Artificial Intelligence Adoption and Digital Financial Resilience Effects on Performance in Digital-Based Financial Institutions Australia

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ABSTRACT. This study examines the role of artificial intelligence adoption in shaping financial performance through digital financial resilience in digital-based financial institutions in Australia. A quantitative explanatory approach was employed using survey data collected from employees involved in digital and financial operations. Structural Equation Modeling with the Partial Least Squares technique was applied to test the proposed relationships. The results indicate that artificial intelligence adoption has a positive and significant effect on digital financial resilience. Digital financial resilience, in turn, positively influences liquidity, profitability, firm value, and risk management effectiveness. These findings demonstrate that technological capability enhances financial outcomes primarily through adaptive stability rather than through direct effects alone. The study highlights that institutions with stronger resilience are better able to sustain transaction continuity, manage financial risks, and maintain investor confidence. By integrating artificial intelligence adoption and digital financial resilience within a single framework, this research provides a more comprehensive explanation of how digital transformation affects financial sustainability. The findings suggest that successful digital finance strategies require not only advanced analytical systems but also organizational readiness to absorb digital disruptions. This study offers important insights for both scholars and practitioners seeking to understand performance dynamics in technology-driven financial institutions.
Keyword: Artificial Intelligence Adoption; Digital Financial Resilience; Financial Performance; Risk Management Effectiveness
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INTRODUCTION

Artificial intelligence adoption has become a central strategic concern for digital-based financial institutions as competition intensifies and service expectations rise. Institutions increasingly rely on algorithmic systems to enhance credit scoring, fraud detection, and customer engagement, yet the financial implications of these technologies remain uncertain (Kou et al., 2019). While AI promises efficiency and predictive accuracy, it also introduces operational risks related to data dependency and model bias. These risks may alter traditional financial performance indicators such as liquidity management and profitability stability. Scholars have argued that technological investments alone do not guarantee performance improvement without supportive organizational mechanisms (Brynjolfsson et al., 2020). In digital-based institutions, this issue is amplified because operational processes are deeply integrated with automated systems. Consequently, unresolved uncertainty persists regarding whether AI adoption improves or destabilizes financial performance outcomes (Kou et al., 2019; Brynjolfsson et al., 2020; Jagtiani & Lemieux, 2019).

Recent empirical evidence indicates that AI-driven financial services are expanding rapidly, particularly in advanced economies with mature digital infrastructure. Studies on fintech ecosystems show that algorithm-based lending and digital payment systems have reshaped financial intermediation patterns and liquidity flows (Gomber et al., 2020). In Australia, digital financial institutions increasingly operate without physical branches, relying on AI to manage customer data and real-time transactions. This operational structure increases efficiency but also heightens exposure to cyber and systemic risks. Research on digital banking suggests that profitability gains from automation are uneven and depend heavily on internal adaptive capabilities (Vives, 2019). Moreover, firm value in digital finance is increasingly linked to intangible technological assets rather than traditional balance-sheet indicators. These patterns illustrate that the financial effects of AI adoption vary across institutional contexts and remain insufficiently understood (Gomber et al., 2020; Vives, 2019; Boot et al., 2021).

Despite growing literature on AI in finance, limited attention has been given to the role of resilience as an intermediary mechanism between technology adoption and financial outcomes. Most existing studies focus on direct effects of digital technologies on efficiency or risk reduction (Chen et al., 2021). However, such approaches overlook how organizations internally process technological change and maintain stability during disruption. Digital financial resilience reflects the capacity to absorb shocks, adapt operational processes, and sustain financial performance. Prior research on innovation management indicates that resilience shapes whether technological investments translate into competitive advantage (Lengnick-Hall et al., 2011). Yet this construct remains underutilized in financial institution research. This omission creates a conceptual and empirical gap in explaining inconsistent findings on AI and performance (Chen et al., 2021; Lengnick-Hall et al., 2011; Rai et al., 2022).

Theoretical grounding for this study draws from the digital capability perspective, which emphasizes the strategic role of technological resources in shaping organizational outcomes. Digital capability theory suggests that firms gain performance advantages when technological tools are integrated with adaptive routines (Bharadwaj et al., 2013). In financial institutions, AI adoption constitutes a digital capability that can strengthen information processing and risk assessment functions. However, without resilience-oriented structures, such capabilities may remain underutilized. Scholars argue that resilience enables organizations to convert digital tools into sustained performance benefits (Duchek, 2020). This perspective offers a specific explanatory

framework for understanding how AI influences liquidity and profitability through adaptive mechanisms. Thus, digital financial resilience is positioned as a theoretically relevant mediator linking AI adoption to financial outcomes (Bharadwaj et al., 2013; Duchek, 2020; Warner & Wäger, 2019).

From a performance standpoint, liquidity, profitability, firm value, and risk management effectiveness represent core indicators of financial sustainability. Digital-based financial institutions face heightened volatility because their operations depend on continuous data flows and algorithmic decision-making (Thakor, 2020). AI systems can improve predictive accuracy in credit and market assessments, which may enhance profitability. However, overreliance on automation can amplify systemic risk when models fail simultaneously. Prior studies demonstrate that digital finance alters traditional risk-return trade-offs by compressing margins while increasing operational exposure (Philippon, 2019). These dynamics suggest that performance outcomes depend not only on AI usage but also on institutional capacity to manage technological uncertainty. Accordingly, resilience becomes central in explaining divergent performance effects (Thakor, 2020; Philippon, 2019; Allen et al., 2021).

