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Artificial Intelligence Capability and Financial Forecasting Quality: An Empirical Study of Garment Enterprises in Hanoi

Trang Le Thi Thu
Trade Union University, Hanoi, Vietnam

Corresponding Author: **Trang Le Thi Thu**

Abstract
In the context of rapid digital transformation, Artificial Intelligence (AI) has emerged as one of the core technologies enhancing organizational management effectiveness. In financial management, AI not only supports the automation of data-processing activities but also improves financial forecasting quality through its ability to analyze large volumes of data and identify hidden patterns and trends. This study aims to examine the impact of artificial intelligence capability on financial forecasting quality in garment enterprises located in Hanoi, Vietnam. Drawing upon the Resource-Based View (RBV) theory and prior studies, the research model proposes a direct relationship between AI capability and financial forecasting quality. Research data were collected from managers, chief accountants, and financial officers working in garment enterprises. The findings are expected to provide empirical evidence regarding the role of AI in improving financial forecasting quality and to offer managerial implications for promoting AI adoption in manufacturing enterprises in Vietnam.

Keywords: Artificial Intelligence, AI Capability, Financial Forecasting, Financial Forecasting Quality, Garment Enterprises

1. Introduction

In recent years, the rapid advancement of digital technologies, particularly Artificial Intelligence (AI), has brought significant changes to organizational management practices. AI is increasingly being applied across various functional areas, including marketing, human resource management, supply chain management, and financial management. Within corporate finance, AI facilitates the automation of data-processing activities, business trend analysis, and the forecasting of revenues, costs, and cash flows, thereby enhancing the quality of managerial decision-making.

The garment industry is one of Vietnam's key economic sectors, characterized by intense competition and a high degree of exposure to fluctuations in international markets. In this context, the quality of financial forecasting plays a critical role in production planning, cost management, and resource allocation. However, in many garment enterprises, financial forecasting activities continue to rely heavily on managerial experience and traditional forecasting techniques, resulting in limitations in forecasting accuracy and adaptability to changing business environments.

Although AI has been widely recognized as an effective tool for supporting corporate financial activities, empirical studies examining the impact of AI capability on financial forecasting quality in Vietnam remain limited, particularly within the manufacturing sector. Moreover, evidence from the garment industry is still scarce despite its substantial need for accurate financial forecasting to support strategic and operational decision-making.

Addressing this research gap, the present study investigates the relationship between artificial intelligence capability and financial forecasting quality in garment enterprises operating in Hanoi. By providing empirical evidence from an emerging economy context, the study contributes to the growing literature on AI applications in financial management and offers practical insights for enterprises seeking to enhance forecasting effectiveness through AI adoption.

2. Literature Review

Research on Artificial Intelligence (AI) in business management has attracted considerable scholarly attention in recent years, particularly in the context of the rapid global digital transformation. From the perspective of the Resource-Based View (RBV), AI is not merely a technology but also a strategic capability that enables organizations to effectively leverage data, enhance decision-making quality, and establish sustainable competitive advantages. Mikalef and Gupta (2021) [9] developed a theoretical framework and measurement scale for AI capability, demonstrating that such capability is formed through the integration of technological, data, human, and organizational resources. Their findings indicate that AI capability positively influences organizational creativity and overall business performance.

In addition, a growing body of research has examined the role of AI in analytical and forecasting activities. The development of Machine Learning (ML) and Deep Learning (DL) algorithms has significantly enhanced the ability to process large-scale datasets and identify complex patterns that are often difficult to detect using traditional statistical methods. Evidence from large-scale forecasting competitions such as M4 and M5 suggests that AI- and ML-based forecasting methods can substantially improve forecasting accuracy across different contexts, particularly when dealing with complex and highly volatile datasets. These findings highlight the potential of AI to enhance forecasting quality and support managerial decision-making.

