

Artificial Intelligence Utilization and Financial Management Optimization in Kendari Startups and Innovative Ventures

Ridha Taurisma Lajaria*, Rastiani Parabang, Khafiza Olivia, Rasty
Universitas Sulawesi Tenggara, Kendari, Southeast Sulawesi, 93116, Indonesia

ABSTRACT

Purpose – This study examines whether Artificial Intelligence (AI) utilization is positively associated with financial management optimization among startups and innovative ventures in Kendari City. It addresses the limited local empirical evidence on how AI utilization capability relates to operational financial outcomes in emerging entrepreneurial ecosystems.

Design/methodology/approach – A quantitative explanatory survey was conducted with 50 startup owners, founders, and financial managers selected through purposive sampling. Data were collected using a structured four-point Likert questionnaire and analyzed with descriptive statistics, Pearson correlation, and simple linear regression.

Finding/Results – AI utilization capability demonstrated a positive and significant association with financial management optimization ($r = 0.681$, $p < 0.001$). Regression analysis confirms that AI utilization capability is positively associated with financial management optimization ($B = 0.646$; standardized $\beta = 0.681$; $p < 0.001$; $R^2 = 0.464$). Startups with higher AI utilization report better operational efficiency, planning and reporting accuracy, cash-flow control, and financial decision quality.

Originality/Value – The study extends the AI-finance literature by providing context-specific evidence from Kendari and by linking AI utilization to four managerial outcome areas of startup financial management. The findings highlight predictive analytics and decision-support functions as especially relevant for financially constrained and uncertainty-prone ventures.

ARTICLE INFO

Keywords:

Artificial Intelligence,
Financial Management,
Startups, Innovative
Ventures, Kendari

Article Information:

Received: 24/07/2026

Revise: 20/08/2026

Accepted: 08/09/2026

ISSN:

2985-3168 (Online)

2985-3222 (Print)

*Corresponding Author at:

Universitas Sulawesi Tenggara, Kendari, Southeast Sulawesi, 93116, Indonesia.

E-mail address: ridhataurisma.mm@gmail.com (Ridha Taurisma Lajaria)

The work is licensed under a [Creative Commons Attribution-ShareAlike 4.0 International \(CC BY-SA 4.0\)](https://creativecommons.org/licenses/by-sa/4.0/)



1. Introduction

Digital transformation has fundamentally reshaped how entrepreneurial firms generate, process, and utilize information for managerial decision-making. Among emerging digital technologies, Artificial Intelligence (AI) has attracted increasing attention because it enables organizations to automate repetitive processes, identify complex patterns, generate predictive insights, and support decisions based on large volumes of data (Dwivedi et al., 2021; Duan et al., 2021). Unlike conventional information systems that primarily support data storage and reporting, AI-based technologies provide analytical capabilities that allow firms to transform financial information into actionable managerial knowledge. The evolution of AI-enabled digital ecosystems has also been associated with broader changes in how firms create, process, and utilize information resources. Previous research highlights that digital technologies, including AI, big data, and intelligent platforms, have transformed organizational decision-making by enabling automation, augmentation, and knowledge-based management practices (Brynjolfsson & McAfee, 2017; Davenport & Ronanki, 2018).

For startups and innovative ventures, these capabilities are particularly relevant because early-stage businesses frequently operate under conditions of limited financial resources, uncertain revenue patterns, restricted managerial capacity, and rapidly changing market environments. Greater AI utilization capability may help these ventures improve operational efficiency, enhance financial visibility, and strengthen decision-making processes through automated reporting, predictive analytics, and intelligent decision-support mechanisms (Jöhnk et al., 2021; Raisch & Krakowski, 2021).

AI applications in financial management extend beyond routine automation by enabling advanced financial analytics and decision-support activities. AI-enabled accounting systems, predictive models, and intelligent financial platforms can assist organizations in transaction classification, real-time reporting, cash-flow forecasting, budgeting scenarios, and financial risk identification (Bhimani & Willcocks, 2021; Issa et al., 2016). The organizational value of AI depends not only on technology availability but also on the capability of firms to integrate AI into existing managerial processes and decision structures (Raisch & Krakowski, 2021).

For small and entrepreneurial firms, digital capability becomes an important condition determining whether technological adoption produces meaningful organizational benefits. Digital transformation research indicates that firms with stronger digital capabilities are better positioned to utilize emerging technologies, adapt business processes, and develop innovation-oriented practices (Verhoef et al., 2021; Li et al., 2018).

Although previous studies have examined AI utilization capability, digital transformation, and technology-enabled decision-making, empirical evidence from startups and innovative ventures in emerging entrepreneurial ecosystems remains limited. Previous studies often discuss AI utilization capability as a general digital transformation phenomenon, while fewer studies examine how AI utilization relates specifically to multidimensional financial-management capabilities, including operational efficiency, reporting accuracy, cash-flow control, and financial decision quality.

This study contributes by providing empirical evidence from startups and innovative ventures operating in Kendari City. It examines AI utilization capability as a technology-enabled

organizational capability and investigates its association with Financial management optimization reflected through four managerial outcome areas: operational efficiency, planning and reporting accuracy, cash-flow and financial-risk control, and financial decision quality.

