International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2027, 17(1), 118-127.

Artificial Intelligence and Financial Performance in Moroccan Startups: The Mediating Effect of Financial Reporting Quality

Ayoub Oussaa*, Abdelhadi Darkaoui, Hind Bouzid, Nouhad Laouane, Hamza Ali Eddine

Laboratory of Multidisciplinary Research in Economics and Management, Sultan Moulay Slimane University, Beni Mellal, Morocco. *Email: ayoub.oussaa@usms.ac.ma

Received: 17 May 2026 **Accepted:** 23 August 2026 **DOI:** https://doi.org/10.32479/irmm.24548

ABSTRACT

Artificial intelligence (AI) is increasingly reshaping financial information systems by automating accounting processes, expanding analytical capabilities, and supporting managerial decision-making. However, evidence remains limited regarding the mechanisms through which AI adoption contributes to financial performance, particularly among startups operating in emerging economies. Drawing on the Resource-Based View and rational decision-making theory, this study examines the effect of AI adoption on the financial performance of Moroccan startups and tests the mediating role of financial reporting quality. A quantitative, cross-sectional design was adopted. Data were collected through a structured online questionnaire distributed to executives, financial managers, and management controllers working in Moroccan startups. Of 160 questionnaires distributed, 125 complete responses were retained for analysis. The proposed model was tested using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4. The findings show that AI adoption positively affects financial reporting quality ($\beta = 0.792$, $P < 0.001$) and financial performance ($\beta = 0.441$, $P < 0.001$). Financial reporting quality also has a positive effect on financial performance ($\beta = 0.472$, $P < 0.001$). In addition, the indirect effect of AI adoption on financial performance through financial reporting quality is positive and significant ($\beta = 0.373$, $P < 0.001$), indicating complementary partial mediation. These findings suggest that AI creates value not only through direct operational and strategic improvements but also, by enhancing the reliability, timeliness, and usefulness of financial information for decision-making. The study contributes to the literature by integrating technological, informational, and performance-related mechanisms within an underexplored Moroccan startup context. Practically, it highlights the importance of combining investments in AI with robust financial reporting processes, data-management practices, and internal control mechanisms.

Keywords: Innovative Technologies, Accounting Information Systems, Corporate Performance, Mediation, PLS-SEM, New Ventures
JEL Classifications: M41, Q56

1. INTRODUCTION

In the past few year few years, firms have had to address more intense digital transformation and more complex economic environments. These environments are marked by increased competition, increased performance demands, and stricter regulations pertaining to the financial information's dependability and transparency of fanancial information. By automating accounting tasks, improving data processing, and assisting with decision-making, artificial intelligence (AI) is gradually emerging as a technological lever capable of revolutionizing financial information systems and managerial control practices (Davenport and Ronanki, 2018; Kokina and Davenport, 2017; Dwivedi et al., 2021).

These technologies could be a strategic opportunity for startups, which are usually characterized by high levels of unpredictability and limited resources, to improve their financial performance and strengthen their informational skills. Morever, the accounting and finance literature highlights that the quality of information generated and distributed through financial reporting is just as important to financial performance as the resources deployed. Superior economic performance is ultimately the result of reduced

This Journal is licensed under a Creative Commons Attribution 4.0 International License

information asymmetries, increased investor confidence, and improved resource allocation efficiency brought about by high-quality financial reporting (Bushman and Smith, 2001; Healy and Palepu, 2001; Dechow et al., 2010).

Financial reporting quality is crucial for both internal managerial steering and external credibility with investors and financial partners in startup contexts, where management control and accounting systems often evolve as firms grow and seek external financing (Davila and Foster, 2007). Digitalization and big data are also transforming the production and use of accounting information (Bhimani and Willcocks, 2014). The potential advantages of artificial intelligence in financial processes are being highlighted by a growing body of research, but it is still unclear how AI adoption leads to better financial performance. According to earlier studies (Brynjolfsson and Hitt, 2000; DeLone and McLean, 2003; Rikhardsson and Yigitbasioglu, 2018), the effects of digital technologies on performance are rarely direct and instead function through intermediate mechanisms linked to enhancements in organizational procedures and information quality.However, empirical data on these mechanisms is still limited, especially in light of startups operating in emerging economies.