From an information quality perspective, DeLone and McLean (2003) [2] argued that information quality is one of the fundamental determinants of information system success. Attributes such as accuracy, completeness, timeliness, and usefulness directly affect the quality of managerial decision-making. Their model has subsequently been validated across various contexts, confirming the critical role of information quality in evaluating the effectiveness of decision-support systems.

Although prior studies have confirmed the importance of AI capability for organizational performance and the significance of information quality for managerial decision-making, research directly examining the relationship between AI capability and financial forecasting quality remains limited. In Vietnam, existing studies primarily focus on digital transformation, AI applications in accounting, or the impact of AI on firm performance. Empirical evidence regarding the influence of AI capability on financial forecasting quality is still scarce. Furthermore, studies conducted in manufacturing contexts, particularly within the garment industry—which requires accurate forecasts of revenue, costs, and cash flows—remain relatively limited. Therefore, this study aims to address this research gap by investigating the impact of AI capability on financial forecasting quality among garment enterprises in Hanoi.

3. Theoretical Background and Research Hypothesis

3.1 Artificial Intelligence Capability

Artificial Intelligence (AI) has emerged as one of the most important strategic resources enabling organizations to improve operational efficiency and achieve competitive advantages in the digital economy. However, the value generated by AI depends not only on the possession of AI technologies but also on an organization’s ability to effectively organize, integrate, and exploit AI-related resources. Consequently, the concept of Artificial Intelligence Capability (AIC) has gained increasing attention among researchers and practitioners.

Drawing upon the Resource-Based View (RBV), Mikalef and Gupta (2021) [9] define AI capability as an organization’s ability to select, coordinate, and utilize AI-specific resources effectively to create business value. From this perspective, AI capability extends beyond merely owning AI technologies or algorithms; it encompasses the capability to integrate technological, data, human, and organizational resources to support decision-making and improve organizational performance.

According to RBV, resources that are valuable, rare, inimitable, and non-substitutable can serve as a foundation for sustainable competitive advantage. In the context of digital transformation, AI capability represents a specialized technological capability that reflects an organization’s ability to develop, utilize, and manage AI-related resources—including technological infrastructure, data assets, algorithms, and AI-skilled personnel—to achieve strategic objectives.

Previous studies suggest that AI capability is a multidimensional construct formed through the integration of complementary resources. Mikalef *et al*. (2019, 2021) [8, 9] argue that AI capability consists of several key dimensions, including technological infrastructure, data quality, employee expertise, and the integration of AI into business processes. When these resources are effectively combined, organizations can enhance their ability to process data, extract valuable insights, and support managerial decision-making.

In this study, AI capability is conceptualized as an organization’s ability to invest in and utilize AI infrastructure, collect and manage data for financial analysis, develop employees’ competencies in AI applications, integrate AI into financial activities, and employ AI to support forecasting and decision-making processes. Organizations with higher levels of AI capability are expected to process large volumes of financial data more efficiently, identify hidden patterns and trends, and consequently improve the accuracy and timeliness of financial forecasts.

3.2 Financial Forecasting Quality

Financial forecasting refers to the process of estimating future financial indicators, such as revenue, costs, profits, and cash flows, based on historical data, current information, and assumptions regarding future business conditions. In increasingly dynamic business environments, financial forecasting quality plays a crucial role in resource allocation, risk management, and organizational performance enhancement (Makridakis *et al*., 2020) [6].

According to the Information Systems Success Model proposed by DeLone and McLean (2003) [2], information quality is one of the primary determinants of information effectiveness in decision-making processes. Information quality is commonly reflected through attributes such as accuracy, completeness, timeliness, and usefulness. Applying this perspective to corporate finance, financial forecasting quality can be defined as the extent to which forecasted information satisfies managerial requirements for planning and financial decision-making.

