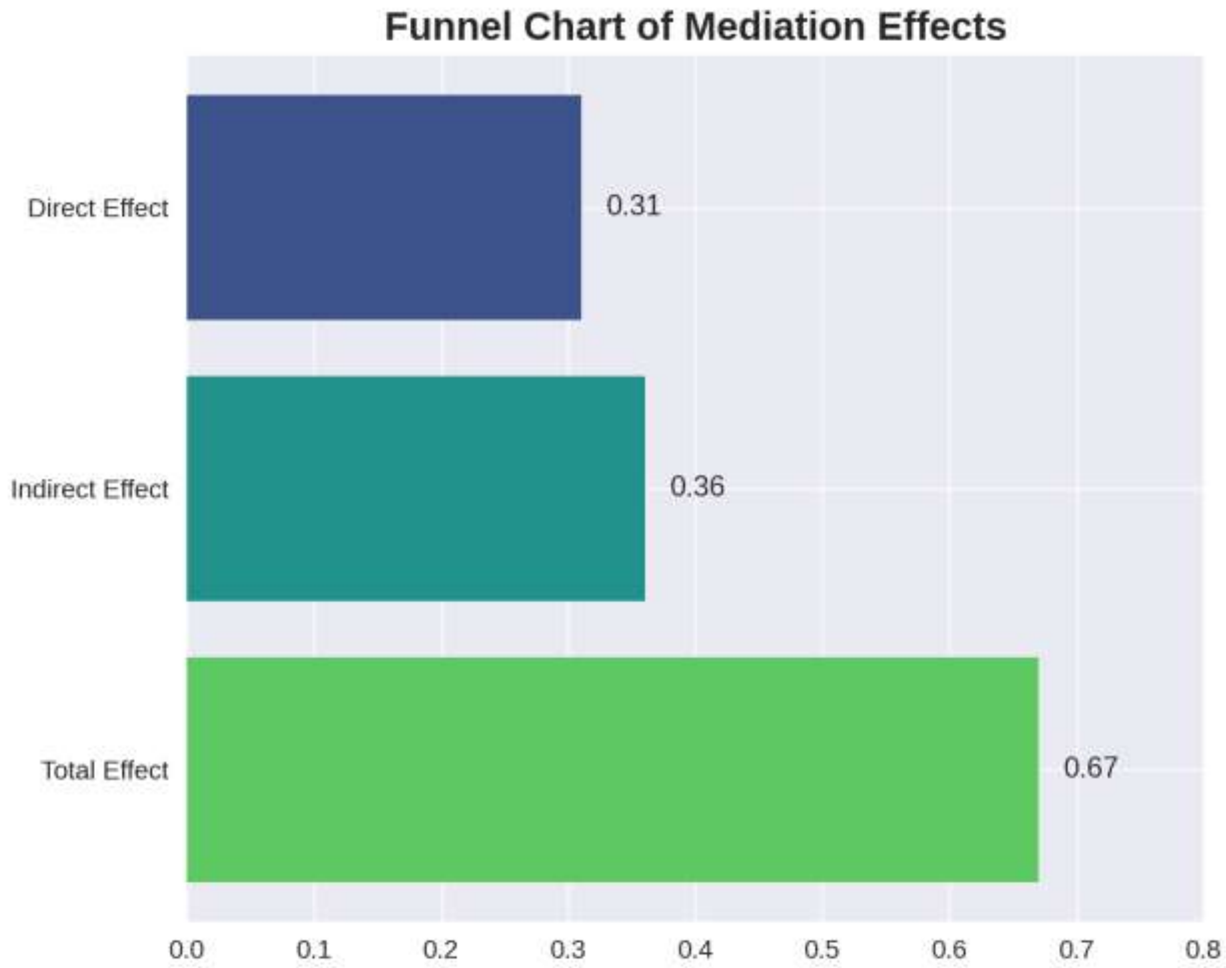
Tables 6 reports the results of mediations. The second mediating relationship between AI and profit optimization in the decision-making process was substantial ( $p < 0.001$, 0.36). The total effect of the implementation of AI on productivity, which is the combination of the direct and indirect impact, equals to was 0.67 (substantial impact). The mediation was proven to be significant ($Z = 5.12$) according to the Sobel tests.