According to this perspective, improving the accuracy of financial reporting seems to be a particularly pertinent explanation for how artificial intelligence might affect financial performance. In developing environments where financial information systems and reporting processes are still at varying stages of maturity, this problem is particularly important. Building on this justification, the current study examines the connections between the adoption of artificial intelligence, the quality of financial reporting, and financial performance using the resource-based view and rational decision-making theory. More precisely, this study aims to evaluate the existence of a supplementary partial mediation mechanism while analyzing the degree to which AI adoption improves financial reporting quality and, subsequently, financial performance in the context of Moroccan startups.

From an empirical perspective, this study is based on data collected from 125 respondents via a structured survey, which was then analyzed using SmartPLS 4's PLS-SEM method. This is how the rest of the paper goes. In section two, the literature is reviewed and the proposed hypotheses are established; in section three, the methodological framework is described; in section four, the empirical analysis and results are presented; in section five, these findings are analyzed and their implications are examined; and in section six, the research is concluded by summarizing its theoretical contributions, addressing its limitations, and suggesting potential avenues for future research.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

According to recent research, the application of artificial intelligence (AI) is key for changing financial information systems and decision-making procedures, and has important ramifications for the quality of reporting and the financial performance of firms.

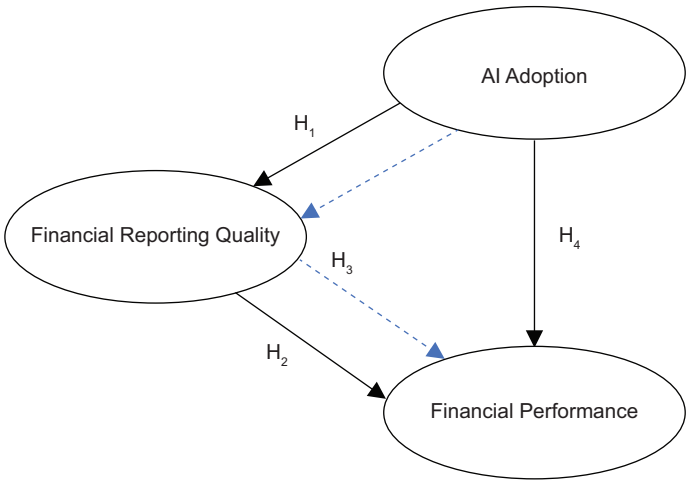
The proposed research model (Figure 1) is based on an integrative theoretical approach that combines rational decision-making theory and the Resource-Based View (RBV), two analytical frameworks that are frequently used to explain the connection between digital technologies, financial data, and organizational performance (Barney, 1991, 2001; Bharadwaj, 2000; Simon, 1977).

The RBV states that a company's performance depends on its capacity to recognize, develop, and efficiently utilize its own resources, especially when those resources are precious, rare, distinctive, and nonreplaceable (Barney, 1991; Barney, 2001). Technological resources play a crucial strategic role in the framework of startups, which are defined by resource limits and high levels of uncertainty, compensating for structural limitations (Bharadwaj, 2000; Wade and Hulland, 2004). Particularly in emerging economies where organizational procedures and information systems are still developing, artificial intelligence is increasingly seen as a strategic resource that can improve firms' informational, analytical, and decision-making capacities (Bharadwaj et al., 2013; Mikalef et al., 2020).

Additionally, rational decision-making theory asserts that the caliber, dependability, and applicability of the information that decision makers have access to have a significant impact on the caliber of managerial judgments (Simon, 1977; Eisenhardt and Zbaracki, 1992). Startups face a rising demand for quick and accurate financial information to assist in financial and strategic decision-making in complicated economic contexts (Healy and Palepu, 2001; Dechow et al., 2010). According to Bushman and Smith (2001) and Otley (2016), financial reporting is an essential tool for the creation and distribution of financial data and is crucial for managerial control, financial appraisal, and performance monitoring.

