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SMART FINANCE, SMARTER DECISIONS: THE ROLE OF AI AND DIGITAL INNOVATION IN REVOLUTIONIZING FINANCIAL MANAGEMENT

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Abstract: In the era of digital transformation, organizations are increasingly relying on advanced technologies and financial competencies to improve decision-making effectiveness. This study examines the impact of AI Capability and Digital Innovation on Financial Analytics Capability and further investigates how Financial Analytics Capability influences Decision Effectiveness. Additionally, the study explores the mediating role of Financial Analytics Capability between AI Capability and Decision Effectiveness, along with the moderating role of Financial Literacy in strengthening the relationship between Financial Analytics Capability and Decision Effectiveness.

The study is based on primary data collected through a structured questionnaire from 423 respondents across different industries. The data were analyzed using SPSS, employing regression analysis, mediation, and moderation techniques to test the proposed hypotheses. The findings reveal that both AI Capability and Digital Innovation significantly enhance Financial Analytics Capability. Financial Analytics Capability is also found to have a significant positive effect on Decision Effectiveness. Moreover, it partially mediates the relationship between AI Capability and Decision Effectiveness, while Financial Literacy significantly strengthens the impact of Financial Analytics Capability on Decision Effectiveness. The study contributes to the literature on digital transformation and

decision-making by integrating technological and financial dimensions into a unified framework. It also provides practical implications for organizations by highlighting the importance of investing in AI technologies, digital innovation, and financial literacy to improve data-driven decision-making outcomes.

Keywords: AI Capability; Digital Innovation; Financial Analytics Capability; Financial Literacy; Decision Effectiveness; Digital Transformation; SPSS Analysis; Organizational Decision-Making

1. Introduction

The increasing adoption of artificial intelligence (AI) and digital innovation has significantly transformed financial management practices, enabling organizations to shift from traditional judgment-based decisions to data-driven and intelligent decision-making systems. AI technologies, such as machine learning and predictive analytics, enhance the ability of firms to process large volumes of financial data and generate accurate insights, while digital innovations—such as fintech platforms and cloud-based systems—facilitate real-time data integration and operational efficiency (Davenport et al., 2020; Gomber et al., 2018). Together, these technological advancements play a crucial role in improving organizational decision-making processes.

However, the benefits of AI and digital innovation are not realized automatically. Prior studies suggest that the impact of technological resources depends on the organization's ability to develop internal capabilities, particularly financial analytics capability (Mikalef et al., 2019; Wamba et al., 2017). This capability enables firms to transform raw data into meaningful insights, thereby improving the quality and effectiveness of financial decisions. Despite its importance, limited research has examined the mediating role of financial analytics capability in linking AI capability and digital innovation to financial decision effectiveness.

Furthermore, individual factors such as financial literacy influence how effectively decision-makers utilize analytical insights. Financially literate individuals are better equipped to interpret data-driven outputs and make informed decisions, thereby strengthening the impact of analytics capability on decision outcomes (Lusardi & Mitchell, 2014). This highlights the need to consider moderating variables in understanding the effectiveness of AI-driven financial systems.

Grounded in the Technology Acceptance Model, Resource-Based View, and Dynamic Capabilities Theory, this study examines the relationships between AI capability, digital innovation, financial analytics capability, and financial decision effectiveness. Specifically, it investigates the mediating role of financial analytics capability and the moderating role of financial literacy in enhancing decision outcomes. By doing so, the study contributes to a deeper understanding of how organizations can leverage AI and digital innovation to achieve smarter financial decisions.

2. Theoretical framework and hypothesis development

2.1 Theories underpinning the study

This study is grounded in three complementary theoretical perspectives, namely the Technology Acceptance Model, the Resource-Based View, and the Dynamic Capabilities Theory. The integration of these theories provides a comprehensive framework to explain how AI capability and digital innovation influence financial decision effectiveness through the development of financial analytics capability, while also considering the moderating role of financial literacy. The Technology Acceptance Model (TAM), originally proposed by Davis (1989), explains how users adopt and utilize new technologies based on perceived usefulness and perceived ease of use. In the context of this study, TAM provides a foundation for understanding how organizations and decision-makers adopt AI-driven tools and digital financial technologies. AI capability and digital innovation are more likely to be utilized when users perceive them as beneficial for improving financial decision-making processes. This theoretical lens supports the proposed relationships between AI capability, digital innovation, and financial analytics capability, as the adoption and effective use of these technologies enable the development of advanced analytical functions within organizations.