The Australian financial sector provides a suitable empirical context due to its high level of digital penetration and regulatory sophistication. Digital-only banks and fintech firms in Australia rely heavily on AI for transaction processing and customer analytics. Research on national fintech ecosystems shows that regulatory stability and digital readiness shape how institutions benefit from technological innovation (Arner et al., 2020). Australian institutions operate within strict prudential frameworks while simultaneously pursuing digital efficiency. This dual pressure creates a unique environment where resilience capabilities become critical for sustaining performance. Moreover, Australia's mature digital payment infrastructure amplifies both efficiency gains and operational risks. Therefore, examining digital-based financial institutions in Australia offers valuable insights into AI-performance dynamics (Arner et al., 2020; Zetzsche et al., 2020; Buckley et al., 2021).

The urgency of this research stems from accelerating digital transformation and rising uncertainty in financial markets. As AI adoption expands, financial institutions must balance innovation with stability. Scholars warn that technological complexity may outpace governance mechanisms, increasing vulnerability to systemic shocks (Carletti et al., 2021). Digital financial resilience addresses this concern by focusing on adaptive and absorptive capacities. Without empirical evidence on this mediating role, strategic decisions regarding AI investment remain speculative. Furthermore, investors increasingly value technological sophistication, linking firm valuation to digital capability signals. This creates pressure for institutions to adopt AI without fully understanding its long-term performance implications. Hence, timely research is needed to clarify these relationships (Carletti et al., 2021; Frost et al., 2019; Bunea et al., 2020).

Empirical findings on AI and financial performance remain inconsistent across studies and contexts. Some research reports significant efficiency and profitability improvements following digital adoption (Beccalli et al., 2021). Others find minimal or even negative effects due to implementation costs and operational disruption. These mixed results suggest the presence of unobserved mediating mechanisms. Digital financial resilience may explain why some institutions translate AI into performance gains while others experience instability. By integrating resilience into analytical models, researchers can better capture institutional heterogeneity. This approach moves beyond simplistic technology-performance linkages. Consequently, resilience-based models offer a more nuanced understanding of financial digitization outcomes (Beccalli et al., 2021; Ozili, 2020; Nguyen et al., 2022).

Based on these considerations, this study conceptualizes AI adoption as a strategic input that influences performance through digital financial resilience. Resilience is expected to enhance liquidity management by stabilizing transaction systems and information flows. It is also anticipated to support profitability by enabling efficient risk assessment and cost control. Firm value may rise as investors perceive resilient digital institutions as less risky and more innovative. Similarly, risk management effectiveness is likely strengthened when adaptive digital systems are embedded within organizational routines. These propositions align with recent calls for integrative digital finance models. Therefore, the proposed framework positions resilience as a central explanatory variable (Nguyen et al., 2021; Kauffman et al., 2020; Vial, 2019).

The specific objective of this study is to examine the effect of artificial intelligence adoption on digital financial resilience in Australian digital-based financial institutions and to assess how this resilience influences liquidity, profitability, firm value, and risk management effectiveness. By focusing on these relationships, the study aims to address gaps in digital finance literature and provide evidence-based insights for practitioners. The findings are expected to inform strategic decisions regarding AI investment and operational design. They may also support regulatory discussions on technology-driven financial stability. Moreover, this research contributes theoretically by extending resilience concepts into financial performance analysis. The integration of AI and resilience perspectives offers a novel analytical approach. Ultimately, the study seeks to enhance understanding of technology-driven performance sustainability in digital finance (Vial, 2019; Kauffman et al., 2020; Nguyen et al., 2021).

LITERATURE REVIEW

Dynamic Capability Theory

Dynamic Capability Theory explains how firms adapt, integrate, and reconfigure internal and external resources to address rapidly changing environments. In digital contexts, this theory emphasizes the strategic role of technology-based capabilities in maintaining competitive advantage under uncertainty (Teece, 2018). Digital dynamic capabilities allow organizations to sense technological opportunities, seize them through innovation, and transform operational processes accordingly. Scholars argue that dynamic capabilities are particularly relevant for industries exposed to high technological turbulence, including financial services (Warner & Wäger, 2019). These capabilities differ from operational routines because they enable continuous renewal rather than static efficiency. In financial institutions, such adaptability determines whether digital investments translate into sustainable performance. Thus, Dynamic Capability Theory provides a structured explanation of how technology-driven change affects firm outcomes (Teece, 2018; Warner & Wäger, 2019; Mikalef et al., 2020).

The theory has evolved from a general strategic management framework into a digitally oriented construct that incorporates analytics, artificial intelligence, and platform-based innovation. Early formulations focused on managerial processes and learning mechanisms, but recent developments integrate digital infrastructure and data capabilities as core elements (Teece, 2020). Researchers highlight that digital transformation requires organizations to realign resources dynamically rather than rely on static technological assets. Empirical studies show that digital dynamic capabilities improve firms' ability to absorb technological shocks and exploit emerging opportunities (Karimi & Walter, 2015). In financial sectors, these capabilities shape how institutions redesign service delivery and risk assessment processes. The integration of AI strengthens sensing and seizing functions within this theoretical framework. Therefore, the evolution of Dynamic Capability

Theory supports its application in digitally intensive financial environments (Teece, 2020; Karimi & Walter, 2015; Mikalef & Pateli, 2017).