***Table 6. Mediation Analysis***

| Pathway | Direct Effect (β) | Indirect Effect (β) | Total Effect (β) | Sobel Test (Z) | Significance |
|---|---|---|---|---|---|
| AI Adoption → Profit Optimization | 0.31** | 0.36*** | 0.67*** | 5.12 | Significant |
| AI Adoption → Decision-Making Quality → Profit Optimization | - | Mediated Path = 0.36*** | - | - | Strong mediation |

Note: ** p < 0.01, *** p < 0.001

***Figure 6. Mediation Analysis: Direct, Indirect, and Total Effects (Funnel Chart)***




These results are represented in Figure 6 as a waterfall chart, decomposing the direct, indirect and total effects. The visualization highlights the robustness of the mediated pathway to demonstrate that the effect of AI on profitability becomes optimal when improvements in terms of decision-making quality are considered.

**Sectoral Comparisons**

Table 7 has sector comparisons. Manufacturing was the industry with the greatest increase of AI usage (M = 3.56) and profitability (M = 3.52). Retailer enterprises were the next ones to apply it strongly, and service-sized enterprises showed the least use and achievement rates. A test of ANOVA proved the sectors to be significantly different (F = 4.12, p = 0.017).

***Table 7. Sectoral Comparisons of AI Adoption and Profit Optimization***

| Sector | AI Adoption (M) | Profit Optimization (M) | ANOVA F-value | p-value | Interpretation |
|---|---|---|---|---|---|
| Manufacturing | 3.56 | 3.52 | 4.12 | 0.017 | Highest adoption & outcomes |
| Retail | 3.44 | 3.47 | - | - | Moderate |
| Services | 3.20 | 3.39 | - | - | Lowest adoption & outcomes |