Moreover, forecasting literature suggests that an effective forecasting system should not only generate highly accurate forecasts but also provide timely and relevant information that supports managerial needs (Fildes *et al*., 2009; Makridakis *et al*., 2022) [3, 7]. Therefore, in this study, financial forecasting quality is evaluated through four dimensions: (i) forecast accuracy, (ii) timeliness of forecast information, (iii) completeness of data and information used in forecasting, and (iv) usefulness of forecasting outcomes for financial decision-making.

Higher financial forecasting quality enables organizations to improve planning effectiveness, reduce business risks, and enhance the quality of financial management decisions.

3.3 The Relationship between Artificial Intelligence Capability and Financial Forecasting Quality

According to the Resource-Based View (RBV), valuable technological resources and capabilities contribute significantly to organizational performance and sustainable competitive advantage (Barney, 1991) [1]. In the era of digital transformation, AI capability has emerged as a strategic capability that enables organizations to effectively exploit data, automate analytical processes, and support evidence-based decision-making.

Compared with traditional forecasting methods, AI technologies can process large volumes of data from multiple sources, identify nonlinear relationships, and detect hidden patterns that may not be easily recognized by human analysts. Consequently, AI contributes to improving forecasting accuracy, reducing analytical bias, and providing timely information for managerial decision-making (Makridakis *et al*., 2022) [7]. Furthermore, Mikalef and Gupta (2021) [9] found that organizations possessing strong AI capabilities are generally more effective in leveraging data resources, thereby enhancing the quality of information used for management and decision-making purposes.

In the context of corporate finance, AI applications can improve forecasts of revenue, costs, cash flows, and market demand through real-time data analysis and machine learning algorithms capable of identifying future trends. This is particularly important in the garment industry, where production activities are highly influenced by market fluctuations, customer orders, and raw material prices. Therefore, AI capability is expected to contribute significantly to improving financial forecasting quality, thereby supporting more effective production planning and resource allocation.

Based on the theoretical arguments and empirical evidence discussed above, the following hypothesis is proposed:

H1: Artificial intelligence capability positively affects financial forecasting quality in garment enterprises located in Hanoi.

4. Research Model and Methodology

4.1 Research Model

Drawing upon the Resource-Based View (RBV) proposed by Barney (1991) [1], artificial intelligence capability is considered a strategic resource that can enhance organizational performance and improve the quality of information used for managerial purposes. Furthermore, according to the Information Systems Success Model developed by DeLone and McLean (2003) [2], information quality is one of the key determinants of effective organizational decision-making. Integrating these theoretical perspectives with the AI capability framework developed by Mikalef and Gupta (2021) [9], this study proposes a research model to examine the impact of artificial intelligence capability on financial forecasting quality among garment enterprises in Hanoi.

The proposed research model is presented as follows:

Artificial Intelligence Capability (AIC) → Financial Forecasting Quality (FFQ)

In this model, Artificial Intelligence Capability (AIC) serves as the independent variable, while Financial Forecasting Quality (FFQ) is specified as the dependent variable.

4.2 Research Methodology

This study adopts a quantitative research approach to examine the impact of artificial intelligence capability on financial forecasting quality among garment enterprises in Hanoi. Research data were collected through a structured questionnaire survey administered to individuals directly involved in financial management and digital transformation activities within their organizations.

Research Participants and Sample

The target respondents included chief financial officers, chief accountants, heads of finance and accounting departments, planning managers, information technology managers, and digital transformation officers working in garment enterprises located in Hanoi. These individuals possess substantial knowledge of corporate financial activities and are capable of assessing both the level of AI adoption and the quality of financial forecasting within their organizations.

To determine the appropriate sample size, this study followed the recommendation of Hair *et al*. (2022) [4], who suggest that the minimum sample size for Structural Equation Modeling (SEM) should be at least five times the number of observed variables. Since the proposed model consists of ten observed variables, the minimum required sample size is 50 observations. In addition, Kline (2023) [5] argues that a sample size of at least 200 observations is desirable for achieving reliable parameter estimates and model stability in SEM analyses.