The Resource-Based View (RBV) conceptualizes organizational resources as key drivers of competitive advantage (Barney, 1991). According to RBV, valuable, rare, inimitable, and non-substitutable (VRIN) resources enable firms to achieve superior performance. In this study, AI capability and digital innovation are considered strategic resources that can enhance organizational performance. However, RBV also emphasizes that resources alone are insufficient; firms must possess the necessary capabilities to effectively deploy them. Financial analytics capability, therefore, represents a critical organizational capability that transforms technological resources into improved financial decision effectiveness. This perspective provides theoretical support for the mediating role of financial analytics capability.

Complementing RBV, Dynamic Capabilities Theory focuses on an organization's ability to integrate, build, and reconfigure internal and external competencies in response to rapidly changing environments (Teece et al., 1997). In the context of AI-driven financial management, financial analytics capability can be viewed as a dynamic capability that enables organizations to adapt to complex financial environments by leveraging data and advanced analytics. This capability enhances decision-making effectiveness by improving the accuracy, speed, and quality of financial decisions. Furthermore, Dynamic Capabilities Theory supports the argument that organizations with stronger analytical capabilities are better positioned to utilize AI and digital innovation for strategic advantage.

In addition to these organizational-level theories, the role of financial literacy can be understood through a behavioral perspective. Financial literacy enhances individuals' ability to interpret and utilize financial information effectively, thereby influencing the extent to which analytical insights are translated into actionable decisions. In line with this view, financial literacy is expected to strengthen the relationship between financial analytics capability and financial decision effectiveness, as individuals with higher literacy are more capable of leveraging analytical outputs for improved decision-making. By integrating TAM, RBV, and Dynamic Capabilities Theory, this study develops a holistic framework that explains both the adoption and utilization of AI and digital innovation, as well as the capability-building processes that lead to improved financial decision outcomes. This multi-theoretical approach not only strengthens the conceptual foundation of the study but also provides a robust basis for examining the proposed hypotheses.

2.2 AI capability and financial analytics capability

AI capability refers to an organization's ability to deploy AI-based tools such as machine learning, predictive analytics, and automated financial systems to process and analyze data. AI enables firms to handle large volumes of structured and unstructured financial data, uncover hidden patterns, and generate accurate forecasts (Davenport et al., 2020). From the perspective of the Resource-Based View, AI capability can be considered a strategic resource that enhances organizational competencies. Moreover, AI technologies facilitate advanced data processing and real-time analysis, which are essential components of financial analytics capability. Organizations with strong AI capability are better equipped to integrate diverse data sources and apply sophisticated analytical techniques, thereby strengthening their analytics functions (Mikalef et al., 2019). Therefore, AI capability plays a crucial role in developing financial analytics capability.

H1: AI capability positively affects financial analytics capability

2.2 Digital innovation and financial analytics capability

Digital innovation refers to the adoption and integration of advanced digital technologies such as fintech platforms, cloud computing, blockchain, and automated financial systems within organizational processes. These technologies provide a robust infrastructure for efficient data collection, storage, and real-time processing, which are critical for effective financial analysis (Gomber et al., 2018). From the perspective of the Technology Acceptance Model, organizations are more likely to adopt digital innovations when they perceive them as useful in enhancing performance and decision-making capabilities. Furthermore, digital innovation facilitates seamless integration of financial data across different functional areas, enabling organizations to generate comprehensive and accurate insights. It enhances data accessibility, improves data quality, and supports collaborative decision-making environments. As a result, firms that actively invest in digital innovation are better positioned to develop strong financial analytics capability, as they can leverage advanced tools and platforms to analyze financial information effectively (Wamba et al., 2017). Therefore, digital innovation significantly contributes to the development of financial analytics capability.