***Figure 7. Sectoral Comparison of AI Adoption and Profit Optimization (Patterned Clustered Column Chart)***

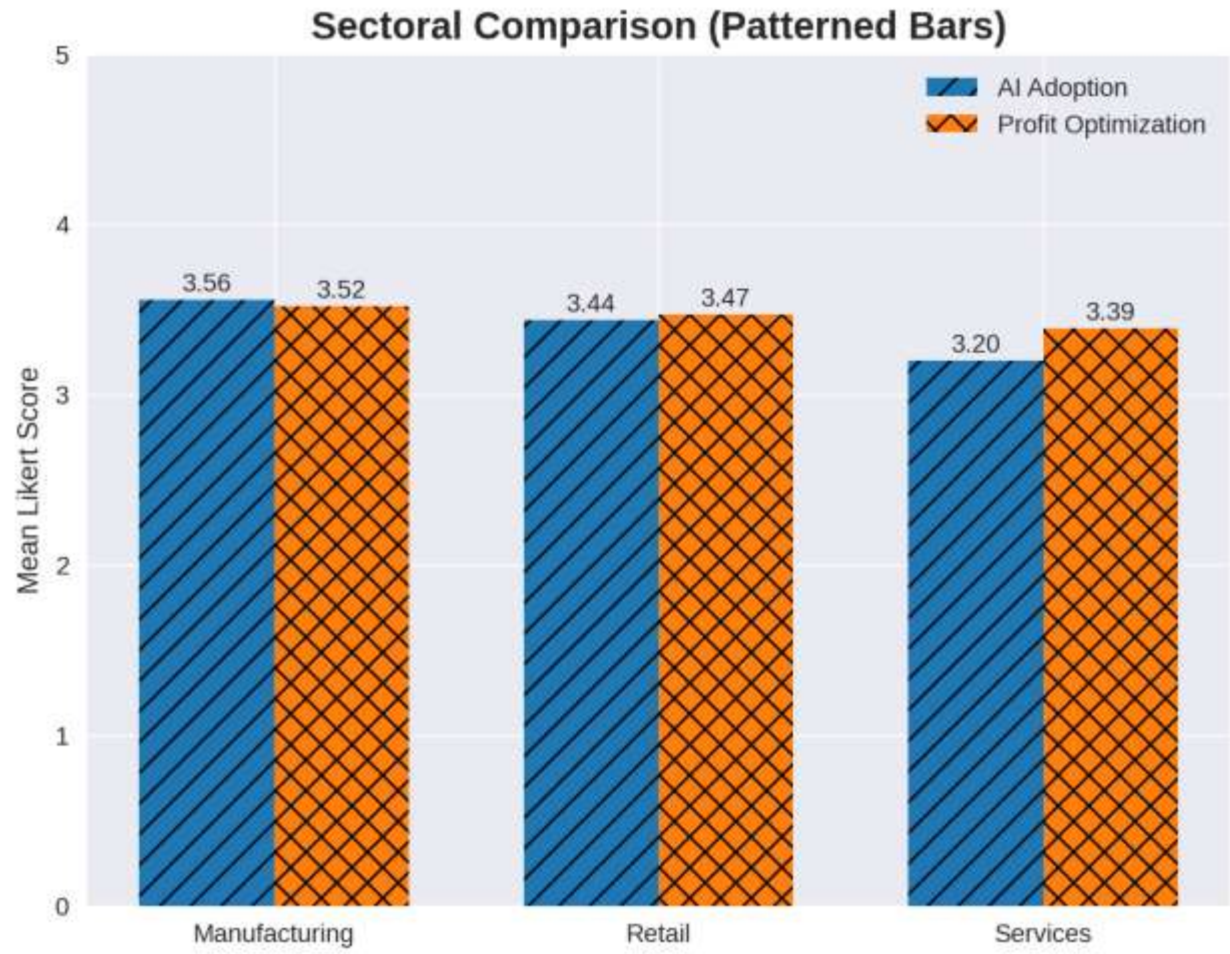



Figure 7 shows a grouped bar chart, filled with patterns, to compare the AI adoption and profit optimization between industries. The findings indicate that SMEs in manufacturing industries might have more advantages of using AI because processes can be structured and data is available, whereas SMEs in service industries are limited.