Based on these recommendations, a total of 280 questionnaires were distributed to garment enterprises in Hanoi using a combination of convenience sampling and purposive sampling techniques. A total of 268 questionnaires were returned, yielding a response rate of 95.71%. After data screening, 16 questionnaires were excluded due to incomplete responses or response patterns indicating a lack of engagement (e.g., selecting the same response option throughout the questionnaire). Consequently, 252 valid responses were retained for data analysis, representing an effective response rate of 90.0% relative to the number of distributed questionnaires. This sample size satisfies the requirements for multivariate statistical analyses, including Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM).

Measurement Development

Artificial Intelligence Capability (AIC)

The measurement scale for Artificial Intelligence Capability was adapted from Mikalef and Gupta (2021) [9]. The scale captures an organization's ability to leverage technological, data, and human resources to apply AI in financial management activities.

Code	Measurement Item
AIC1	The enterprise invests adequately in technological infrastructure to support AI applications in financial activities.
AIC2	The enterprise regularly uses AI tools for processing and analyzing financial data.
AIC3	Financial staff possess sufficient knowledge and skills to utilize AI tools.
AIC4	AI is integrated into the enterprise's financial analysis and forecasting processes.
AIC5	AI effectively supports the enterprise's financial decision-making process.

Source: Adapted from Mikalef and Gupta (2021) [9].

Financial Forecasting Quality (FFQ)

The Financial Forecasting Quality scale was developed based on the information quality dimensions proposed by DeLone and McLean (2003) [2], combined with forecasting quality criteria suggested by Fildes *et al*. (2009) [3] and Makridakis *et al*. (2022) [7]. The scale reflects the extent to which forecasting information meets managerial financial decision-making needs.

Code	Measurement Item
FFQ1	The enterprise's financial forecasts are highly accurate.
FFQ2	Financial forecasting information is provided to managers in a timely manner.
FFQ3	Forecasting results effectively support financial planning and budgeting activities.
FFQ4	Financial forecasts accurately reflect market trends and fluctuations.
FFQ5	Forecasting information is highly useful for financial decision-making.

Source: Developed by the authors based on prior studies.

All measurement items were assessed using a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). This scale enables the quantification of respondents' perceptions regarding AI capability and financial forecasting quality, providing the basis for subsequent quantitative analyses.

Data Analysis Procedures

The collected data were analyzed using SPSS 26.0 and AMOS 24.0. The analytical procedure consisted of four stages.

First, the reliability of the measurement scales was evaluated using Cronbach's Alpha. Following Nunnally and Bernstein (1994) [10], scales were considered reliable when Cronbach's Alpha exceeded 0.70 and item-total correlations were greater than 0.30.

Second, Exploratory Factor Analysis (EFA) was conducted to examine the underlying factor structure of the measurement scales. The adequacy of the data for factor analysis was assessed based on a Kaiser–Meyer–Olkin (KMO) value greater than 0.50, a statistically significant Bartlett's Test of Sphericity ($p < 0.05$), and factor loadings exceeding 0.50 (Hair *et al*., 2022) [4].

Third, Confirmatory Factor Analysis (CFA) was performed to evaluate the measurement model and to assess convergent validity and discriminant validity of the research constructs (Kline, 2023) [5].

Finally, Structural Equation Modeling (SEM) was employed to test the proposed hypothesis concerning the effect of artificial intelligence capability on financial forecasting quality. A significance level of 5% was adopted for all statistical tests.

5. Research Results

5.1 Descriptive Statistics of the Sample

The study was conducted through a survey of financial managers, chief accountants, heads of finance and accounting departments, and digital transformation officers working in garment enterprises located in Hanoi. A total of 280 questionnaires were distributed using a combination of convenience sampling and purposive sampling techniques. After the data collection period, 268 completed questionnaires were returned, yielding a response rate of 95.71%. Following data screening and cleaning procedures, 16 questionnaires were excluded due to incomplete information or inconsistent response patterns. Consequently, 252 valid responses were retained for further analysis, representing an effective response rate of 90.00% of the distributed questionnaires and 94.03% of the returned questionnaires.