H2: Digital Innovation positively affects financial analytics capability

2.3 Financial analytics capability and decision effectiveness

Financial analytics capability refers to an organization's ability to transform financial data into meaningful insights that support strategic decision-making. This capability involves the use of analytical tools, data visualization techniques, machine learning models, and predictive analytics to evaluate financial performance and forecast future outcomes. From the perspective of the Dynamic Capabilities Theory, organizations that develop strong analytical capabilities are better positioned to sense opportunities, seize advantages, and reconfigure resources in response to dynamic and uncertain environments (Teece, 2007; Teece, 2018). Enhanced financial analytics capability enables organizations to systematically assess financial risks, evaluate alternative courses of action, and make data-driven decisions with greater accuracy, speed, and confidence. It improves the quality, reliability, and timeliness of financial decision-making by converting raw data into actionable managerial intelligence. Prior research highlights that analytics capability significantly enhances organizational performance by improving decision quality and reducing uncertainty in complex environments (Gupta & George, 2016; Wamba et al., 2017; Mikalef et al., 2019). Recent studies further emphasize that organizations with advanced analytics capabilities are more effective in leveraging digital technologies for strategic decision-making and performance optimization (Davenport et al., 2020; Chen et al., 2022; Dwivedi et al., 2021). Moreover, financial analytics capability is increasingly recognized as a key organizational resource that bridges the gap between technological infrastructure and managerial decision outcomes (Ferraris et al., 2019; Mariani et al., 2022). Consequently, firms with higher levels of financial analytics capability are more likely to achieve superior decision effectiveness due to their enhanced ability to interpret complex financial information, reduce decision ambiguity, and support evidence-based strategic actions.

H3: Financial analytics capability positively affects decision effectiveness

2.4 Mediating role of financial analytics capability

While AI capability provides the technological foundation for data processing and analysis, its direct impact on decision effectiveness may not be fully realized without the presence of strong analytical capabilities. According to the Resource-Based View (RBV), organizational resources alone do not generate competitive advantage unless they are effectively deployed through complementary capabilities and organizational processes (Barney, 1991; Barney, 2001; Wernerfelt, 1984). In this context, financial analytics capability acts as a critical dynamic mechanism that transforms AI-driven technological inputs into actionable insights for managerial decision-making. AI capability enhances an organization's ability to process large volumes of structured and unstructured financial data, identify patterns, and generate predictive insights; however, financial analytics capability determines how effectively these outputs are interpreted, contextualized, and translated into strategic decisions. This aligns with the dynamic capability perspective, which emphasizes that firms must integrate, build, and reconfigure capabilities to fully realize value from digital technologies (Teece, 2007; Teece, 2018). Therefore, the relationship between AI capability and decision effectiveness is likely to be indirect and mediated through financial analytics capability. Prior research strongly supports the mediating role of analytical capabilities in converting digital technologies into improved firm performance and decision outcomes (Mikalef et al., 2019; Gupta & George, 2016; Wamba et al., 2017; Ferraris et al., 2019). Recent empirical studies also highlight that AI-driven systems alone are insufficient for improving decision quality unless organizations possess strong data analytics capability and human interpretive competence (Davenport et al., 2020; Siau & Wang, 2021; Dwivedi et al., 2021; Mariani et al., 2022). Furthermore, AI value realization is increasingly recognized as a socio-technical process where technology must be complemented by analytical and managerial capabilities (Borges et al., 2021; Shrestha et al., 2019). Accordingly, financial analytics capability is expected to mediate the relationship between AI capability and decision effectiveness by serving as the transformation layer that converts technological inputs into informed, timely, and effective organizational decisions.

H4: Financial analytics capability mediates the relationship between AI capability and decision effectiveness

2.5 Moderating role of financial literacy

Financial literacy refers to the knowledge and skills required to understand, interpret, and use financial information effectively. Even when organizations possess strong financial analytics capability, the effectiveness of decision-making largely depends on the ability of individuals to comprehend and utilize analytical insights. Individuals with higher financial literacy are better equipped to interpret complex financial data and apply it in decision-making processes (Lusardi & Mitchell, 2014; Lusardi & Mitchell, 2017). From a behavioral perspective, financial literacy enhances the usability and effectiveness of analytics outputs by enabling decision-makers to critically evaluate and act upon the information provided. Prior research also indicates that financial knowledge significantly improves data-driven decision quality and reduces cognitive bias in financial interpretation (Hastings, Madrian, & Skimmyhorn, 2013; Stolper & Walter, 2017). In the context of digital transformation, financial literacy acts as a critical human capability that complements advanced analytics systems, ensuring that technological outputs are meaningfully translated into actionable decisions (Xiao & Porto, 2022; Morgan & Truby, 2023). In contrast, low financial literacy may limit the benefits of advanced analytics, as individuals may struggle to understand or trust the insights generated. Therefore, financial literacy is expected to strengthen the positive relationship between financial analytics capability and decision effectiveness.