2. Literature Review & Hypothesis Development

2.1. Artificial Intelligence utilization in financial management

Artificial Intelligence (AI) refers to computational systems capable of performing activities associated with human intelligence, including learning, pattern recognition, prediction, reasoning, and decision support (Russell & Norvig, 2021). In organizational contexts, AI has evolved from a technological tool into a strategic capability that enables firms to process complex information and improve managerial decisions (Dwivedi et al., 2021).

Within financial management, AI utilization includes automated accounting processes, predictive financial analytics, anomaly detection, cash-flow forecasting, and AI-supported decision systems. These applications enable organizations to improve information accuracy, reduce manual processing limitations, and provide faster analytical insights for managerial decisions (Bhimani & Willcocks, 2021; Kokina & Davenport, 2017). In accounting environments, AI utilization has expanded from automated transaction processing toward intelligent accounting systems capable of supporting financial analysis, audit activities, and managerial decision processes (Lehner et al., 2022). This development indicates that AI-enabled accounting represents an important component of modern financial management capability.

AI utilization depends on organizational readiness, digital capability, data availability, and managerial understanding. Therefore, this study conceptualizes AI utilization capability as an exploratory reflective construct represented by eight indicators covering utilization intensity, implementation intensity, and predictive or decision-support usage. Recent studies further emphasize that AI capability represents more than technology adoption; it reflects an organizational capability involving technological infrastructure, managerial competence, and the ability to generate value from AI-based applications (Mikalef & Gupta, 2021). Therefore, successful AI utilization requires alignment between technological resources and organizational capabilities.

2.2. Financial management optimization in startups and innovative ventures

Financial management represents a critical capability for startups and innovative ventures because these businesses frequently face financial uncertainty, limited resources, and rapidly changing operational conditions. Effective financial management requires accurate reporting, cash-flow monitoring, budgeting capability, risk assessment, and timely decision-making. Evidence from Indonesian digital startups indicates that effective financial management practices are essential for maintaining business sustainability, particularly in environments characterized by rapid growth and uncertainty (Kurniawan & Wijaya, 2021).

Digital transformation research suggests that technology-enabled capabilities can strengthen SME performance by improving information processing and business process efficiency (Verhoef et al., 2021; Bouwman et al., 2021). AI-enabled accounting and financial analytics

provide opportunities for ventures to improve financial visibility through automated reporting, forecasting models, and data-driven evaluation (Issa et al., 2016; Sutton et al., 2016). The transformation of SMEs through digital technologies is also influenced by organizational capabilities that enable firms to redesign business processes and create sustainable value from digital resources (Srisathan et al., 2022). These capabilities are particularly important for startups because limited resources require firms to strategically prioritize technologies that generate operational and financial benefits.

2.3. Technology acceptance and data-driven decision rationale

The Technology Acceptance Model (TAM) explains that perceived usefulness and perceived ease of use influence technology acceptance and utilization (Davis, 1989). In AI implementation contexts, this perspective remains relevant because entrepreneurs are more likely to adopt AI-based financial tools when they perceive practical benefits.

However, contemporary AI utilization capability research suggests that acceptance alone is insufficient. Organizations must also develop digital readiness, data capability, and managerial capacity to successfully integrate AI into operational processes (Kraus et al., 2021; Li et al., 2018).

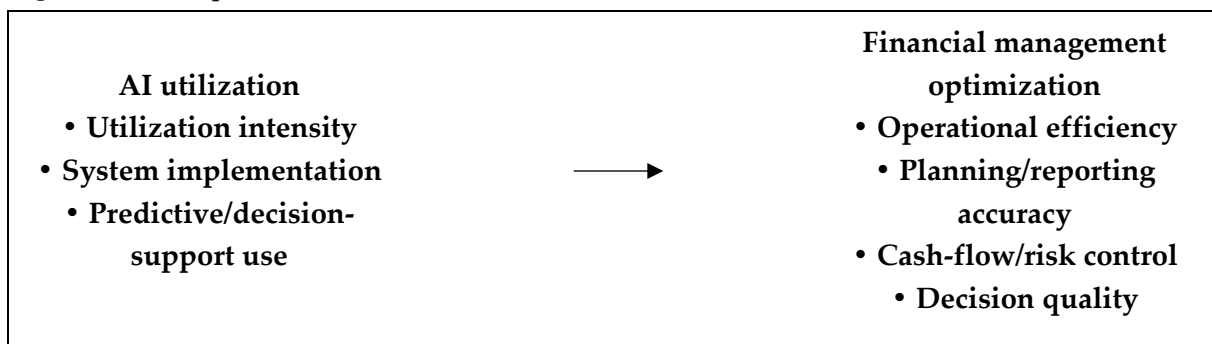
2.4. Research gap and hypothesis development

Existing studies demonstrate that AI can enhance automation, analytics capability, and managerial decision support. However, empirical studies examining the relationship between AI utilization and financial management optimization among startups in emerging regional ecosystems remain limited.