The combination of these two theoretical stances implies that financial performance is not automatically and immediately enhanced by artificial intelligence. Instead, it is likely to have an impact through intermediate informational mechanisms, mainly through improving the quality of financial reporting, which facilitates more logical, knowledgeable, and efficient decision-

Figure 1: Research model



making processes (DeLone and McLean, 2003; Rikhardsson and Yigitbasioglu, 2018; Moll and Yigitbasioglu, 2019).

2.1. AI and Financial Reporting Quality

AI includes a variety of advanced technology instruments, such as automated intelligence processes, natural language processing systems, and machine learning approaches. These technologies allow organizations to process massive datasets, uncover hidden patterns, and enhance managerial and operational decision-making.(Russell and Norvig, 2021; Dwivedi et al., 2021). In the financial domain, AI is being increasingly integrated into financial information systems to automate accounting processes, enhance financial statement preparation, and strengthen financial reporting reliability (Kokina and Davenport, 2017; Sutton et al., 2016).

Financial reporting quality constitutes a central concept in financial accounting and information systems research. It refers to the ability of financial reports to offer trustworthy, pertinent, comparable, understandable, and timely information in accordance with international conceptual frameworks (Dechow et al., 2010; International Accounting Standards Board, 2018). In startup contexts, where accounting systems are often less formalized and organizational resources are limited, the financial reporting quality largely depends on the effectiveness of the technologies used for financial data processing and analysis (Moll and Yigitbasioglu, 2019).

By automating data processing, lowering human error, and bolstering internal control mechanisms, artificial intelligence integration into financial information systems considerably improves reporting quality, according to growing empirical research (Appelbaum et al., 2017; Rikhardsson and Yigitbasioglu, 2018). In addition, AI can extend the capabilities of advanced analytics and decision-support systems in accounting, thus improving how well financial information supports internal and external stakeholders (Kokina and Davenport, 2017; Sutton et al., 2016).

According to the ressource-based view (RBV), artificial intelligence can be viewed as an organizational resource that creates value when it improves the quality of financial data generated by the company. In the context of startups, this technological resource helps compensate for structural resource constraints by improving the reliability and credibility of financial reporting, which plays a key role in relationships with investors and financial partners (Mikalef et al., 2020; Olan et al., 2022).

Hypothesis 1 (H_1). Artificial intelligence adoption has a positive effect on financial reporting quality.

2.2. Financial Reporting Quality and Financial Performance

The ability of a company to meet its financial goals in terms of growth, profitability, and value creation is referred to as financial performance (Venkatraman and Ramanujam, 1986; Richard et al., 2009). Since it affects access to outside capital and investor trust (Davila et al., 2003; Healy and Palepu, 2001), financial performance is a crucial indicator of survival and sustainability in the context of startups.

The quality of the data used to inform investment, financing, and cost-control choices is strongly correlated with financial success, according to the accounting and finance literature (Bushman and Smith, 2001; Dechow et al., 2010). Greater financial performance and more effective resource allocation result from high-quality financial reporting, which also improves financial transparency, strengthens managerial discipline, and lessens information asymmetries between managers and external stakeholders (Francis et al., 2004; Barth et al., 2013).

Rational decision-making theory states that timely, accurate, and pertinent information is necessary to make better financial decisions (Simon, 1977; Eisenhardt, 1989). According to Otley (2016) and (Kaplan and Atkinson, 2014), financial reporting thus plays a crucial role in providing managers with a synthesis of financial indicators that help with performance monitoring and risk anticipation. Financial reporting quality becomes a crucial lever for improving financial performance in startup environments, as choices are frequently made under high levels of uncertainty (Davila and Foster, 2007).

Hypothesis 2 (H_2). Financial reporting quality has a positive effect on financial performance.