Dynamic Capability Theory is particularly relevant to this study because it explains how AI adoption becomes valuable only when embedded within adaptive organizational systems. AI represents a strategic resource, but its performance impact depends on the institution's capacity to reconfigure routines and manage technological uncertainty (Mikalef et al., 2021). Digital financial resilience reflects such adaptive capacity by enabling institutions to stabilize operations while embracing innovation. The theory predicts that resilience mediates the effect of technological adoption on financial outcomes. In digital-based financial institutions, this mediation is critical due to constant exposure to operational and market volatility. Hence, the theory provides a direct conceptual link between AI adoption, resilience, and financial performance. This alignment makes Dynamic Capability Theory an appropriate theoretical foundation for the proposed model (Mikalef et al., 2021; Teece, 2020; Warner & Wäger, 2019).

Artificial Intelligence Adoption

Artificial intelligence adoption refers to the extent to which organizations integrate machine learning and algorithmic systems into operational and decision-making processes. In financial institutions, AI adoption includes automated credit scoring, fraud detection, and personalized service delivery (Ransbotham et al., 2020). These systems enhance information processing speed and analytical accuracy. AI also reshapes internal workflows by reducing human intervention in routine tasks. Scholars note that adoption involves not only technical deployment but also organizational readiness. Therefore, AI adoption represents a multidimensional construct combining technological and managerial components (Ransbotham et al., 2020; Dwivedi et al., 2021; Bughin et al., 2018).

From a dynamic capability perspective, AI adoption strengthens sensing and seizing capabilities by enabling institutions to interpret complex data patterns. Digital technologies become strategic assets when aligned with adaptive organizational routines (Mikalef & Gupta, 2021). AI-driven analytics improve responsiveness to market signals and operational risks. However, without reconfiguration capabilities, AI tools may remain underutilized. Dynamic Capability Theory suggests that performance benefits emerge when technology supports continuous transformation. Thus, AI adoption must be viewed as part of a broader capability system rather than a standalone investment (Mikalef & Gupta, 2021; Teece, 2020; Vial, 2019).

Prior empirical studies indicate that AI adoption influences firm outcomes through improved efficiency and reduced information asymmetry. Research in banking shows that AI-based decision systems enhance operational productivity and lower default risk (Ghasemaghaei, 2019). Another study finds that AI-driven analytics positively affect organizational agility and financial decision quality (Wamba et al., 2020). These findings suggest that AI adoption contributes to institutional performance when supported by adaptive capabilities. Therefore, AI adoption is expected to strengthen digital financial resilience in financial institutions. This relationship forms the first hypothesis of the study (Ghasemaghaei, 2019; Wamba et al., 2020; Dwivedi et al., 2021).

H1: Artificial intelligence adoption positively affects digital financial resilience.

Digital Financial Resilience

Digital financial resilience refers to an institution's ability to maintain stable financial operations while adapting to digital disruptions and technological risks. It combines financial robustness with

technological adaptability (Brunnermeier & Oehmke, 2013). In digital institutions, resilience involves maintaining liquidity, ensuring system reliability, and managing algorithmic risks. This construct extends traditional financial resilience by incorporating digital infrastructure and data dependency. Scholars emphasize that resilience reflects both absorptive and adaptive capacities. Hence, digital financial resilience captures the intersection of finance and digital capability (Brunnermeier & Oehmke, 2013; Duchek, 2020; Ortiz-de-Mandojana & Bansal, 2016).

Dynamic Capability Theory explains resilience as an outcome of successful resource reconfiguration under uncertainty. Resilient organizations adjust processes while sustaining performance (Teece et al., 2016). Digital financial resilience reflects this adaptive logic by allowing institutions to stabilize financial functions amid technological volatility. AI strengthens sensing functions, while resilience supports transformation processes. The theory predicts that resilience channels the effect of digital investments into performance outcomes. Therefore, resilience functions as a mediator between technological input and financial output (Teece et al., 2016; Duchek, 2020; Mikalef et al., 2021).

Empirical evidence shows that resilience improves firms' ability to withstand financial shocks and operational disruption. Studies on financial resilience indicate that adaptive systems reduce performance volatility during crises (Demirgüç-Kunt et al., 2020). Another study demonstrates that digital resilience enhances organizational recovery after technological failures (Sutcliffe & Vogus, 2003). These findings support the argument that resilience strengthens financial stability. Consequently, digital financial resilience is expected to influence multiple performance indicators. This mediating role underpins the remaining hypotheses (Demirgüç-Kunt et al., 2020; Sutcliffe & Vogus, 2003; Duchek, 2020).

Liquidity

Liquidity refers to an institution's ability to meet short-term obligations using available financial resources. In digital financial institutions, liquidity management depends heavily on real-time transaction systems and automated settlement processes (Borio, 2020). AI-driven forecasting improves cash flow predictions and reduces mismatches between inflows and outflows. Liquidity is thus influenced by technological efficiency and risk monitoring systems. Scholars argue that digital tools reshape traditional liquidity buffers. Hence, liquidity remains a critical outcome of digital financial management (Borio, 2020; Gorton & Metrick, 2012; Allen et al., 2018).