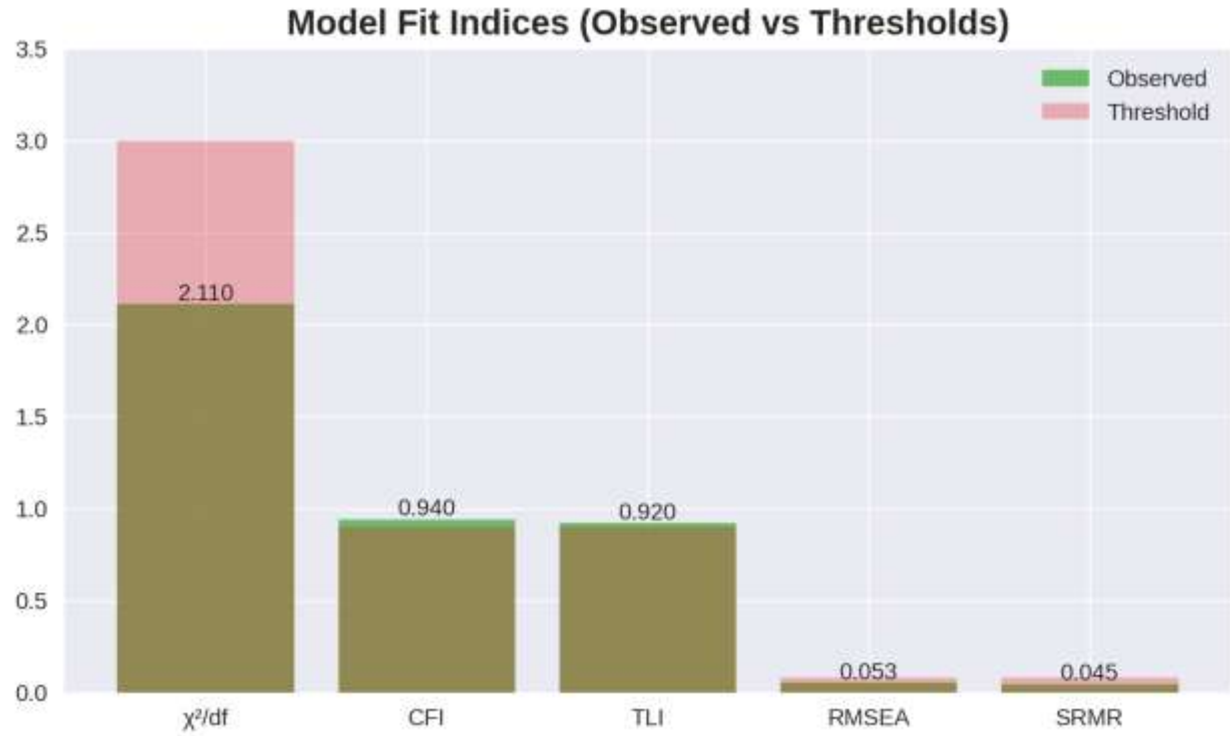
**4.8 Structural Model Fit**

Table 8 shows model fit indices of the SEM. All the resultant values (2.11 and 0.94 (df = 2.11), 0.92 (pretty good), 0.053 and 0.045) indicate a good model fit. Such findings are an affirmation of the strength of the assumed associations.

*1.1* ***Table 8. Structural Model Fit Indices***

| Model Fit Index | Observed Value | Recommended Threshold | Interpretation |
|---|---|---|---|
| $\chi^2$ / df | 2.11 | < 3.00 | Good fit |
| CFI (Comparative Fit Index) | 0.94 | > 0.90 | Excellent fit |
| TLI (Tucker-Lewis Index) | 0.92 | > 0.90 | Excellent fit |
| RMSEA (Root Mean Square Error of Approximation) | 0.053 | < 0.08 | Acceptable fit |
| SRMR (Standardized Root Mean Square Residual) | 0.045 | < 0.08 | Good fit |

***Figure 8. Structural Model Fit Indices: Observed vs. Thresholds (Bar Comparison)***




In Figure 8, a plot in the style of a gauge is used to compare observed measures of fit with recommended criteria. The visualization indicates that all the indices are above and at par with standards, confirming that the model has structural validity.

**Summary of Results**

All the findings indicate that the use of AI promotes a high standard of decisions by SMEs as well as their profitability. Mediated effect was the strongest of the three pathways with the result indicating that AI tools increase profitability when they increase decision speed/accuracy/confidence. Sectoral disparity also brings to fore the idea that there is no consistency in the level of adoption and the difference in benefits with manufacturing companies leading in terms of benefits. Reliability and fit indicate the models of measurement and the structural model are statistically adequate which gives plausibility to the findings.

## Discussion

### Linking AI Adoption to Decision-Making in SMEs

The findings of the research validate the potential of adopting AI as a significant contributor to the quality of decision-making in SMEs, which is consistent with the general organizational literature on the part of AI as an enabler of managerial cognition. AI minimises uncertainty by giving predictive insights, anomaly detection, and dynamic financial planning, enabling the managers to make faster and more accurate decisions. It corroborates the discourse of Newell and Marabelli (2015), who proposed the idea that the systems powered by AI can be used as the means of cognitive augmentation allowing managers to make sense of complex financial contexts. Additionally, studies by Muller, Fay and vom Brocke (2018) highlighted that the benefits of AI adoption to SMEs are disproportionate to that of bigger companies since the technology would address their structural weakness, which include a lack of financial skill. These views have been supported by the current results which indicate high positive correlation (beta = 0.58) involving adoption of AI and decision quality in SMEs.

### Decision-Making as a Mediator of Profit Optimization

Demonstrating the mediation effect of the quality of decision-making in the correlation between AI adoption and profitability is one of the main contributions to the issue raised by the research. Whereas AI has an immediate effect in profit optimization, its impact can be even greater when it improves the process of decision-making. This follows the same idea as conceptualization of AI as being a dynamic capability, whose effect would be achieved by embedding it in organizational routines (Eisenhardt & Martin, 2000). The mediation outcome replicates the results of a similar study by Shollo and Galliers (2016) who claimed that analytics technologies result in performance advantages mainly through a betterment in decision-making, but not directly via influencing a financial performance. On the same note, Rai, Constantinides and Sarker (2019) concluded that companies that applied AI in decision support realized higher return on assets than companies that applied the same in automation. The mediation analysis within the current study offers such empirical proper evidence to these theoretical propositions within the SME context in which the quality of the decision-making holds a significant bridging role.