2.3. The Mediating Role of Financial Reporting Quality

According to research on digital technologies and organizational performance (Brynjolfsson and Hitt, 2000; DeLone and McLean, 2003; Wamba et al., 2017), the effects of digital technologies frequently function through intermediary mechanisms linked to enhancements in organizational procedures and information quality. Recent studies do, however, also recognize that improved operational effectiveness and strategy responsiveness may have direct performance consequences. According to this perspective, firms' informational and decision-making capacities are the main ways in which artificial intelligence adds value to organizations (Appelbaum et al., 2017; Dwivedi et al., 2021).

By automating accounting procedures, strengthening internal controls, and increasing the speed and dependability of financial information creation, artificial intelligence (AI) initially improves the quality of financial reporting in startup contexts (Kokina and Davenport, 2017; Sutton et al., 2016). More logical, data-driven, and educated financial decisions that are in line with performance goals are made possible by improved reporting quality, which eventually ultimately results in improved financial performance (Healy and Palepu, 2001; Otley, 2016).

Therefore, from an RBV perspective, financial reporting quality can be seen as a crucial transformation mechanism through which artificial intelligence, as a strategic technological resource, produces favorable effects on startups' financial performance (Barney, 2001; Wade and Hulland, 2004; Mikalef et al., 2020).

Adoption of AI may have a direct effect on financial performance by enhancing operational effectiveness and strategic responsiveness, in addition to its indirect impact through reporting quality.

As a result, it is anticipated that financial reporting quality will play a significant role in explaining how AI-enabled informational advancements translate into quantifiable financial results.

Hypothesis 3 (H_3). Financial reporting quality acts as a mediator in the relationship between the adoption of artificial intelligence and financial performance.

2.4. Artificial Intelligence Adoption and Financial Performance

Beyond its influence through financial reporting quality, artificial intelligence adoption may also directly impact on financial performance. The literature on digital transformation and organizational performance suggests that advanced technologies generate value not only by improving information quality, but also by enhancing operational efficiency, cost reduction, and strategic responsiveness (Brynjolfsson and Hitt, 2000; Bharadwaj et al., 2013; Wamba et al., 2017).

Artificial intelligence enables firms to automate repetitive tasks, optimize resource allocation, improve forecasting accuracy, and reduce operational inefficiencies. In startup environments, where resources are limited and competitive pressure is high, such efficiency gains can translate directly into improved profitability and growth performance (Mikalef et al., 2020; Olan et al., 2022).

From a ressourc-based view (RBV), AI can be viewed as a strategic technological capability that enhances firm performance when it is effectively deployed and integrated into organizational processes (Barney, 2001; Wade and Hulland, 2004). AI-based analytics improve demand forecasting, pricing strategies, working capital management, and risk assessment, thereby directly contributing to financial outcomes.

Furthermore, decision-augmentation theory suggests that AI systems complement managerial judgment, enabling faster and more accurate strategic and financial decisions (Davenport and Ronanki, 2018; Jarrahi, 2018). These improvements in decision speed and quality can have an immediate positive effect on financial performance, independent of reporting mechanisms.

Therefore, in addition to indirect effects through financial reporting quality, AI adoption is expected to directly improve financial performance.

Hypothesis 4 (H_4). Artificial intelligence adoption has a positive direct effect on financial performance.

3. METHODOLOGY

3.1. Data Collection Tools and Sample

The study used a rigorous methodological framework to guarantee the validity and reliability of the findings. The main instrument used to gather the necessary data was a structured survey questionnaire. Actors working for Moroccan startups were given access to the online survey. Chief executive officers, financial managers, and management controllers were among the respondents who were targeted because of their roles in financial management and decision-making. Data collection took place over a predetermined time frame, providing respondents with enough time to submit their answers and to increase participation, and follow-up reminders were sent to prospective respondents.

A total of 160 surveys were distributed to Moroccan startups. Following the data collection process, 125 complete and useful responses were gathered for analysis, yielding a 78.1% response rate. For PLS-SEM analysis, which is appropriate for researchers with comparatively small to medium sample sizes, the maintained sample was deemed sufficient.