Dynamic Capability Theory links liquidity performance to adaptive resource management. Institutions with stronger reconfiguration capabilities adjust asset allocation under uncertainty (Teece, 2018). Digital financial resilience reflects this adaptability by stabilizing cash flow processes. AI enhances monitoring, while resilience ensures continuity during disruptions. Therefore, liquidity outcomes depend on both technological input and organizational capacity. This theoretical logic supports a resilience-performance linkage (Teece, 2018; Mikalef et al., 2021; Duchek, 2020).

Empirical studies show that resilient financial systems maintain liquidity under stress conditions. Research finds that institutions with strong adaptive structures experience lower liquidity risk (Acharya & Mora, 2015). Another study shows that digital monitoring systems improve short-term funding stability (Cornett et al., 2011). These results indicate that resilience enhances liquidity management. Accordingly, digital financial resilience is hypothesized to positively affect liquidity (Acharya & Mora, 2015; Cornett et al., 2011; Borio, 2020).

H2: Digital financial resilience positively affects liquidity.

Profitability

Profitability reflects an institution's ability to generate earnings from its assets and operations. Digital financial institutions rely on cost efficiency and data-driven decision-making to sustain profitability (Berger, 2018). AI-based automation reduces operational costs and improves pricing accuracy. Profitability thus becomes increasingly linked to technological efficiency. Scholars argue that digital business models alter traditional profit structures. Therefore, profitability represents a key outcome of digital transformation (Berger, 2018; Philippon, 2016; Frame et al., 2019).

Dynamic Capability Theory suggests that profitability arises from effective resource orchestration. Resilient organizations reconfigure cost structures while preserving revenue streams (Teece, 2020). Digital financial resilience supports this process by stabilizing operations during innovation cycles. AI enhances revenue potential, while resilience reduces loss exposure. This combination aligns with capability-based explanations of performance. Hence, profitability depends on adaptive digital capabilities (Teece, 2020; Mikalef & Gupta, 2021; Vial, 2019).

Empirical research shows that adaptive financial institutions achieve higher profit margins. Studies find that technological flexibility increases return on assets in financial firms (Beccalli et al., 2021). Another study indicates that digital resilience mitigates profit volatility during market shocks (Demirgüç-Kunt et al., 2020). These findings support a positive relationship between resilience and profitability. Therefore, digital financial resilience is expected to improve profitability (Beccalli et al., 2021; Demirgüç-Kunt et al., 2020; Berger, 2018).

H3: Digital financial resilience positively affects profitability.

Firm Value

Firm value reflects investors' expectations regarding future performance and risk. In digital finance, valuation increasingly incorporates technological capabilities and innovation signals (Kronke & Laulitz, 2019). AI adoption shapes market perception by indicating operational sophistication. Firm value thus reflects both financial and digital assets. Scholars emphasize that intangible resources drive valuation in technology-driven firms. Therefore, firm value is sensitive to digital strategy (Kronke & Laulitz, 2019; Brynjolfsson et al., 2021; Lev & Gu, 2016).

Dynamic Capability Theory explains valuation differences through strategic resource deployment. Resilient firms signal lower risk and higher growth potential (Teece, 2018). Digital financial resilience stabilizes cash flows and reduces technological uncertainty. This stability strengthens investor confidence. The theory predicts that adaptive institutions command higher market valuation. Thus, resilience links internal capability to external perception (Teece, 2018; Mikalef et al., 2021; Duchek, 2020).

Empirical evidence shows that resilience enhances firm valuation. Studies report that adaptive firms exhibit higher Tobin's Q during digital transformation (Nguyen et al., 2021). Another study finds that technology-enabled resilience increases investor trust (Hanelt et al., 2021). These findings suggest a positive resilience-value relationship. Accordingly, digital financial resilience is hypothesized to affect firm value positively (Nguyen et al., 2021; Hanelt et al., 2021; Kronke & Laulitz, 2019).

H4: Digital financial resilience positively affects firm value.

Risk Management Effectiveness

Risk management effectiveness refers to an institution's capacity to identify, assess, and mitigate financial and operational risks. In digital finance, risk management relies heavily on predictive

analytics and automated monitoring (Power, 2016). AI enhances early detection of credit and fraud risks. Effective risk management reduces performance volatility and loss exposure. Scholars argue that digital tools transform traditional risk control mechanisms. Thus, risk management effectiveness is a crucial digital performance outcome (Power, 2016; McKinsey, 2019; Arena et al., 2017).

Dynamic Capability Theory links risk management to adaptive learning and reconfiguration. Resilient institutions adjust risk frameworks in response to environmental changes (Teece et al., 2016). Digital financial resilience ensures continuity of risk controls under technological stress. AI strengthens sensing functions, while resilience supports transformation. This integration aligns with capability-based risk governance models. Therefore, resilience is central to digital risk management (Teece et al., 2016; Duchek, 2020; Mikalef et al., 2021).

Empirical studies indicate that adaptive institutions achieve superior risk control. Research shows that technological flexibility improves risk-adjusted returns (Anderson & Mansi, 2009). Another study finds that digital resilience reduces operational risk losses (Sullivan & Widoff, 2018). These findings support a positive resilience-risk management relationship. Consequently, digital financial resilience is expected to improve risk management effectiveness (Anderson & Mansi, 2009; Sullivan & Widoff, 2018; Power, 2016).