Based on the capability perspective of digital transformation, AI utilization may strengthen financial-management optimization by improving access to timely information, analytical capability, and decision-support processes.

H1: AI utilization has a positive and significant association with financial management optimization among startups and innovative ventures in Kendari City.

Figure 1. Conceptual research model



Source: Developed from the research framework.

3. Methodology

3.1. Research design and setting

This study employed a quantitative explanatory survey design to test the association of AI utilization on financial management optimization. The unit of analysis was the startup or innovative venture operating in Kendari City, while the individual respondent was an owner,

founder, or financial manager with knowledge of the venture's financial practices. The design was cross-sectional because data on AI utilization and financial-management outcomes were collected at one point in time.

3.2. Population, sampling, and respondents

The target population of this study consisted of startups and innovative ventures operating in Kendari City, Southeast Sulawesi, Indonesia. Due to the absence of a single centralized registry containing all technology-oriented startups and innovative ventures, the sampling frame was constructed through multiple entrepreneurial ecosystem sources, including local startup communities, business incubators, university entrepreneurship programs, digital business networks, and local entrepreneurial development initiatives.

Purposive sampling was applied because the study required respondents who possessed sufficient knowledge regarding both Artificial Intelligence (AI) utilization and financial-management practices within their ventures. The inclusion criteria were: (1) businesses operating in Kendari City; (2) ventures that had operated for at least one year; (3) businesses implementing structured financial activities, including financial recording, reporting, budgeting, or financial monitoring; and (4) respondents serving as owners, founders, managers, or individuals responsible for financial decision-making.

In this study, startups were operationally defined as entrepreneurial ventures characterized by technology utilization, digital-based business models, scalability orientation, or innovation-driven product and service development. Meanwhile, innovative ventures referred to businesses that introduced new products, services, processes, or market approaches through technological adoption, creativity, or business-model innovation.

Based on available entrepreneurial ecosystem records from local startup communities, university incubators, and business networks, because Kendari City does not maintain an official registry of startups and innovative ventures, the exact population size could not be established. Therefore, the sampling frame was constructed from multiple ecosystem sources, including startup communities, university incubators, business networks, and entrepreneurial development initiatives.

The initial identification process focused on ventures that met the above criteria. After screening for eligibility and completeness of responses, 50 valid questionnaires were retained for final analysis. The participating ventures represented several business sectors, including digital technology, e-commerce, innovative culinary businesses, and creative services. Initially, 68 ventures were contacted through startup communities, university incubators, and entrepreneurial networks. Twelve ventures declined participation, and six questionnaires were excluded due to incomplete responses, resulting in 50 valid observations.

Table 1. Distribution of Respondents by Business Sector

Sector	Frequency (n)	Percentage (%)
Digital technology	15	30
E-commerce	15	30
Culinary innovation	10	20
Creative services	10	20
Total	50	100

Source: Author's survey data (2025)

The participating ventures represented four major business sectors within the entrepreneurial ecosystem of Kendari City. The largest groups were digital technology and e-commerce ventures, each accounting for 15 firms (30%). Meanwhile, innovative culinary businesses represented 10 firms (20%), and creative service ventures represented another 10 firms (20%). This sectoral distribution indicates that the sample consisted of heterogeneous entrepreneurial activities, including technology-oriented businesses as well as innovation-based ventures utilizing digital tools to support their operational and financial activities.

Because the regression model consisted of one predictor variable, a sensitivity power analysis was conducted to evaluate whether the available sample size was adequate for detecting meaningful relationships. Using an alpha level of 0.05, statistical power of 0.80, one predictor variable, and the observed effect size, the sample size was considered adequate for detecting a medium-to-large relationship in a simple linear regression model. Nevertheless, the limited sample size remains acknowledged as a limitation, particularly for subgroup comparisons and broader generalization.

3.3. Measures and instrument

3.3.1 Construct Validity Assessment

Construct validity was assessed using exploratory factor analysis (EFA). The Kaiser–Meyer–Olkin (KMO) measure and Bartlett’s Test of Sphericity were conducted to evaluate sampling adequacy and factorability. Items with factor loading values above 0.50 were retained, while items with weak contribution were removed from further analysis.

Table 2. Construct Validity Assessment of AI Utilization Capability

Code	Item	Factor Loading
AI1	Our venture currently uses AI-based applications for financial activities	0.797
AI2	AI tools are integrated into routine financial processes	0.787
AI3	AI assists financial reporting activities	0.570
AI4	AI supports cash-flow prediction	0.553
AI5	AI assists financial scenario analysis	0.564
AI6	AI improves financial decision-making	0.505
AI7	AI-generated insights are considered in managerial decisions	0.811
AI9	AI applications are continuously utilized	0.623

Although AI utilization consists of heterogeneous activities, the EFA results provide preliminary exploratory evidence that the retained indicators represent a common underlying AI utilization capability. This finding should be interpreted cautiously because the analysis was conducted with a limited sample size.