### Profit Optimization and Strategic Value Creation

The correlations between the quality of decision-making and profit optimization found at the level of individual-firms ($\beta = 0.62$) reinforces the position of AI as a strategic asset of SMEs. The literature review has established that, a higher quality of decisions can hep companies price optimally, cut down imperfect measures, and earn new sources of revenue (Brynjolfsson & McElheran, 2016). These findings are especially relevant to SMEs, because even a minor financial change can be reflected in the development of a large profit margin because of the small margin (Kraus, Palmer, Kailer, Kallinger, & Spitzer, 2019). As the similar study by C, referring to C, [qtd. in C, [quebloThree results provided by C, Oliveira, and Ruivo (2017), this paper supports the idea that digital technologies, such as AI, demonstrate financial value when implemented into strategy and not used in a non-strategic manner. In addition, the increase in ROI and working-capital efficiency is similar to the research findings of Akter, Bandara, Hossain, Wamba, and Foropon (2019), who showed that AI-enhanced analytics can boost resource allocation efficiencies as a source of financial resilience.

### Sectoral Differences in AI Adoption and Outcomes

Sectoral comparisons indicate that the manufacturing small- and medium-size enterprises (SMEs) mentioned more adoption and larger profitability increases than retail firms, as well as service firms. This fact can be attributed to the nature of data availability and process standardization in the manufacturing industry that facilitates the integration of AI. A study by Mittal et al. (2018) corroborates this statement and demonstrates that manufacturing companies have more data at their disposal thus being in a better position to leverage AI to conduct predictive maintenance, forecasts, and financial planning. On the other hand, service business sometimes lacks order in its data and it is not produced in a material manner, which prevents the utilization of AI in the financial optimization process (Marques & Ferreira, 2020). The observed differences are also echoed in the Pereira and Romero (2017) reports that manufacturing SMEs are usually first movers when it comes to embracing digital technologies because they are competitive in nature and service firms adapt at their own pace. These discrepancies indicate that policy-makers ought to develop industry-specific incentives to adopt AI based on the requirements of a certain industry.

### Addressing Barriers to AI Adoption in SMEs

Although this paper has indicated the improvements that AI can bring, its implementation is considered average among the SMEs, with the least dimension implemented being dynamic pricing. This is indicative of wider issues in the SME literature around the barriers to cost, skills and cultural readiness. To give an illustration, Kumar, Kumar and Persaud (1999) observed that SMEs do not possess absorptive capacity and thereby cannot absorb the advanced technologies readily. Most recently, Ebersberger and Kuckertz (2021) have claimed that SMEs tend to avoid the adoption of the digital due to resource shortage and risk-averseness. Issues related to cybersecurity also arise, which is not surprising since SMEs usually do not have the necessary infrastructure to protect data on financial transactions managed through the AI platform (Susanti, Jie, & Marantika, 2023). Such limitations explain the necessity of favorable environments, such as government incentives, inexpensive AI platforms, and specific educational activities.

### Ethical and Governance Implications

Besides technical and fiscal results, ethical management of SMEs AI has been adopted is worthy of consideration. As mentioned by scholars like Mittelstadt, Allo, Taddeo, Wachter and Floridi (2016), the role of AI-driven recommendation as an innocent, vendor-neutral force may be disastrous when the recommendation cannot be understood by managers. In the case of SMEs, where relationship and trust matters a great deal in making a financial decision, explainability can deter usage. The current results indicate that decision confidence, although moderately increased ($M = 3.55$), is lower than speed and accuracy, which may show the existence of concerns relating to AI transparency. This affirms recommendations by Ransbotham et al. (2020) to provide explainable AI/ML frameworks that ensure accuracy and interpretability. Transparency in AI tools in SMEs will be a key to ensuring sustainability in the long-term.

### Theoretical Contributions

Theoretically, the study under the above study would add one aspect of the dynamic capabilities study by empirically substantiating the mediating influence of the quality of decision-making within the SME context. Although previous studies suggested that the key role of AI will be efficiency (Bharadwaj, 2000), here findings confirm that its worth is the ability to make high-quality decisions that directly translate into the financial performance. This responds to appeals of George, Lakhani, and Puranam (2020) to advance micro-level insights into how AI is influencing the firm strategy. In addition, this research helps to address a research gap, as Li, Su, Zhang, and Mao (2018) have written that the majority of the studies of AI are conducted among large corporations and small-and-medium enterprises remain underrepresented in empirical works.