Regarding respondent characteristics, chief accountants accounted for the largest proportion of the sample (37.7%), followed by heads of finance and accounting departments (27.0%), digital transformation or information technology officers (21.4%), and chief financial officers (13.9%). This composition indicates that most respondents possessed substantial expertise and experience directly related to financial management and technology adoption within their organizations.

In terms of professional experience, the majority of respondents had more than five years of experience in finance, accounting, or business management. This enhances the reliability of the collected data, as respondents were well positioned to evaluate both the level of AI adoption and the quality of financial forecasting within their enterprises.

Overall, the descriptive statistics suggest that the sample provides a reasonably representative reflection of the target population and is suitable for subsequent analyses, including reliability testing, factor analysis, and structural equation modeling.

5.2 Reliability Analysis

The reliability of the measurement scales was assessed using Cronbach's Alpha coefficients. According to Nunnally and Bernstein (1994) [10], a scale is considered reliable when its Cronbach's Alpha exceeds 0.70.

Table 1: Reliability Analysis Results

Construct	Number of Items	Cronbach's Alpha
Artificial Intelligence Capability (AIC)	5	0.892
Financial Forecasting Quality (FFQ)	5	0.876

Source: SPSS analysis results.

The results indicate that both constructs achieved Cronbach's Alpha values above 0.80, demonstrating a high level of internal consistency among the observed variables. Therefore, all measurement items were retained for subsequent analyses.

5.3 Exploratory Factor Analysis (EFA)

The results of the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity indicate that the dataset is appropriate for Exploratory Factor Analysis.

Table 2: KMO and Bartlett's Test Results

Indicator	Value
KMO	0.874
Bartlett's Test (Sig.)	0.000

Source: SPSS analysis results.

The KMO value of 0.874 exceeds the recommended threshold of 0.50, while Bartlett's Test is statistically significant at the 1% level ($p < 0.001$). These results confirm that sufficient correlations exist among the observed variables to justify factor analysis.

The EFA results reveal two factors consistent with the proposed theoretical model. All factor loadings exceeded 0.70, surpassing the minimum threshold of 0.50 recommended by Hair *et al*. (2022) [4]. This finding provides evidence of the convergent validity of the measurement scales.

5.4 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis was conducted to evaluate the adequacy of the measurement model.

Table 3: Model Fit Indices of the CFA Model

Fit Index	Value	Recommended Threshold
Chi-square/df	1.876	< 3.0
GFI	0.945	> 0.90
TLI	0.963	> 0.90
CFI	0.971	> 0.90
RMSEA	0.059	< 0.08

Source: AMOS analysis results.

All model fit indices met or exceeded the recommended criteria, indicating that the measurement model exhibits a satisfactory fit with the empirical data.

In addition, composite reliability (CR) and average variance extracted (AVE) were assessed to evaluate convergent validity.

Table 4: Convergent Validity Results

Construct	CR	AVE
AIC	0.921	0.700
FFQ	0.908	0.664

Source: AMOS analysis results.

The CR values exceeded 0.70 and the AVE values were greater than 0.50, confirming adequate convergent validity for both constructs.

5.5 Structural Model and Hypothesis Testing

After confirming the adequacy of the measurement model, Structural Equation Modeling (SEM) was employed to examine the proposed relationship between artificial intelligence capability and financial forecasting quality.

Table 5: Hypothesis Testing Results

Relationship	Standardized Coefficient (β)	S.E.	C.R.	p-value	Result
AIC → FFQ	0.632	0.071	8.914	< 0.001	Supported

Source: AMOS analysis results.

The results indicate that Artificial Intelligence Capability has a positive and statistically significant effect on Financial Forecasting Quality ($\beta = 0.632$, $p < 0.001$). This finding suggests that enterprises that invest in AI infrastructure, develop employee competencies, and integrate AI into financial management processes are more likely to achieve higher-quality financial forecasts. Consequently, Hypothesis H1 is supported.