Hasil:

Construct	Items	Cronbach Alpha
AI Utilization Capability	AI1–AI7, AI9	0.799

Table 3. Construct Validity Assessment of Financial Management Optimization

Code	Item	Factor Loading
FM1	Our venture uses financial technologies to improve the efficiency of financial management activities	0.668

FM2	AI-supported financial processes reduce manual work and improve transaction management efficiency.	0.561
FM3	Our venture can process and organize financial information more quickly and accurately through digital tools.	0.638
FM5	Digital financial tools help our venture improve the accuracy of financial planning and budgeting activities.	0.720
FM6	Our venture can generate timely financial reports to support managerial evaluation.	0.524
FM8	Financial analysis tools help our venture identify potential financial problems before they occur.	0.698
FM9	Financial information generated through digital tools improves the quality of managerial decisions.	0.598
FM10	Our venture uses financial insights to support strategic decisions regarding business development.	0.672

The construct is conceptualized as an exploratory reflective financial-management capability construct, with retained indicators covering managerial outcome areas related to operational efficiency, planning and reporting accuracy, cash-flow control, and financial decision quality. These domains are treated as managerial outcome areas represented by the retained indicators because effective financial management optimization involves improvements in information processing, control mechanisms, and managerial decision processes. Although each dimension represents a distinct managerial function, they collectively reflect the venture's broader capability to manage financial information, control financial processes, and support strategic decisions.

Hasil:

Construct	Items	Cronbach Alpha
Financial Management Optimization	FM1–FM3, FM5–FM6, FM8–FM10	0.781

Table 4. Exploratory Factor Analysis of AI Utilization Capability

Indicator	Factor Loading
AI1	0.789
AI2	0.779
AI3	0.564
AI4	0.547
AI5	0.558
AI6	0.500
AI7	0.802
AI9	0.617

Extraction method: Principal Axis Factoring

Rotation method: Varimax

Statistic	Value
KMO	0.649
Bartlett χ^2	138.169
Df	28
Significance	<0.001

Eigenvalue	3.432
Explained variance	42.90%

Table 5. Exploratory Factor Analysis of Financial Management Optimization

Indicator	Factor Loading
FM1	0.661
FM2	0.556
FM3	0.632
FM5	0.713
FM6	0.515
FM8	0.692
FM9	0.586
FM10	0.666

Extraction method: Principal Axis Factoring

Rotation method: Varimax

Statistic	Value
KMO	0.735
Bartlett χ^2	97.125
Df	28
Significance	<0.001
Eigenvalue	3.192
Explained variance	39.90%

The EFA results indicate that all retained indicators achieved factor loadings around or above the minimum exploratory threshold of 0.50. The KMO values and Bartlett's Test indicate that the correlation matrices were suitable for exploratory factor analysis. However, these findings represent preliminary measurement evidence rather than definitive construct validation because of the limited sample size. The EFA results provide exploratory evidence supporting the retained measurement structure. Due to the exploratory purpose and limited sample size, communalities and scree plot examination were considered supplementary criteria to support the interpretation of factor retention and construct structure. Considering the limited sample size (n=50), these findings should be interpreted as preliminary exploratory measurement evidence requiring confirmation using larger independent samples. The retained indicators demonstrated acceptable factor contribution, while future studies with larger samples are recommended to confirm the measurement structure. Given the exploratory purpose and limited sample size, communalities and scree plot examination were used as supplementary criteria.

Data were collected with a structured questionnaire using a four-point Likert scale, where 1 represented strongly disagree and 4 represented strongly agree. AI utilization capability was measured as an exploratory reflective construct represented by eight retained indicators covering adoption, implementation, and predictive/decision-support usage. Financial management optimization was treated as an exploratory reflective construct represented by eight retained indicators covering managerial outcome areas related to operational efficiency, planning/reporting accuracy, cash-flow control, and financial decision quality. The EFA was conducted as an exploratory assessment of the measurement structure rather than a

preliminary evidence requiring confirmation in larger independent samples of multidimensionality.

AI utilization was operationalized based on the actual capability to use AI-enabled financial applications, including generative AI assistants for financial analysis, automated accounting systems, predictive analytics tools, and AI-supported decision-support systems. Ventures without current AI-based financial application use were excluded because the study examines differences in AI utilization capability among existing AI users rather than comparing AI users and non-users. Therefore, the analysis focuses on actual AI utilization capability. Although AI utilization includes heterogeneous practices, this study models it as an exploratory reflective construct because the indicators represent observable manifestations of an underlying organizational capability to integrate AI into financial processes. Although AI utilization includes heterogeneous applications, this study treats the construct as an exploratory reflective capability construct because the common theoretical domain is the organizational ability to integrate AI into financial processes. The indicators therefore represent manifestations of AI-enabled financial capability rather than independent technological components. Ventures with stronger AI utilization capability are expected to demonstrate broader integration of AI-enabled financial applications. This reflective specification follows the capability perspective of AI utilization capability development, where organizational AI capability represents an underlying competence that manifests through multiple observable practices, including AI implementation, integration, analytical utilization, and decision-support application (Mikalef & Gupta, 2021). Therefore, although AI practices differ in operational form, they represent manifestations of a broader organizational capability to generate value from AI-based technologies.