3.2. Measurement of Variables

The measurement items were developed and adapted to the context of Moroccan startups on the basis of prior conceptual literature. AI adoption was assessed through items related to the integration of AI tools into financial processes, including process automation, financial data analytics, and decision-support systems (Kokina and Davenport, 2017; Sutton et al., 2016). Financial reporting quality was assessed through items reflecting the qualitative characteristics of financial information, namely, reliability, clarity, timeliness, and transparency (Dechow et al., 2010; IASB, 2018). Financial performance was assessed through perceived improvements in profitability, cost control, overall financial condition, and relative performance compared with those of competitors (Venkatraman and Ramanujam, 1986; Richard et al., 2009). Because the items were adapted to the study context, their reliability and validity were assessed empirically through the PLS-SEM measurement model.

Each variable was evaluated through a five-point Likert scale, where 1 corresponds to “strongly disagree” and 5 to “strongly agree.”

4. RESULTS

4.1. Descriptive Analysis

For every variable in the research model, descriptive statistics were used to evaluate the skewness, kurtosis, and standard and mean deviation. The results in Table 1 demonstrate that all item mean values are greater than their corresponding standard deviations, indicating a modest dispersion of answers around the average and adequate data representation. The results show that the mean values for AI adoption items range from 4.184 to 4.272, indicating a high perceived level of AI tool integration inside the financial processes of the start-ups assessed.

The mean scores for financial reporting quality range from 4.336 to 4.392, suggesting that respondents typically view financial reporting as timely, relevant, and dependable. The observed mean values for financial performance range from 4.160 to 4.328, indicating that the startups polled evaluate their financial success at a comparatively high level.

All the variables have negative skewness coefficients, which indicates that the responses are concentrated at the higher end of the Likert scale. Kurtosis values are positive for most indicators, but they stay within acceptable bounds, indicating that there is no significant departure from the assumptions of a normal distribution.

Table 1: Descriptive analysis

Construct	Mean	Standard deviation	Kurtosis	Skewness
IA1	4.272	0.975	1.792	−1.517
IA2	4.224	0.995	2.005	−1.550
IA3	4.232	0.997	1.866	−1.512
IA4	4.248	0.952	2.892	−1.644
IA5	4.184	0.975	1.825	−1.428
FRQ1	4.344	0.859	3.506	−1.729
FRQ2	4.336	0.857	2.804	−1.636
FRQ3	4.360	0.833	2.841	−1.603
FRQ4	4.392	0.809	3.251	−1.663
FRQ5	4.352	0.822	2.660	−1.525
PERF1	4.312	0.824	3.505	−1.596
PERF2	4.288	0.847	3.399	−1.633
PERF3	4.304	0.896	3.446	−1.721
PERF4	4.160	0.924	0.942	−1.064
PERF5	4.328	0.883	3.090	−1.684

Table 2: Internal consistency reliability of the constructs

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
AI adoption	0.965	0.965	0.973
Financial performance	0.943	0.949	0.957
Financial reporting quality	0.956	0.958	0.966

Overall, these findings support the viability of the gathered data for further structural analysis and validate their statistical soundness.

These descriptive statistics suggest favorable perceptions of AI integration, financial reporting quality, and financial performance among Moroccan startups, providing an appropriate basis for structural model estimation.

4.2. PLS-SEM Results

Structural equation modeling (SEM) and SmartPLS 4 software, were used to evaluate the conceptual model linking AI use, financial reporting quality, and the financial success of Moroccan businesses. The PLS-SEM approach is useful for analyzing models with latent variables and many causal links, especially in explanatory and predictive research contexts.

PLS-SEM is widely regarded as a second-generation multivariate analysis technique that enables the modeling of unobservable constructs and the simultaneous estimation of relationships between latent variables and their measurement indicators as well as structural relationships among constructs (Chin, 1998). This method provides a significant degree of flexibility for empirically assessing theoretical frameworks that include both direct and indirect effects. Its usage is justified by the current study's examination of the mediating role of financial reporting quality in the relationship between AI adoption and financial performance.

In accordance with recognized PLS-SEM methodological guidelines, the model was assessed in two main stages (Hair et al., 2019). The measuring model (the outer model) was initially assessed to assess construct validity and reliability. The structural model, sometimes referred to as the inner model, was evaluated to investigate the predicted correlations between the latent variables and test the research hypotheses.