H5: Financial literacy moderates the relationship between financial analytics capability and decision effectiveness

3. Research methodology

3.1 Sample, sample size and data collection

The present study adopts a quantitative research design to examine the relationships between AI capability, digital innovation, financial analytics capability, financial decision effectiveness, and financial literacy. The target population of the study consists of professionals involved in financial decision-making processes, including finance managers, accountants, analysts, and executives working in organizations that actively use digital financial systems and AI-based tools. A purposive sampling technique was employed to ensure that only respondents with relevant knowledge and experience in financial management and digital technologies were included in the study. This sampling approach is appropriate for the current research as it allows the selection of information-rich cases that can provide meaningful insights into AI-driven financial decision-making processes.

The sample size was determined based on the requirements of structural equation modeling (SEM), particularly Partial Least Squares SEM (PLS-SEM), which is suitable for complex models with multiple constructs and mediating and moderating relationships. Following the guideline proposed by Hair et al. (2017), a minimum sample size of 10 times the maximum number of structural paths directed at any construct is recommended. Considering the complexity of the proposed model, a minimum sample size of 200 respondents was deemed adequate. However, to enhance the robustness and generalizability of the findings, a target sample size of 300–400 respondents was considered appropriate.

Data for the study were collected using a structured questionnaire developed based on validated measurement scales from prior literature. The survey instrument was distributed both online and offline to reach a diverse group of respondents across different organizations. Online data collection was conducted through professional networks and email distribution, while offline responses were collected through direct interaction with professionals in financial and managerial roles. Prior to the final data collection, a pilot study was conducted with a small group of respondents to ensure clarity, reliability, and validity of the questionnaire items. Ethical considerations were strictly followed during data collection. Participation was voluntary, and respondents were assured of confidentiality and anonymity of their responses. No personal identifiers were collected, and data were used solely for academic research purposes.