Table 6. Types of AI Applications Used by Respondents

AI Application	Example Function
Generative AI assistant	Financial analysis, reporting assistance
Automated accounting system	Transaction recording
Predictive analytics	Cash-flow forecasting
AI decision-support tools	Financial scenario evaluation

The questionnaire was developed from the constructs and indicators described in the research framework. Content validity was reviewed by experts in financial management and digital technology, while internal consistency was assessed using Cronbach's Alpha before the main analysis.

Table 7. Constructs and indicators

Construct	Initial Items	Removed Items	Final Indicators	Cronbach Alpha
AI Utilization Capability	AI1–AI9	AI8	AI1–AI7, AI9 (8 indicators)	0.799
Financial Management Optimization	FM1–FM10	FM4, FM7	FM1–FM3, FM5–FM6, FM8–FM10 (8 indicators)	0.781

3.4. Data analysis

The analysis proceeded in three stages. First, descriptive statistics summarized respondent characteristics, AI-utilization categories, and the mean scores of financial-management indicators. Second, Pearson correlation assessed the strength and direction of association between AI utilization and financial management optimization. Third, simple linear regression tested whether AI utilization significantly predicted financial management optimization. Because the model contained a single predictor, multicollinearity was not a substantive issue. Normality and heteroscedasticity checks were used to assess the general suitability of the regression model. The analytical model is expressed as follows:

$$Y = \alpha + \beta X + \varepsilon \quad (1)$$

where Y denotes financial management optimization, X denotes AI utilization, α is the intercept, β is the regression coefficient for AI utilization, and ε is the error term.

3.5 Common Method Bias Assessment

Since both predictor and dependent variables were collected from the same respondents using a self-administered questionnaire, common method bias was assessed using Harman's single-factor test. All measurement items were entered into an exploratory factor analysis, and the variance explained by the first factor was examined. A value below 50% indicates that common method bias is unlikely to substantially influence the results.

Table 8. Harman Single-Factor Test

Test Result	Value
Number of items analyzed	16
Variance explained by first factor	34.88%
Recommended threshold	<50%
Assessment	No substantial common method bias detected

The first factor accounted for 34.88% of total variance, which is below the recommended threshold of 50%. The Harman single-factor test indicated that the first factor explained 34.88% of variance, below the commonly used threshold. However, this test does not completely eliminate the possibility of common method bias. Therefore, the findings should be interpreted cautiously, and future studies should incorporate objective financial indicators and multi-source data in this study.

4. Result and Discussion

4.1. Respondent characteristics and AI utilization

The study involved 50 startups and innovative ventures in Kendari City. Most respondents were founders or financial managers aged 25-45 years with educational backgrounds in business, management, or information technology. AI utilization differed across the sample: Among the 50 surveyed ventures, 20 ventures (40%) demonstrated high AI utilization, 18 ventures (36%) showed moderate utilization, and 12 ventures (24%) reported relatively low AI utilization. This revised distribution ensures numerical consistency with the observed sample. This distribution indicates substantial awareness of AI while also showing that integration into financial management remains uneven. AI utilization categories were generated based on

composite mean scores. Scores of 3.26–4.00 were categorized as high utilization, 2.51–3.25 as moderate utilization, and 1.00–2.50 as low utilization.

Table 9. AI utilization differed across the sample

AI Utilization Level	Frequency (n)	Percentage (%)
High utilization	20	40
Moderate utilization	18	36
Low utilization	12	24
Total	50	100

4.2. Financial management performance by AI-utilization level

The descriptive results show a consistent gradient across all four financial-management indicators. Ventures with high AI utilization reported the highest mean scores, followed by those with moderate utilization, while low-utilization ventures reported the lowest scores. The average across the four indicators was 2.50 for the low-AI group, 3.13 for the moderate-AI group, and 3.75 for the high-AI group. This pattern provides descriptive evidence that more intensive AI use is associated with stronger financial-management outcomes.