4.2.1. Measurement model

The associations between each latent concept and its reflective indicators obtained from the questionnaire are described in the measurement model. This study examined three reflecting constructs: financial performance, financial reporting quality, and AI adoption. Several evaluation criteria, such as discriminant validity, convergent validity, individual indicator reliability (outer loadings), internal consistency, and reliability, were used to guarantee the robustness of the measurement model. These standards enable the evaluation of the consistency, unidimensionality, and compatibility of the measuring scales with the theoretical framework supporting the study. Before understanding the structural links among the variables, evaluating the quality of the measurement model is crucial because the data are based on perceptual measures that were gathered using a Likert scale.

4.2.1.1. Internal consistency reliability

Following suggested PLS-SEM protocols, internal consistency reliability was evaluated using Cronbach's alpha, composite reliability (rho_a), and composite reliability (rho_c) (Chin, 1998; Hair et al., 2019). Generally, a latent variable's reliability can be confirmed with a value of 0.70 or higher (Tenenhaus et al., 2005).

According to the findings, every variable has a high degree of internal consistency reliability. Reliability coefficients over the suggested threshold are reported by the AI adoption construct, indicating strong coherence across the indicators gauging the incorporation of AI tools into financial processes. In a similar vein, the quality of financial reporting highly reliable, verifying the uniformity of items capturing the timeliness, relevance, and dependability of financial data. Finally, the financial performance construct consistently measures profitability, cost control, and total financial improvement, surpassing the 0.70 threshold by a significant margin (Table 2).

The measurement scales are reliable and suitable for structural analysis, as evidenced by the fact that all the reliability coefficients generally exceed the lowest suggested criterion. These results support the validity of the measurement model and show that the indicators appropriately capture their corresponding latent variables.

4.2.1.2. Indicator reliability

The evaluation results for each questionnaire item are shown in Table 3. The results demonstrate that all the indicators associated with the reflective constructs exhibit outside loadings over the generally accepted PLS-SEM study threshold of 0.70.

The majority of items have loadings that are significantly greater than this cutoff, meaning that each latent construct accounts for at least 50% of the variance in each observed variable. These results validate the indicators' suitability and congruence with the underlying theoretical features under assessment.

Table 3: Outer loading

Indicator	Outer loading	T-statistics
FRQ1 <- Financial reporting quality	0.910	31.777
FRQ2 <- Financial reporting quality	0.938	55.964
FRQ3 <- Financial reporting quality	0.957	89.423
FRQ4 <- Financial reporting quality	0.926	36.141
FRQ5 <- Financial reporting quality	0.883	24.413
IA1 <- AI adoption	0.927	51.842
IA2 <- AI adoption	0.952	78.890
IA3 <- AI adoption	0.946	63.996
IA4 <- AI adoption	0.939	60.008
IA5 <- AI adoption	0.920	43.718
PERF1 <- Financial performance	0.925	42.767
PERF2 <- Financial performance	0.949	64.925
PERF3 <- Financial performance	0.925	43.457
PERF4 <- Financial performance	0.835	19.141
PERF5 <- Financial performance	0.878	29.606

Outer loadings below 0.70 necessitate careful consideration of the indicator's retention inside the model, in accordance with recognized methodological norms. However, all the factor loadings in the current investigation are higher than this cutoff, demonstrating the stability and reliability of the measurement model.

4.2.1.3. Convergent validity

A convergent validity threshold greater than 0.50 is typically advised in PLS-SEM research (Hair et al., 2017). The average variation extracted (AVE), which represents the average amount of variation that a latent concept collects from its related indicators, is used to assess convergent validity. Because the AVE values are significantly higher than the suggested cutoff of 0.50, the results shown in Table 4 show satisfactory convergent validity across all the measurement scales. Speciafically, the AVE values are 0.816 for financial performance, 0.852 for financial reporting quality, and 0.878 for AI adoption.