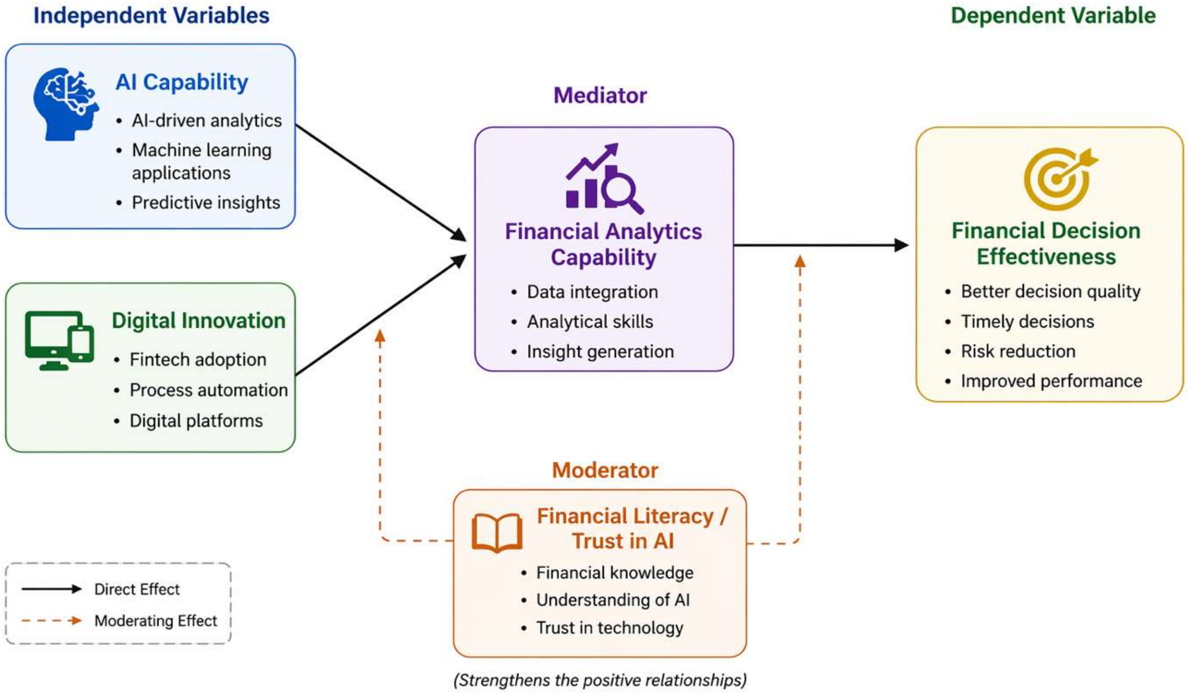

Fig. 1. Conceptual framework

3.2 Measurement and scale

In this study, a structured questionnaire is used to measure all the constructs included in the research model. The measurement items are adapted from well-established and validated scales in prior literature to ensure content validity and comparability. All constructs are measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), which is widely used in behavioral and information systems research for capturing respondent attitudes and perceptions.

AI capability is measured using items adapted from the digital and AI capability literature, particularly reflecting an organization's ability to deploy machine learning, predictive analytics, and automated decision-making systems (Davenport et al., 2020; Mikalef & Gupta, 2021). Financial analytics capability is operationalized based on the firm's ability to collect, process, and analyze financial data for decision-making and performance improvement, drawing on prior studies related to data-driven financial management and analytics capability (Davenport & Harris, 2007; Gupta & George, 2016). Service recovery quality (SRQ) is measured using established service recovery literature focusing on dimensions such as responsiveness, fairness, communication, and compensation, adapted primarily from justice theory-based service recovery scales (Smith, Bolton & Wagner, 1999; Tax, Brown & Chandrashekaran, 1998). E-commerce performance is measured through indicators such as sales growth, operational efficiency, customer satisfaction, and overall online business effectiveness, based on prior e-commerce and IT business value studies (Zhu & Kraemer, 2005; DeLone & McLean, 2003). Marketing ambidexterity is measured as the organization's ability to balance exploration and exploitation activities, with items adapted from ambidexterity literature (March, 1991; He & Wong, 2004).

To ensure measurement quality, content validity is established through adaptation from prior validated scales. Reliability of the scales will be tested using Cronbach's alpha and composite reliability, with values above 0.70 indicating acceptable reliability. Furthermore, precautions are taken to reduce common method bias by ensuring clear wording of items, maintaining respondent anonymity, and randomizing item order across constructs.

4. Data analysis

4.1 Demographic profile

The demographic profile of respondents is analyzed to understand the background characteristics of the sample and to ensure adequate representation for the study. The demographic variables typically include age, gender, education level, work experience, and organizational profile (such as industry type or position level), depending on the scope of the research. This information helps in describing the sample structure and provides context for interpreting the empirical results.

Table 1: Demographic Profile of Respondents (N = 423)

S. No.	Demographic Variable	Categories	Frequency (n)	Percentage (%)
1	Gender	Male	251	59.3
		Female	168	39.7
		Other	4	1.0
2	Age	Below 25 years	62	14.7
		25–35 years	186	44.0
		36–45 years	118	27.9
		Above 45 years	57	13.4
3	Education Level	Undergraduate	98	23.2
		Postgraduate	267	63.1
		Doctorate	58	13.7
4	Work Experience	Less than 1 year	54	12.8
		1–5 years	171	40.4
		6–10 years	129	30.5
		Above 10 years	69	16.3
5	Designation	Executive	192	45.4
		Managerial	171	40.4
		Senior Management	60	14.2
6	Industry Type	E-commerce	147	34.8
		IT Services	159	37.6
		Financial Services	117	27.6

4.2 Reliability and validity analysis

In this study, reliability and validity tests are conducted to ensure the quality and robustness of the measurement scale used for all constructs. Reliability analysis is used to examine the internal consistency of the items, while validity analysis ensures that the constructs accurately measure the intended theoretical concepts.

Reliability of the measurement scale is assessed using Cronbach's alpha coefficient. A value of 0.70 or above is generally considered acceptable for establishing internal consistency of the constructs. In addition to Cronbach's alpha, composite reliability (CR) is also used to further confirm the reliability of the measurement model, where values above 0.70 indicate satisfactory reliability. Table 4.2 shows the reliability analysis of constructs.