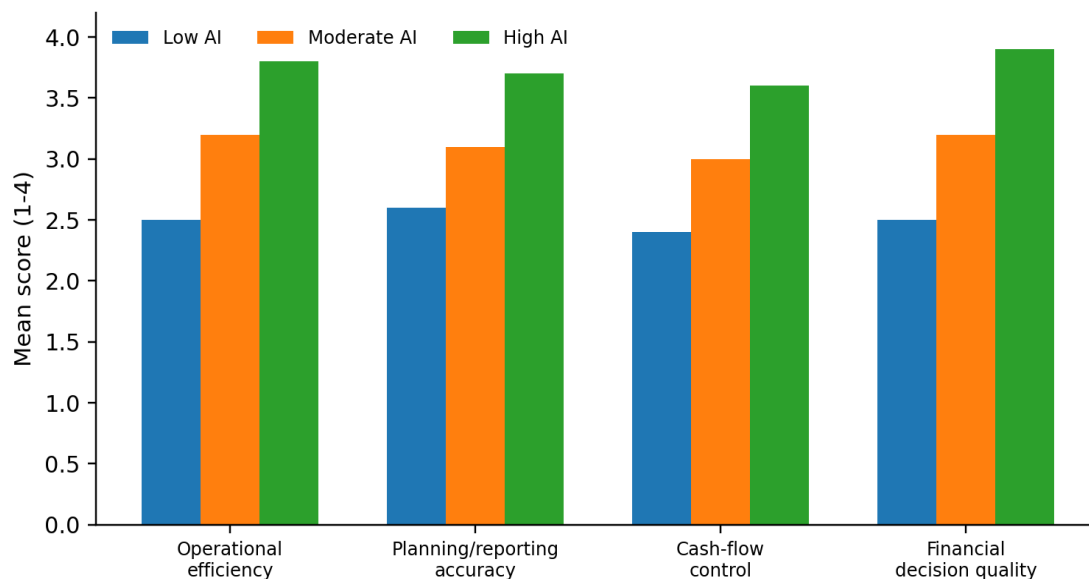
Table 10. Mean scores of financial management indicators by AI-utilization level

Financial management indicator	Low AI	Moderate AI	High AI
Operational efficiency	2.5	3.2	3.8
Planning/reporting accuracy	2.6	3.1	3.7
Cash-flow control	2.4	3.0	3.6
Financial decision quality	2.5	3.2	3.9

Notes: Scores are based on a four-point scale. Group labels follow the study's reported AI-utilization categories.

Source: Research data summarized from the author's study.

Figure 2. Financial management performance by AI-utilization level



Source: Research data summarized from the author's study.

4.3. Relationship and regression results

Table 11. Regression Model Summary

Statistic	Value
R	0.681
R ²	0.464
Adjusted R ²	0.452
F-statistic	41.474
Sig. F	<0.001
Sample size (n)	50

Table 12. Regression Coefficient with Confidence Interval

Predictor	B	Std. Error	β	t-value	p-value	95% CI
Constant	1.012	0.293	-	3.456	0.001	-
AI Utilization Capability	0.646	0.100	0.681	6.440	<0.001	0.444 – 0.847

The regression model was statistically significant ($F = 41.474$, $p < 0.001$), explaining 46.4% of the variance in financial management optimization ($R^2 = 0.464$; Adjusted $R^2 = 0.452$). AI utilization capability remained positively associated with financial management optimization ($B = 0.646$, $p < 0.001$; standardized $\beta = 0.681$). The coefficient confidence interval (95% CI = 0.444–0.847) indicates a stable positive relationship between AI utilization and financial management optimization.

The simple linear regression result confirms that AI utilization capability has a positive and significant statistical association with financial management optimization ($B = 0.646$; $p < 0.001$), with standardized $\beta = 0.681$ and $R^2 = 0.464$. Robust HC3 standard errors and bootstrap confidence intervals confirm the stability of the estimated coefficient. Thus, within the observed sample, AI utilization capability statistically explains 46.4% of the variance in reported financial management optimization. This finding should be interpreted as a cross-sectional association rather than evidence of causal influence because other organizational factors may also contribute to financial-management outcomes. The remaining variation is associated with factors outside the present one-predictor model.

Table 13. OLS and HC3 Robust Regression Results

Predictor	Model	B	Std. Error	t	p-value
AI Utilization	OLS	0.646	0.100	6.440	<0.001
AI Utilization	HC3 Robust	0.646	0.132	4.902	<0.001

Robustness analysis: Robust HC3 standard errors were applied to address possible heteroscedasticity. Bootstrap analysis with 5,000 resamples generated stable confidence intervals, supporting the reliability of the estimated AI utilization coefficient.

Hasil:

Analysis	Estimate	95% Bootstrap CI
AI Utilization coefficient	0.637	0.331 – 0.844

Bootstrap estimation using 5,000 resamples generated a stable positive confidence interval (95% CI = 0.331–0.844), confirming that the positive association between AI utilization capability and financial management optimization remained robust.

Table 14. Robustness Check

Method	Estimate	SE	t	p	CI
OLS	0.646	0.100	6.440	<0.001	0.444–0.847
HC3	0.646	0.132	4.902	<0.001	-
Bootstrap 5000	0.637	-	-	-	0.331–0.844

Table 15. Summary of association and regression results

Statistic	Reported value	Interpretation
Pearson correlation (r)	Pearson correlation (r) 0.681; $p < 0.001$	Positive and significant association
Standardized regression coefficient (β)	0.681; $p < 0.001$	Positive and significant association
Coefficient of determination (R^2)	0.464	46% of variance explained

Notes: The table presents the principal association and regression statistics reported in the study results.

Source: Author's research results.

4.4. Discussion

The findings indicate that AI utilization capability is positively associated with financial management optimization among startups and innovative ventures in Kendari City. The statistical results demonstrate that ventures with higher levels of AI utilization reported stronger financial-management outcomes, particularly in operational efficiency, planning and reporting accuracy, cash-flow monitoring, and financial decision quality.