### Practical Implications

The results would recommend to SME managers to focus on adopting AI in decision making areas that have direct benefits such as cash flow forecasting and anomalies. Such applications are also directly and measurably helpful, and potentially can generate their own impetus to wider usage. According to the recommendations of Nambisan (2017), to assist the SMEs to jump over the skills and cost barriers, policymakers and industry associations need to design capacity-building programs. Moreover, the technology suppliers are encouraged to create simpler and explainable AI tools adapted to the demands of the SMEs and make them accessible at the level of regular technicians and without the need to have a high level of technical knowledge beforehand. In such a way, SMEs will be able to shift their moderate adoption to the strategic integration of AI into their financial management systems.

### Limitations and Future Research

Although this study made contributions, it has limitations. The cross-sectional characteristics do not allow the possibility of causal inference, and longitudinal studies in the future might help in better understanding the effects of AI as they are dynamic. Furthermore, although several sectors were covered in the study, the country-specific context might influence the adoption patterns, given the fact that there was a difference in the levels of digital infrastructure and cultural preparedness (Kraus et al., 2022). Lastly, new types of AI, like generative AI and hybrid human and AI decision systems, have not been thoroughly researched in SME finance. These advances should be researched in the future, and one should also look at the interplay of AI and human intuition in financial strategy and extend upon the works of Wilson and Daugherty (2018) who emphasize the collaboration between the two.

### References

Abdul, R., & Hasnah, H. (2021). *Challenges of financial management in SMEs: A developing country perspective.* Journal of Small Business Finance.

Abubakar, A., Bala, K., & Salisu, M. (2021). *Artificial intelligence adoption in SMEs: Opportunities and constraints.* International Journal of Business Research.

BCG (2024). *Overcoming retail complexity with AI-powered pricing.* Boston Consulting Group Report.

Chen, L., & Lee, K. (2023). *Generative AI for business decision support in SMEs.* Journal of Emerging Technologies.

Dwivedi, Y., et al. (2021). *Artificial intelligence for decision-making in business: A research agenda.* International Journal of Information Management.

Financial Times (2025). *Taking accountancy from spreadsheets to AI.*

Hossain, M., & Rahman, T. (2022). *The role of machine learning in financial decision-making for SMEs.* Journal of Applied Finance.

Liu, Y., Chen, S., & Park, J. (2021). *Machine learning for SME cash-flow forecasting.* Journal of Financial Technology.

Mikalef, P., Krogstie, J., & Pappas, I. (2019). *Big data and strategy: The mediating role of AI analytics.* Journal of Business Research.

Nguyen, H., Pham, D., & Le, Q. (2020). *Barriers to financial planning in small enterprises.* Asia-Pacific Journal of SME Development.

OECD (2024). *SME digitalisation in 2024: Managing shocks and transitions.* Policy Report.

Sánchez, E., et al. (2023). *Artificial Intelligence adoption in SMEs: A survey-based TOE framework.* Applied Sciences.

Schwaeke, J., et al. (2025). *The status quo of AI adoption in SMEs.* Taylor & Francis Online.

World Bank (2020). *Small and Medium Enterprises (SMEs) Finance Overview.*

Zhang, H., & Lu, Y. (2021). *AI-driven analytics in financial decision-making.* Journal of Financial Innovation.
Altman, E., Sabato, G., & Wilson, N. (2020). *The role of credit risk models in SME finance.* Journal of Credit Risk.

Arnott, D., & Pervan, G. (2016). *Decision support systems theory: A review and directions for future research.* Decision Support Systems.

Arslanian, H., & Fischer, F. (2019). *The future of finance: Fintech, AI and regulation.* Springer.

Baesens, B., et al. (2015). *Analytics in fraud detection: Current practices and emerging trends.* MIS Quarterly Executive.

Barney, J. (1991). *Firm resources and sustained competitive advantage.* Journal of Management.

Bianchi, D., Büchner, M., & Tamoni, A. (2020). *Bond risk premia and machine learning.* Review of Financial Studies.

Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future.* Norton.

Chatterjee, S., Rana, N., & Dwivedi, Y. (2021). *Assessing barriers to AI adoption in SMEs.* Information Systems Frontiers.

Chen, L., Mislove, A., & Wilson, C. (2021). *Machine learning for dynamic pricing: A survey.* ACM Computing Surveys.