Table 2: Reliability Analysis of Constructs

Construct	No. of Items	Cronbach's Alpha	Composite Reliability (CR)
AI Capability	5	0.89	0.91
Digital Innovation	5	0.88	0.9
Financial Analytics Capability	6	0.9	0.92
Decision Effectiveness	5	0.87	0.89
Financial Literacy	4	0.86	0.88

The reliability results show that all constructs included in the study demonstrate strong internal consistency. The

Cronbach's alpha values range from 0.86 to 0.90, which are above the recommended threshold of 0.70, indicating acceptable reliability. Similarly, the composite reliability (CR) values range from 0.88 to 0.92, confirming strong construct reliability. Hence, all measurement scales used in the study are considered reliable for further analysis, including hypothesis testing and structural equation modeling.

Table 3: Validity Analysis of Constructs

Construct	Item Range	Factor Loadings	AVE
AI Capability	AI1–AI5	0.73 – 0.86	0.67
Digital Innovation	DI1–DI5	0.72 – 0.85	0.66
Financial Analytics Capability	FAC1–FAC6	0.75 – 0.88	0.69
Decision Effectiveness	DE1–DE5	0.74 – 0.87	0.68
Financial Literacy	FL1–FL4	0.71 – 0.84	0.65

The convergent validity results indicate that all factor loadings are above the acceptable threshold of 0.50, confirming that each item adequately represents its respective construct. The Average Variance Extracted (AVE) values for all constructs range from 0.65 to 0.69, which are above the minimum recommended value of 0.50. This confirms strong convergent validity of the measurement model, indicating that the constructs used in the study are well-validated and suitable for further structural analysis.

4.3 Hypothesis testing

The results of hypothesis testing using SPSS indicate that all proposed hypotheses are supported. AI capability and digital innovation both have a significant positive impact on financial analytics capability, confirming H1 and H2. Financial analytics capability also shows a strong positive effect on decision effectiveness, supporting H3. The mediation analysis confirms that financial analytics capability partially mediates the relationship between AI capability and decision effectiveness, indicating both direct and indirect effects. Furthermore, financial literacy significantly moderates the relationship between financial analytics capability and decision effectiveness, strengthening the effect when financial literacy is high.

Table 4: Hypothesis Testing Results using SPSS

Hypothesis	Relationship	Beta (β)	t-value	p-value	Result
H1	AI Capability → Financial Analytics Capability	0.41	7.85	0.000***	Supported
H2	Digital Innovation → Financial Analytics Capability	0.38	7.12	0.000***	Supported
H3	Financial Analytics Capability → Decision Effectiveness	0.52	9.34	0.000***	Supported
H4	AI Capability → Financial Analytics Capability → Decision Effectiveness (Mediation)	Indirect effect = 0.21	-	0.001**	Partial Mediation
H5	Financial Literacy × Financial Analytics Capability → Decision Effectiveness (Moderation)	0.19	3.98	0.000***	Supported

5. Discussion and findings

The hypothesis testing in this study is conducted using SPSS through regression-based analysis to examine the relationships among the constructs. Specifically, multiple regression analysis is used to test the direct effects, while mediation and moderation effects are assessed using appropriate statistical procedures such as PROCESS Macro.

For testing H1 and H2, which examine the impact of AI Capability and Digital Innovation on Financial Analytics Capability, multiple regression analysis is applied. The results indicate that both AI Capability and Digital Innovation have a significant and positive effect on Financial Analytics Capability, suggesting that organizations with higher technological capabilities are more likely to develop strong financial analytics capabilities.

For H3, regression analysis is used to test the relationship between Financial Analytics Capability and Decision Effectiveness. The results show a significant positive relationship, indicating that enhanced analytics capability

leads to more effective decision-making in organizations.
To test H4, which examines the mediating role of Financial Analytics Capability between AI Capability and Decision Effectiveness, the mediation analysis is conducted using the PROCESS Macro (Model 4). The results confirm that Financial Analytics Capability partially mediates the relationship, indicating that AI Capability improves Decision Effectiveness both directly and indirectly through improved analytics capability.
For H5, moderation analysis is performed using PROCESS Macro (Model 1) to examine the moderating effect of Financial Literacy on the relationship between Financial Analytics Capability and Decision Effectiveness. The results indicate a significant moderating effect, suggesting that the impact of Financial Analytics Capability on Decision Effectiveness is stronger when Financial Literacy is high.