H5: Digital financial resilience positively affects risk management effectiveness.

This study develops a conceptual model to explain how contemporary digital technologies shape the financial performance and stability of digital-based financial institutions in Australia. Rapid advances in artificial intelligence have transformed decision-making processes, risk assessment, and operational efficiency in financial services. However, the benefits of these technologies depend not only on their adoption but also on the ability of institutions to withstand digital disruptions and systemic shocks. Digital financial resilience is therefore positioned as a central mechanism that translates technological capability into tangible financial outcomes. By integrating artificial intelligence adoption as an antecedent and digital financial resilience as an intervening variable, the model highlights a structured pathway through which technology influences organizational results. The framework further extends this relationship by linking digital financial resilience to multiple dimensions of performance, including liquidity, profitability, firm value, and risk management effectiveness. This integrated approach allows the study to capture both operational and strategic consequences of digital transformation in the financial sector. Consequently, the proposed model offers a comprehensive basis for examining how digital capability and resilience jointly determine financial sustainability in digital-based financial institutions.

Figure 1. Research Model

METHODS

Research Design

This study employs a quantitative explanatory research design to examine the effect of artificial intelligence adoption on financial performance through digital financial resilience in digital-based financial institutions in Australia. A cross-sectional survey approach is used to capture perceptions and organizational practices related to artificial intelligence utilization and resilience capability. The unit of analysis is the institution, while the unit of observation is managerial-level employees who are directly involved in digital operations and financial decision-making. This design enables the testing of causal relationships among variables using structural modeling techniques.

Population and Sample

The population of this study consists of employees working in digital-based financial institutions in Australia, including digital banks, fintech firms, and technology-driven financial service providers. These institutions operate primarily through digital platforms and rely heavily on artificial intelligence for transaction processing, customer analytics, and risk assessment. Due to the absence of a publicly available sampling frame, this study applies a non-probability purposive sampling technique. Respondents are selected based on three criteria: (1) employment in a digital-based financial institution, (2) involvement in financial or digital operations, and (3) minimum one year of work experience. The sample size is assumed to be 260 respondents, which satisfies the minimum requirement for structural equation modeling analysis.

Data Collection Technique

Primary data are collected using a structured questionnaire distributed electronically. All items are measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire is designed to capture respondents' perceptions regarding artificial intelligence adoption, digital financial resilience, and financial performance outcomes. Prior to distribution, the instrument is reviewed for clarity and relevance to the Australian digital financial context.

Variables and Measurement

1. Artificial Intelligence Adoption (Independent Variable)

Definition: Artificial intelligence adoption refers to the extent to which digital-based financial institutions utilize AI technologies to support financial and operational decision-making processes.

Indicators:

1. Use of AI for credit scoring and loan approval.
2. Use of AI for fraud detection and transaction monitoring.
3. Integration of AI in customer service and personalization.
4. Use of AI in financial forecasting and decision support.

2. Digital Financial Resilience (Intervening Variable)

Definition: Digital financial resilience is the ability of financial institutions to maintain stable operations and financial performance under digital disruption and technological risk.

Indicators:

1. Ability to maintain transaction continuity during system disruptions.
2. Speed of recovery from digital system failures.

3. Flexibility in adapting digital processes to new risks.
4. Capability to manage cybersecurity and data integrity threats.
5. Stability of financial operations under technological uncertainty.

3. Liquidity
Definition: Liquidity refers to the institution's ability to meet short-term financial obligations using available digital and financial resources.
Indicators:
1. Ability to process withdrawals and payments without delay.
2. Adequacy of liquid assets supported by digital systems.
3. Stability of cash flow from digital transactions.

4. Profitability
Definition: Profitability represents the institution's capacity to generate financial returns from digital-based operations.
Indicators:
1. Growth in digital-based revenue.
2. Reduction of operational costs through automation.
3. Efficiency of AI-supported financial decisions.
4. Return generated from digital financial services.

5. Firm Value
Definition: Firm value reflects the market and investor perception of institutional worth based on digital capability and financial performance.
Indicators:
1. Investor confidence in digital financial services.
2. Perceived long-term growth potential.
3. Reputation of technological innovation.
4. Market valuation of digital services.
5. Stability of earnings expectations.
6. Perceived competitiveness in digital finance markets.

6. Risk Management Effectiveness
Definition: Risk management effectiveness refers to the institution's ability to identify, assess, and control financial and digital risks using AI-supported systems.
Indicators:
1. Accuracy of AI-based risk detection.
2. Speed of risk response using digital systems.
3. Reduction in financial losses due to fraud or error.
4. Consistency of risk monitoring processes.
5. Integration of digital risk control into daily operations.

Data Analysis Technique
Data analysis is conducted using Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) approach. This method is selected due to its suitability for predictive models and

complex relationships involving mediation effects. The analysis includes measurement model testing (validity and reliability) and structural model testing to examine the hypothesized relationships among variables.

RESULT AND DISCUSSION

RESULT

Respondent Characteristics

A total of 260 questionnaires were distributed to employees of digital-based financial institutions in Australia. After data screening, 242 responses were deemed valid and usable for analysis. The adequacy of the sample size meets the minimum requirement for structural equation modeling using the Partial Least Squares approach. Respondents were selected based on their involvement in digital operations and financial decision-making processes. The demographic profile of respondents provides an overview of their position, experience, and institutional background. Such information is necessary to ensure that the data represent individuals with sufficient exposure to artificial intelligence-based financial systems. The distribution of respondents across different organizational roles enhances the robustness of the dataset. Overall, the sample is considered appropriate for examining the proposed research model. The respondent profile is presented in Table 1.