The results of the analysis measuring results suggest that each variable accounts for a significant share of the variance in its indicators, confirming the reliability and appropriateness of the measurement model.

4.2.1.4. Discriminant validity

Following the recommendations of Evrard et al. (2003), discriminant validity was assessed to ensure that the constructs represented distinct concepts within the proposed model. As a result, construct should account for a greater amount of variance in its own indicators than in those associated with other constructs in the model. The Fornell-Larcker (1981) criterion was used to assess discriminant validity. According to this method, each construct's square root of the AVE must be greater than its correlations with the other latent variables.

The results reported in Table 5 confirm that this requirement is fulfilled for all the constructs. Therefore, discriminant validity is established, indicating that each construct represents a distinct concept within the proposed model.

4.2.2. Structural model

To investigate the connections between the latent variables contained in the conceptual framework, the structural model

Table 4: Outer loading

Construct	AV
AI adoption	0.878
Financial performance	0.816
Financial reporting quality	0.852

Table 5: Correlation matrix

Construct	1	2	3
AI adoption	0.937		
Financial performance	0.813	0.903	
Financial reporting quality	0.792	0.823	0.923

also known as the "inner model", was assessed. Following established PLS-SEM guidelines (Hair et al., 2017), the evaluation concentrated on the model's explanatory and predictive power using the coefficients of determination (R^2), the Stone-Geisser predictive relevance coefficient (Q^2 predict), and the bootstrapping procedure to evaluate direct, indirect, and total effects.

Before the explanatory power of the model was assessed, collinearity among predictor constructs was examined using the variance inflation factor (VIF). According to Hair et al. (2017), VIF values less than 5 indicate that multicollinearity is not a critical issue in the structural model.

The results indicate that all the VIF values are below the recommended threshold. Specifically, the VIF value for the relationship AI adoption → financial reporting quality is 1.000, whereas the VIF values for AI adoption → financial performance and financial reporting quality → financial performance are 2.677 (Table 6). These findings confirm that multicollinearity does not bias the estimation of the structural paths and that the model is statistically robust.

The amount of an endogenous construct's variance that its predictor can explain is known as the coefficient of determination, or R. According to Croutsche (2002), a structural model is deemed significant if its R^2 value is more than 0.10. According to the data in Table 7, financial reporting quality has an R^2 value of 0.627, which means that AI adoption accounts for 62.7% of its variance. AI adoption and financial reporting quality together account for 74.7% of the variance in financial performance, as indicated by the R^2 value of 0.747. These values are significantly higher than the suggested cutoff, indicating the structural model's strong explanatory power and verifying that a sizable amount of the variance in the endogenous constructs is captured by the suggested framework.

According to Hair et al. (2017), R^2 values of 0.75, 0.50, and 0.25 can be described as substantial, moderate, and weak, respectively. The R^2 value of 0.747 for financial performance can therefore be considered substantial, further reinforcing the robustness and explanatory strength of the proposed model within the startup context.

The predictive relevance of the model was further assessed using the blindfolding procedure to compute Q^2 predict values. As

Table 6: Collinearity assessment

Structural path	VIF
AI adoption -> Financial performance	2.677
AI adoption -> Financial reporting quality	1.000
Financial reporting quality -> Financial performance	2.677

Table 7: Predictive capability evaluation results

Construct	R-square	R-square adjusted	Q^2 predict
Financial reporting quality	0.627	0.623	0.623
Financial performance	0.747	0.743	0.661

Table 8: Effect sizes (f^2)

Structural path	f-square
AI adoption -> Financial performance	0.287
AI adoption -> Financial reporting quality	1.677
Financial reporting quality -> Financial performance	0.328

Table 9: Model fit indices

Fit index	Value
SRMR	0.043
NFI	0.880

reported in Table 7, the Q^2 predict coefficients are positive for both endogenous variables, with values of 0.623 for financial reporting quality and 0.661 for financial performance. In accordance with the PLS-SEM standards, positive Q^2 predict values indicate satisfactory predictive relevance. These findings therefore confirm that the model possesses not only explanatory strength but also predictive ability.