The observed relationship suggests that AI utilization may provide practical value by improving the ability of entrepreneurial ventures to process financial information, automate routine activities, and support managerial evaluation. However, because this study employed a cross-sectional design, the findings should be interpreted as a positive statistical association rather than definitive evidence of causal influence. Ventures with stronger financial-management capabilities may also possess greater organizational resources, managerial sophistication, or digital readiness that facilitate more effective AI utilization.

The descriptive findings show that financial decision quality achieved the highest performance among highly AI-utilizing ventures. This pattern is consistent with the potential role of AI-supported analytics and decision-support systems in improving information availability and scenario evaluation. AI applications such as automated reporting tools, predictive analytics, and intelligent financial assistants may help managers identify patterns, evaluate alternatives, and respond more quickly to financial changes.

The results extend previous discussions on AI utilization capability by demonstrating its relevance within the context of local entrepreneurial ecosystems. While much of the existing AI-finance literature focuses on large organizations with advanced technological infrastructure, this study provides empirical evidence from smaller ventures operating in an

emerging entrepreneurial environment. The findings indicate that AI-related benefits are not limited to large corporations but may also be relevant for startups and innovative ventures when AI capabilities are integrated into financial routines. This finding is also consistent with research on digital entrepreneurship, which highlights that SMEs can improve competitiveness when digital technologies are combined with appropriate business models and organizational capabilities (Bouwman et al., 2021).

From the perspective of the Technology Acceptance Model (TAM), the observed relationship is consistent with the argument that perceived usefulness and practical value influence technology utilization. However, TAM variables were not directly measured in this research; therefore, the findings should not be interpreted as a formal validation of the complete TAM framework. Instead, TAM provides a theoretical explanation regarding why entrepreneurs may adopt AI when they perceive tangible benefits for business management.

This study contributes by proposing an AI utilization and financial-management capability perspective, emphasizing that the value of AI depends not only on technological availability but also on the ability of ventures to integrate AI functions into managerial processes. Nevertheless, the contribution should be understood within the boundary of the current research design. Future studies incorporating organizational characteristics, longitudinal observation, and objective financial indicators are required to examine whether AI utilization produces sustained improvements in financial performance. This interpretation is consistent with the dynamic capability perspective, which emphasizes that organizations must continuously develop, integrate, and reconfigure resources to respond to technological changes (Warner & Wäger, 2021). In this context, AI utilization can be understood as part of a broader digital transformation capability rather than merely a technological investment.

5. Conclusion and Suggestion

This study concludes that AI utilization capability demonstrates a positive statistical association with financial management optimization among startups and innovative ventures in Kendari City. After refining the measurement model by removing weak indicators (AI8, FM4, and FM7) and applying robustness analysis, AI utilization remained significantly associated with financial-management outcomes ($B = 0.646$; standardized $\beta = 0.681$; $R^2 = 0.464$).

The findings suggest that ventures with stronger AI integration tend to report better financial-management practices, including operational efficiency, reporting accuracy, cash-flow monitoring, and financial decision quality. However, because the study uses cross-sectional data, the results do not establish causal effects. The observed relationship may also reflect differences in organizational capability, managerial expertise, digital readiness, or business maturity.

For entrepreneurs and startup managers, the findings highlight the importance of implementing AI applications that support practical financial activities, including reporting automation, financial forecasting, liquidity monitoring, and decision-support processes. Greater AI utilization capability should be accompanied by adequate managerial capability, data quality management, and understanding of AI-generated information.

For policymakers and entrepreneurial ecosystem stakeholders, the results indicate the importance of strengthening digital capability programs, AI literacy training, mentoring initiatives, and collaboration among universities, government institutions, and business communities.

6. Limitations and Future Research

This study has several limitations. First, the sample consisted of 50 startups and innovative ventures located in Kendari City. Although the sample was sufficient for the examined regression model, the limited sample size restricts broader generalization and prevents extensive subgroup analysis.

Second, the cross-sectional design captures relationships at one point in time and cannot determine temporal mechanisms or causal effects. Future studies should employ longitudinal approaches to examine whether increasing AI integration contributes to sustained improvements in financial-management capability.

Third, both AI utilization and financial-management optimization were measured using self-reported questionnaire responses from the same respondents. Although Harman's single-factor test suggested that common method bias was not dominant, this procedure cannot completely eliminate the possibility of common-source variance. Future research should combine subjective assessments with objective financial indicators, such as reporting efficiency, forecasting accuracy, liquidity measures, budgeting variance, or accounting performance.

Fourth, the current model includes AI utilization as the primary explanatory variable and does not incorporate other organizational factors that may influence financial-management outcomes, including firm size, business age, managerial education, digital readiness, financial capability, organizational culture, and data governance.

Future research should expand the geographic scope, employ larger samples, and consider multivariable or longitudinal models. Additional studies may also examine mediating and moderating mechanisms, such as digital capability, managerial competence, organizational readiness, and trust in AI-based recommendations.