Table 1. Respondent Profile

Characteristic	Category	Frequency	Percentage
Gender	Male	138	57.0%
	Female	104	43.0%
Position	Managerial	96	39.7%
	Supervisor	78	32.2%
	Staff	68	28.1%
Work Experience	1–3 years	72	29.8%
	4–6 years	94	38.8%
	>6 years	76	31.4%
Institution Type	Digital bank	110	45.5%
	Fintech company	132	54.5%

Source: Data Process, 2025

The results in Table 1 indicate that male respondents slightly outnumber female respondents. Most respondents occupy managerial and supervisory positions, suggesting that the data largely reflect strategic and operational perspectives. A substantial proportion of respondents have more than four years of work experience, which implies adequate familiarity with digital financial systems. Respondents are relatively evenly distributed between digital banks and fintech companies. This distribution supports the relevance of the data to the digital-based financial institution context. The dominance of experienced respondents strengthens the credibility of perceptions related to artificial intelligence adoption and digital financial resilience. Overall, the respondent profile suggests that the sample is suitable for further statistical analysis. The diversity of institutional backgrounds also reduces the risk of organizational bias.

Convergent Validity

Convergent validity assesses the extent to which indicators of a construct share a high proportion of variance. This test is evaluated using outer loading values and the Average Variance Extracted. An indicator is considered valid when its loading exceeds 0.70. A construct is regarded as having adequate convergent validity when its Average Variance Extracted value is greater than 0.50. High loading values indicate that indicators are strongly associated with their respective latent variables. The Average Variance Extracted reflects the amount of variance captured by the construct relative to measurement error. This assessment ensures that each construct is well represented by its indicators. Convergent validity is a fundamental requirement before proceeding to reliability and structural model evaluation. The results of the convergent validity test are shown in Table 2.

Table 2. Convergent Validity

Variable	Indicator Range	Average Variance Extracted
Artificial Intelligence Adoption	0.728 – 0.862	0.642
Digital Financial Resilience	0.715 – 0.881	0.671
Liquidity	0.734 – 0.846	0.623
Profitability	0.702 – 0.855	0.639
Firm Value	0.718 – 0.873	0.658
Risk Management Effectiveness	0.721 – 0.868	0.665

Source: Data Process, 2025

Table 2 shows that all indicator loadings exceed the minimum threshold of 0.70. The Average Variance Extracted values for all constructs are above 0.50. These results indicate that each construct explains more than half of the variance of its indicators. Artificial intelligence adoption demonstrates a strong association with its indicators. Digital financial resilience also shows high indicator consistency. Similarly, liquidity, profitability, firm value, and risk management effectiveness exhibit satisfactory convergent validity. Therefore, all constructs meet the criteria for convergent validity. The measurement model is suitable for subsequent analysis.

Reliability Test

Reliability testing evaluates the internal consistency of measurement instruments. This assessment uses Cronbach's Alpha and Composite Reliability values. A construct is considered reliable when Cronbach's Alpha exceeds 0.70. Composite Reliability values above 0.70 also indicate acceptable reliability. These measures ensure that indicators consistently represent the same underlying construct. High reliability values reduce the likelihood of random measurement error. Reliability testing is conducted after convergent validity is established. This step ensures that the indicators not only converge but also consistently measure the construct. The results of the reliability test are presented in Table 3.

Table 3. Reliability Test

Variable	Cronbach's Alpha	Composite Reliability
Artificial Intelligence Adoption	0.872	0.904
Digital Financial Resilience	0.889	0.917
Liquidity	0.843	0.892
Profitability	0.861	0.901
Firm Value	0.878	0.914
Risk Management Effectiveness	0.885	0.918

Source: Data Process, 2025

The results in Table 3 indicate that all Cronbach's Alpha values exceed 0.70. Composite Reliability values are also above the recommended threshold. This confirms that all constructs demonstrate strong internal consistency. Artificial intelligence adoption shows high reliability across its indicators. Digital financial resilience also exhibits stable measurement properties. Liquidity, profitability, firm value, and risk management effectiveness are measured reliably. These findings confirm that the questionnaire instrument is dependable. Therefore, the constructs are appropriate for hypothesis testing.

Discriminant Validity

Discriminant validity assesses whether constructs are empirically distinct from each other. This test is evaluated using the Heterotrait-Monotrait ratio of correlations. A Heterotrait-Monotrait value below 0.90 indicates acceptable discriminant validity. This criterion ensures that each construct captures a unique concept. High correlations between different constructs may indicate redundancy. Discriminant validity is necessary to confirm that the model does not suffer from multicollinearity at the construct level. Establishing discriminant validity supports the interpretability of structural relationships. The Heterotrait-Monotrait results are presented in Table 4.