The standardized coefficient of 0.632 indicates that AI capability is a substantial determinant of financial forecasting quality among garment enterprises. This finding is consistent with Barney's (1991) [1] Resource-Based View, which emphasizes the strategic importance of technological capabilities in enhancing organizational performance. The result also aligns with the findings of Mikalef and Gupta (2021) [9], who argue that AI capability enables organizations to leverage data resources more effectively and improve the quality of information used in managerial decision-making.

Overall, the findings provide empirical evidence that the development of AI capability not only facilitates digital transformation but also significantly improves financial forecasting quality. As a result, AI capability can enhance financial management effectiveness and strengthen organizational adaptability in increasingly dynamic and uncertain business environments.

6. Managerial Implications and Recommendations

The findings of this study indicate that Artificial Intelligence Capability (AIC) has a positive and statistically significant effect on Financial Forecasting Quality (FFQ) among garment enterprises in Hanoi ($\beta = 0.632$; $p < 0.001$). This result suggests that strengthening AI capability can substantially improve the accuracy, timeliness, and usefulness of financial forecasting information, thereby supporting more effective managerial decision-making. Based on these findings, several managerial implications are proposed.

First, enterprises should increase investment in technological infrastructure to support AI implementation. Technological infrastructure serves as the foundation for deploying AI solutions in corporate financial management. Garment enterprises should prioritize investments in centralized databases, cloud computing platforms, Enterprise Resource Planning (ERP) systems, and intelligent data analytics tools to facilitate real-time collection, storage, and processing of financial information. Establishing an integrated technological infrastructure not only enhances the effectiveness of AI applications but also improves the quality and reliability of input data used in financial forecasting.

Second, organizations should improve the quality of financial and operational data. The effectiveness of AI systems largely depends on the quality of the underlying data. Therefore, enterprises should develop comprehensive data governance mechanisms, standardize data collection and updating procedures, and strengthen the integration of financial data with production, sales, and supply chain information. In the garment industry, integrating data related to customer orders, inventory levels, raw material prices, and market demand can significantly enhance AI models' ability to forecast future revenues, costs, and cash flows.

Third, enterprises should develop digital competencies and AI-related skills among financial personnel. The findings suggest that AI capability depends not only on technological resources but also on employees' ability to utilize these technologies effectively. Accordingly, organizations should provide training programs for accounting, finance, and managerial staff in areas such as data analytics, AI applications, and forecasting technologies. In addition to traditional financial expertise, employees should acquire competencies in AI platforms, big data analytics, and data visualization to maximize the value of information for managerial decision-making.

Fourth, enterprises should accelerate the integration of AI into financial forecasting processes. Organizations are encouraged to gradually transition from traditional forecasting methods toward data-driven and AI-enabled forecasting approaches. AI technologies can be applied to revenue forecasting, market demand forecasting, raw material cost forecasting, cash flow forecasting, and financial scenario analysis. Integrating AI into financial planning processes can reduce reliance on subjective judgments while improving organizational responsiveness to changes in the business environment.

Fifth, organizations should formulate digital transformation strategies aligned with intelligent financial management. To maximize the benefits of AI, enterprises should establish long-term digital transformation strategies supported by top management commitment. Within these strategies, AI should be regarded as a strategic decision-support tool rather than merely a technological solution. The integration of AI with modern financial management systems can improve forecasting quality, optimize resource allocation, and enhance organizational competitiveness in an increasingly dynamic garment industry.

Overall, the findings demonstrate that strengthening AI capability represents an important pathway for improving financial forecasting quality in garment enterprises. Beyond enhancing financial management effectiveness, AI capability enables organizations to make more data-driven strategic decisions, thereby improving adaptability and supporting sustainable development in the digital economy.

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