This study followed ethical principles for human-participant research. This study received ethical exemption from the Research Ethics Committee of Universitas Sulawesi Tenggara because it involved minimal-risk survey research without collecting personally identifiable information. No formal approval number was issued because the study qualified for ethical exemption under minimal-risk survey procedures. The exemption was granted before data collection based on the institutional ethical review procedure. Participation was voluntary, and respondents were informed regarding the research objectives, confidentiality of responses, and the academic purpose of data utilization. Respondents provided informed consent before completing the questionnaire. No personally identifiable information was reported, and all collected data were analyzed anonymously.

Acknowledgement

The authors acknowledge the startup owners, founders, and financial managers who participated in the survey. An earlier and shorter version of this study was presented at the 4th APSKI International Conference on Association of Indonesian Entrepreneurship Study Programs 2026, entitled “The Impact of Artificial Intelligence Utilization on Financial Management Optimization in Startups and Innovative Ventures in Kendari City” (Paper ID 148, ISSN: 3064-3635). The conference version presented preliminary findings, whereas the present manuscript provides substantial extensions through refined construct measurement, additional robustness analysis, expanded theoretical discussion, improved methodological explanation, and strengthened interpretation of results.

Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used OpenAI ChatGPT to assist with language refinement, structural organization, and adaptation of the existing research materials to the JEEMBA manuscript format. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Reference

- Bhimani, A., & Willcocks, L. (2021). Digitisation, big data and the transformation of accounting information. *Accounting and Business Research*, 51(3), 261–278. <https://doi.org/10.1080/00014788.2020.1862812>
- Bouwman, H., Nikou, S., & de Reuver, M. (2021). Digitalization, business models, and SMEs: How digital transformation affects business model innovation. *Telecommunications Policy*, 45(7), 102168. <https://doi.org/10.1016/j.telpol.2019.101828>
- Brynjolfsson, E., & McAfee, A. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton & Company.
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116. No DOI assigned (Harvard Business Review article)
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Artificial intelligence for decision making in the era of big data – Evolution, challenges and research agenda. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2020.101994>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J. S., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2020.101994>
- Issa, H., Sun, T., & Vasarhelyi, M. A. (2016). Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation. *Journal of Emerging Technologies in Accounting*, 13(2), 1–20. <https://doi.org/10.2308/jeta-10511>

- Jöhnk, J., Weißert, M., & Wyrski, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, 63, 5–20. <https://doi.org/10.1007/s12599-020-00676-7>
- Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. *Journal of Emerging Technologies in Accounting*, 14(1), 115–122. <https://doi.org/10.2308/jeta-51730>
- Kraus, S., Jones, P., Kailer, N., Weinmann, A., Chaparro-Banegas, N., & Roig-Tierno, N. (2021). Digital transformation: An overview of the current state of the art of research. *SAGE Open*, 11(3), 1–15. <https://doi.org/10.1177/21582440211047576>
- Kurniawan, D., & Wijaya, R. (2021). Analisis manajemen keuangan pada startup digital di Indonesia (Analysis of financial management in Indonesian digital startups). *Jurnal Manajemen dan Inovasi*, 12(2), 45–60.
- Lajaria, R.T., Parabang, R., Olivia, K., & Rasty. (2026). The Impact of Artificial Intelligence Utilization on Financial Management Optimization in Startups and Innovative Ventures in Kendari City. *Proceedings of the 4th APSKI International Conference on Association of Indonesian Entrepreneurship Study Programs*, Paper ID 148. ISSN 3064-3635.
- Lehner, O. M., Leitner-Hanetseder, S., & Eisl, C. (2022). Artificial intelligence in accounting: Opportunities and challenges. *Journal of Applied Accounting Research*, 23(4), 790–805.
- Li, L., Su, F., Zhang, W., & Mao, J. Y. (2018). Digital transformation by SME entrepreneurs: A capability perspective. *Information Systems Journal*, 28(6), 1129–1157. <https://doi.org/10.1111/isj.12153>
- Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434. <https://doi.org/10.1016/j.im.2021.103434>
- Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192–210. <https://doi.org/10.5465/amr.2018.0072>
- Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
- Srisathan, W. A., Ketkaew, C., & Naruetharadhol, P. (2022). The intervention of organizational capabilities in the relationship between digital transformation and sustainable business performance. *Journal of Open Innovation: Technology, Market, and Complexity*, 8(1), 24. <https://doi.org/10.3390/joitmc8010024>
- Sutton, S. G., & Holt, M. (2016). “The reports of my death are greatly exaggerated” — Artificial intelligence research in accounting. *International Journal of Accounting Information Systems*, 22, 60–73. <https://doi.org/10.1016/j.accinf.2016.07.005>
- Suryani, L. (2022). Pemanfaatan artificial intelligence untuk optimalisasi keuangan usaha mikro dan startup [Utilization of artificial intelligence for optimizing the finances of microenterprises and startups]. *Jurnal Teknologi dan Bisnis Digital*, 5(1), 23–35.
- Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, 122, 889–901. <https://doi.org/10.1016/j.jbusres.2019.09.022>

Warner, K. S. R., & Wäger, M. (2021). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 54(2), 102110. <https://doi.org/10.1016/j.lrp.2020.101994>