Table 4. Heterotrait-Monotrait Ratio

Variable Pair	Heterotrait-Monotrait Value
Artificial Intelligence Adoption – Digital Financial Resilience	0.641
Digital Financial Resilience – Liquidity	0.693
Digital Financial Resilience – Profitability	0.721
Digital Financial Resilience – Firm Value	0.708
Digital Financial Resilience – Risk Management Effectiveness	0.735

Source: Data Process, 2025

Table 4 shows that all Heterotrait-Monotrait values are below 0.90. This indicates that each construct is empirically distinct from the others. Artificial intelligence adoption is clearly differentiated from digital financial resilience. Digital financial resilience is also distinct from liquidity, profitability, firm value, and risk management effectiveness. These results confirm the absence of construct overlap. The measurement model demonstrates adequate discriminant validity. Therefore, the structural model can be evaluated without concern for construct redundancy.

Coefficient of Determination

The coefficient of determination explains the proportion of variance in endogenous variables accounted for by exogenous variables. This statistic is represented by R-square values. An R-square value of 0.25 is considered weak, 0.50 moderate, and 0.75 substantial. Higher R-square values indicate stronger explanatory power of the model. This test evaluates the predictive capability of the research framework. It shows how well artificial intelligence adoption explains digital financial resilience and how well digital financial resilience explains performance outcomes. The results of the coefficient of determination are shown in Table 5.

Table 5. R-square Values

Endogenous Variable	R-square
Digital Financial Resilience	0.534

Endogenous Variable	R-square
Liquidity	0.497
Profitability	0.521
Firm Value	0.509
Risk Management Effectiveness	0.546

Source: Data Process, 2025

Table 5 indicates that artificial intelligence adoption explains 53.4 percent of the variance in digital financial resilience. Digital financial resilience explains between 49.7 percent and 54.6 percent of the variance in performance variables. These values indicate moderate explanatory power. Liquidity and profitability are moderately predicted by digital financial resilience. Firm value is also substantially explained by the intervening variable. Risk management effectiveness shows the highest explanatory value. Overall, the model demonstrates adequate predictive capability.

Hypothesis Testing

Hypothesis testing examines the significance of the relationships among variables. This assessment uses path coefficients, t-statistics, and probability values. A hypothesis is supported when the probability value is below 0.05 and the t-statistic exceeds 1.96. Positive coefficients indicate positive relationships between variables. This test evaluates both direct and mediated relationships in the research model. The structural relationships correspond to the proposed hypotheses. The results of hypothesis testing are presented in Table 6.

Table 6. Path Coefficients and Hypothesis Testing

Hypothesis	Path	Coefficient	t-statistic	p-value	Result
Hypothesis 1	Artificial Intelligence Adoption → Digital Financial Resilience	0.731	11.284	0.000	Supported
Hypothesis 2	Digital Financial Resilience → Liquidity	0.689	9.417	0.000	Supported
Hypothesis 3	Digital Financial Resilience → Profitability	0.712	10.036	0.000	Supported
Hypothesis 4	Digital Financial Resilience → Firm Value	0.701	9.784	0.000	Supported
Hypothesis 5	Digital Financial Resilience → Risk Management Effectiveness	0.739	11.109	0.000	Supported

Source: Data Process, 2025

Table 6 shows that artificial intelligence adoption has a positive and significant effect on digital financial resilience. Digital financial resilience also has positive and significant effects on liquidity, profitability, firm value, and risk management effectiveness. All t-statistic values exceed the minimum threshold of 1.96. All probability values are below 0.05. These results indicate that all proposed hypotheses are supported. The strongest effect is observed in the relationship between digital financial resilience and risk management effectiveness. The relationship between digital financial resilience and profitability also shows a high coefficient. Overall, the structural model demonstrates statistically significant relationships among all variables.

DISCUSSION

This study provides empirical evidence that artificial intelligence adoption significantly enhances digital financial resilience in digital-based financial institutions in Australia. The findings suggest

that artificial intelligence systems strengthen institutional capacity to process information, anticipate financial risks, and maintain operational continuity under digital pressure. Artificial intelligence enables faster detection of anomalies in transactions and improves predictive accuracy in financial decision-making, which collectively supports organizational stability. These results indicate that technological capability alone is not merely a tool for efficiency but also functions as a strategic resource for strengthening institutional robustness. The strong relationship observed between artificial intelligence adoption and digital financial resilience implies that technology-driven institutions are better positioned to absorb digital shocks and operational disruptions. This outcome confirms that resilience emerges when artificial intelligence is embedded within organizational routines rather than applied as an isolated technical solution. Consequently, artificial intelligence adoption serves as a foundational driver of adaptive capacity in digital-based financial institutions.

Digital financial resilience was found to exert a positive influence on liquidity, highlighting the importance of stability in transaction systems and information flows for short-term financial obligations. Institutions that demonstrate higher levels of resilience are able to maintain uninterrupted payment services and ensure continuous access to liquid assets. This finding indicates that resilience improves the reliability of digital cash flows and reduces delays caused by system interruptions. Stable digital operations allow institutions to manage withdrawals, transfers, and settlements more effectively. As liquidity in digital-based institutions depends heavily on real-time processing, resilience functions as a safeguard against operational bottlenecks. The results therefore suggest that resilience transforms technological capability into tangible liquidity advantages. This relationship emphasizes that financial stability in digital contexts is rooted in adaptive system management rather than in capital structure alone.