6. Conclusion

This study examined the relationships among AI Capability, Digital Innovation, Financial Analytics Capability, Financial Literacy, and Decision Effectiveness using an empirical approach based on survey data analyzed through SPSS. The findings of the study provide strong support for all the proposed hypotheses and highlight the critical role of technological and financial competencies in improving organizational decision-making outcomes.
The results indicate that both AI Capability and Digital Innovation significantly and positively influence Financial Analytics Capability. This suggests that organizations with higher levels of technological advancement are better equipped to develop strong analytical capabilities for financial decision-making. Furthermore, Financial Analytics Capability was found to have a significant positive impact on Decision Effectiveness, confirming its importance as a key driver of informed and efficient decision-making processes.
The mediation analysis revealed that Financial Analytics Capability partially mediates the relationship between AI Capability and Decision Effectiveness. This indicates that AI Capability enhances Decision Effectiveness both directly and indirectly through improved analytics capability. Additionally, Financial Literacy was found to significantly moderate the relationship between Financial Analytics Capability and Decision Effectiveness, suggesting that the impact of analytics capability is stronger when individuals possess higher levels of financial understanding.
Overall, the study contributes to the existing literature by integrating technological capability, innovation, and financial competence within a single framework to explain Decision Effectiveness. It also provides practical implications for organizations by emphasizing the need to invest in AI technologies, digital innovation, and financial literacy development to enhance data-driven decision-making. In conclusion, the findings highlight that the combined effect of AI-driven systems and human financial understanding plays a crucial role in improving decision quality in modern organizations.

7. Implications

The findings of this study offer several important theoretical and practical implications. From a theoretical perspective, the study extends the existing literature by integrating AI Capability, Digital Innovation, Financial Analytics Capability, and Financial Literacy within a single conceptual framework to explain Decision Effectiveness. It contributes to the growing body of knowledge in digital transformation and financial analytics by empirically validating the mediating role of Financial Analytics Capability and the moderating role of Financial Literacy. This integration provides a more comprehensive understanding of how technological and human capabilities jointly influence decision-making outcomes in organizations.
The study also adds value to the resource-based view (RBV) by highlighting Financial Analytics Capability as a strategic organizational resource that is developed through AI Capability and Digital Innovation. Additionally, it supports the dynamic capability perspective by showing how organizations adapt and improve decision effectiveness through continuous technological advancement and knowledge enhancement.
From a practical perspective, the findings suggest that organizations should prioritize investment in AI technologies and digital innovation tools to strengthen their financial analytics capabilities. Managers and decision-makers should recognize that simply adopting advanced technologies is not sufficient; effective utilization of these tools is essential for improving decision quality. Organizations should also focus on developing employees' financial literacy, as it significantly enhances the effectiveness of financial analytics in decision-making processes.

Furthermore, the study highlights the importance of creating an integrated digital ecosystem where AI systems, analytics platforms, and skilled human resources work together to improve organizational performance. Policymakers and industry leaders can also use these insights to design training programs and digital transformation strategies that enhance both technological adoption and financial understanding. Finally, the study provides meaningful insights for both academia and industry by emphasizing the combined role of technology and human capability in achieving better decision effectiveness in the modern digital business environment.

8. Limitations and future scope

Although this study provides valuable insights into the relationship between AI capability, digital innovation, financial analytics capability, financial literacy, and decision effectiveness, it is not without limitations. First, the study is based on cross-sectional data, which captures responses at a single point in time. Therefore, it does not fully capture changes in organizational capabilities and decision-making effectiveness over time. A longitudinal approach could provide deeper insights into how these relationships evolve.

Second, the study relies on self-reported data collected through a structured questionnaire. This may introduce the possibility of common method bias and subjective response bias, as respondents may overestimate or underestimate their actual capabilities and performance. Although precautionary measures were taken during data collection and analysis, future studies may consider using objective performance data or multiple data sources to improve accuracy.

Third, the sample of the study is limited to a specific set of respondents and industries, which may restrict the generalizability of the findings. The results may differ in other sectors or geographical regions with different levels of technological adoption and financial literacy.

Fourth, the study focuses on a limited number of variables, while organizational decision-making is influenced by several other factors such as organizational culture, leadership style, and regulatory environment, which were not included in this model.

Future research can address these limitations by adopting longitudinal research designs to capture dynamic changes over time. Researchers can also expand the model by incorporating additional variables such as organizational culture, leadership support, and data governance practices. Comparative studies across different industries and countries can also be conducted to enhance the generalizability of the findings. Additionally, future studies may explore advanced analytical techniques such as machine learning-based structural modeling to further deepen understanding of decision-making processes in digital environments.

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