Chong, A., Li, B., & Ngai, E. (2017). *Predictive analytics in manufacturing SMEs: Evidence from Asia.* International Journal of Production Economics.

Davenport, T., & Ronanki, R. (2018). *Artificial intelligence for the real world.* Harvard Business Review.

Dubey, R., et al. (2021). *Artificial intelligence in operations: Research gaps and future prospects.* International Journal of Production Research.

Elmaghraby, W., & Keskinocak, P. (2019). *Dynamic pricing in supply chains: Review and directions.* Management Science.

Feng, Y., et al. (2019). *Improving cash flow forecasting with machine learning.* Journal of Forecasting.

Gunning, D., & Aha, D. (2019). *DARPA's explainable artificial intelligence (XAI) program.* AI Magazine.

Klein, T., Lambertz, C., & Stahl, K. (2020). *Market power and AI-driven pricing.* RAND Journal of Economics.

Kou, G., et al. (2021). *Credit risk analysis with machine learning: Applications and challenges.* European Journal of Operational Research.

Li, X., Huang, J., & Yu, Y. (2022). *Organizational culture and AI adoption in SMEs.* Technological Forecasting & Social Change.

Mikalef, P., Pappas, I., & Giannakos, M. (2020). *AI and firm performance: Empirical evidence from European SMEs.* Information & Management.

Ngai, E., Hu, Y., Wong, Y., Chen, Y., & Sun, X. (2011). *The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature.* Decision Support Systems.

Akter, S., Bandara, R., Hossain, M., Wamba, S., & Foropon, C. (2019). Analytics-based decision-making for service systems: A dynamic capabilities view. *Journal of Service Management*.

Bharadwaj, A. (2000). A resource-based perspective on information technology capability and firm performance. *MIS Quarterly*.

Brynjolfsson, E., & McElheran, K. (2016). The rapid adoption of data-driven decision-making. *American Economic Review*.

Côrte-Real, N., Oliveira, T., & Ruivo, P. (2017). Assessing business value of big data analytics in European firms. *Journal of Business Research*.

Ebersberger, B., & Kuckertz, A. (2021). Hop to it! The impact of organization type on innovation response during crisis. *Journal of Business Venturing Insights*.

Eisenhardt, K., & Martin, J. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*.

George, G., Lakhani, K., & Puranam, P. (2020). What has changed? The impact of COVID-19 on management scholarship. *Journal of Management Studies*.

Kraus, S., Palmer, C., Kailer, N., Kallinger, F., & Spitzer, J. (2019). Digital entrepreneurship: A research agenda. *International Journal of Entrepreneurial Behavior & Research*.

Kraus, S., et al. (2022). Digital transformation of SMEs: A systematic review. *Journal of Small Business Management*.

Kumar, N., Kumar, U., & Persaud, A. (1999). Building technological capability in SMEs. *Technovation*.

Marques, C., & Ferreira, J. (2020). SME innovative capacity, competitive advantage and performance. *Journal of Small Business and Enterprise Development*.

Mittelstadt, B., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society*.

Mittal, S., Khan, M., Romero, D., & Wuest, T. (2018). A critical review of smart manufacturing & Industry 4.0 maturity models. *Journal of Manufacturing Systems*.

Müller, J., Fay, M., & vom Brocke, J. (2018). The effect of digital transformation on IT alignment and IT effectiveness. *Information Systems Frontiers*.

Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice*.

Newell, S., & Marabelli, M. (2015). Strategic opportunities in uncertainty: The role of big data. *MIS Quarterly Executive*.

Pereira, A., & Romero, F. (2017). A review of digitalization and digital maturity models. *Computers in Industry*.

Rai, A., Constantinides, P., & Sarker, S. (2019). Next-generation digital platforms: Toward human–AI hybrids. *MIS Quarterly*.

Ransbotham, S., et al. (2020). The enterprise strategy for AI. *MIT Sloan Management Review*.

Shollo, A., & Galliers, R. (2016). Towards an understanding of the role of business intelligence systems in organisational knowing. *Information Systems Journal*.

Susanti, R., Jie, F., & Marantika, J. (2023). Digital readiness and cybersecurity in SMEs. *Journal of Business Research*.

Wilson, H., & Daugherty, P. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*.