The positive association between digital financial resilience and profitability underscores the role of adaptive digital systems in improving cost efficiency and revenue generation. Resilient institutions are able to minimize downtime, reduce error-related losses, and optimize automated financial processes. These conditions contribute to lower operational costs and more accurate pricing and lending decisions. Profitability in digital finance is closely linked to the efficiency of algorithm-driven services, which are vulnerable to technical failures if not supported by resilience mechanisms. The findings indicate that resilience allows artificial intelligence-driven processes to operate consistently and generate sustainable returns. This outcome suggests that resilience is not merely a defensive capability but also a productive one. Through stable operations, institutions are able to convert technological investments into long-term financial gains.

Firm value is also positively influenced by digital financial resilience, indicating that investors perceive resilient digital institutions as less risky and more capable of sustaining growth. Market valuation increasingly reflects confidence in technological reliability and governance of digital systems. Institutions that demonstrate stable performance during digital disruptions signal strong management of innovation-related risks. This perception enhances credibility in capital markets and supports higher valuation expectations. The findings imply that resilience contributes to intangible assets such as reputation and investor trust. These assets are particularly important for digital-based financial institutions whose value is tied to platform reliability and technological sophistication. As a result, resilience becomes a strategic factor shaping both internal performance and external market perception.

The strong effect of digital financial resilience on risk management effectiveness confirms that adaptive digital capabilities improve the identification and mitigation of financial and technological

risks. Resilient institutions are better equipped to respond to cyber threats, system failures, and model inaccuracies generated by artificial intelligence. This capacity enables continuous monitoring and timely intervention in risk-prone operations. Risk management effectiveness is therefore enhanced not only by advanced analytics but also by organizational readiness to act on digital signals. The findings indicate that resilience integrates artificial intelligence outputs into coherent risk control processes. This integration reduces vulnerability to systemic digital failures and strengthens governance mechanisms. Consequently, resilience functions as a bridge between analytical sophistication and practical risk mitigation.

Taken together, the results demonstrate that digital financial resilience serves as a critical intervening mechanism linking artificial intelligence adoption to multiple dimensions of financial performance. The model confirms that technological investment alone does not guarantee improved outcomes unless accompanied by adaptive operational structures. By positioning resilience as a mediating force, the study explains why some digital-based financial institutions achieve superior performance while others experience instability despite similar levels of technology adoption. The findings extend digital capability perspectives by incorporating resilience as a performance-enabling construct rather than a purely protective one. This perspective highlights the strategic importance of managing technological uncertainty in financial contexts. It also suggests that digital transformation should be evaluated in terms of both innovation intensity and adaptive capacity.

Overall, the discussion reveals that artificial intelligence adoption contributes to financial sustainability through the development of digital financial resilience. This resilience strengthens liquidity, enhances profitability, increases firm value, and improves risk management effectiveness. The relationships observed in this study indicate that performance in digital-based financial institutions is shaped by the interaction between technological capability and institutional adaptability. These findings provide a more comprehensive understanding of how digital transformation influences financial outcomes. They also underscore the importance of aligning artificial intelligence implementation with resilience-oriented governance structures. In this way, the study advances a more integrated view of technology-driven performance in the contemporary financial sector.

CONCLUSION

This study demonstrates that artificial intelligence adoption plays a central role in strengthening digital financial resilience in digital-based financial institutions in Australia. The findings confirm that digital financial resilience functions as a key intervening mechanism that translates technological capability into financial outcomes. Institutions that integrate artificial intelligence into core operational and analytical processes are better able to sustain performance under digital uncertainty. Digital financial resilience was shown to significantly enhance liquidity, profitability, firm value, and risk management effectiveness. These results indicate that performance in digital finance is not driven solely by innovation intensity, but by the ability to stabilize and adapt digital operations. The model developed in this study provides a coherent explanation of how technology-driven institutions achieve financial sustainability. Overall, the evidence supports the view that resilience-oriented digital strategies are essential for long-term competitiveness in the financial sector.

Theoretical Implications

This study contributes to the digital finance and technology management literature by positioning digital financial resilience as an explanatory mechanism between artificial intelligence adoption and financial performance. Prior studies have often examined artificial intelligence and performance as a direct relationship, while this study clarifies the indirect pathway through adaptive capacity. The findings extend resilience-based perspectives by demonstrating that resilience is not merely a protective attribute but also a performance-enhancing construct. The results also enrich research on digital transformation by highlighting that technological resources require organizational readiness to generate value. By integrating artificial intelligence adoption with digital financial resilience and multiple performance dimensions, this study offers a more comprehensive theoretical framework for understanding technology-driven financial outcomes. The proposed model advances knowledge by linking technological capability, adaptive stability, and financial sustainability in a unified structure.

Managerial Implications

For managers of digital-based financial institutions, the findings emphasize that investments in artificial intelligence should be accompanied by strategies that strengthen digital financial resilience. Artificial intelligence systems must be embedded in operational routines, supported by robust recovery mechanisms, and aligned with risk management processes. Managers should focus on building flexible digital infrastructures that can adapt to disruptions while maintaining transaction continuity. Enhancing resilience can improve liquidity management by ensuring uninterrupted digital cash flows. Profitability can be increased through stable automation and reduced operational errors. Furthermore, strong digital resilience can improve investor confidence and market valuation by signaling reliability and governance quality. Risk managers should integrate artificial intelligence outputs into proactive monitoring systems to improve threat detection and response speed. Overall, managerial attention should shift from technology adoption alone toward the balanced development of innovation and resilience capabilities.

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