The effect size (f^2) was examined to assess the magnitude of each structural relationship. According to Cohen (1988), values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

The results (Table 8) show that AI adoption has a very large effect on financial reporting quality ($f^2 = 1.677$). Financial reporting quality strongly effects financial performance ($f^2 = 0.328$). In contrast, the direct effect of AI adoption on financial performance has a medium effect size ($f^2 = 0.287$).

Overall, these findings confirm that the relationships in the structural model are not only statistically significant but also substantively meaningful.

To evaluate the adequacy of the proposed model, two fit indices were considered: the standardized root mean square residual (SRMR) and the normed fit index (NFI). The SRMR value obtained (0.043) is considerably lower than the recommended limit of 0.08, suggesting strong agreement between the theoretical model and the observed data (Table 9). Moreover, the NFI score of 0.880 indicates a satisfactory degree of model fit. These indicators collectively confirm that the structural model provides an appropriate representation of the empirical data and supports the reliability of the proposed conceptual framework. Although model fit indices are not the primary focus in PLS-SEM, the reported values further support the adequacy of the proposed model.

Using bootstrapping and a significance level of 5%, the structural correlations were assessed. Hypothesis 1 is supported by the results shown in Table 10, which show that AI adoption has a favorable and statistically significant effect on financial reporting quality ($\beta = 0.792$; $t = 15.775$; $P < 0.001$). Furthermore, financial performance is positively and significantly impacted by financial reporting quality ($\beta = 0.472$; $t = 4.943$; $P < 0.001$), supporting Hypothesis 2. Crucially, adoption of AI also supports Hypothesis 4, as it has a positive and statistically significant direct effect on financial performance ($\beta = 0.441$; $t = 4.809$; $P < 0.001$). These findings show that the use of AI improves reporting quality and directly affects financial performance.

To formally test the mediating role of financial reporting quality, the specific indirect effect of AI adoption on financial performance was examined. As shown in Table 11, the indirect effect is positive and statistically significant ($\beta = 0.373$; $t = 4.615$; $P < 0.001$), confirming Hypothesis 3. These findings demonstrate that part of the influence of AI adoption on financial performance operates through improvements in financial reporting quality.

The total effects, reported in Table 12 and Figure 2, further highlight the overall strength of the relationships within the model. The total effect of AI adoption on financial performance is positive and highly significant ($\beta = 0.815$; $t = 18.154$; $P < 0.001$), indicating a substantial overall contribution of AI adoption to financial outcomes.

To determine the nature of the mediation, the (VAF) was calculated as the ratio of the indirect effect to the total effect. The VAF value is computed as follows:

$$VAF = 0.373/0.815 \approx 0.458\ (45.8\%)$$

Since the VAF lies between 20% and 80%, the mediation can be classified as partial mediation according to commonly accepted thresholds in mediation analysis. These results indicate that AI adoption influences financial performance both directly and indirectly through financial reporting quality. Therefore, financial reporting quality functions as a complementary mediating mechanism in the relationship between AI adoption and financial performance. Overall, the structural model demonstrates strong explanatory power, satisfactory predictive relevance, and robust support for the hypothesized relationships.

5. DISCUSSION

This study analyzes the relationship between artificial intelligence adoption and the financial performance of Moroccan startups, paying particular attention to the mediating role of financial reporting quality. Drawing on the resource-based view and rational decision-making theory, AI is considered not only as a technological tool but also as an organizational capability whose value depends on its integration with data resources, managerial expertise, and internal processes (Mikalef and Gupta, 2021; Enholm et al., 2022). This perspective is consistent with prior research showing that the benefits of AI are not automatic and depend on complementary organizational capabilities. Whereas

Table 10: Direct effects and hypothesis testing results

Structural path	Orig sam (O)	Sam mean (M)	Standard deviation	T-statistics	P-value
AI adoption -> Financial performance	0.441	0.439	0.092	4.809	0.000
AI adoption -> Financial reporting quality	0.792	0.787	0.050	15.775	0.000
Financial reporting quality -> Financial performance	0.472	0.471	0.095	4.943	0.000

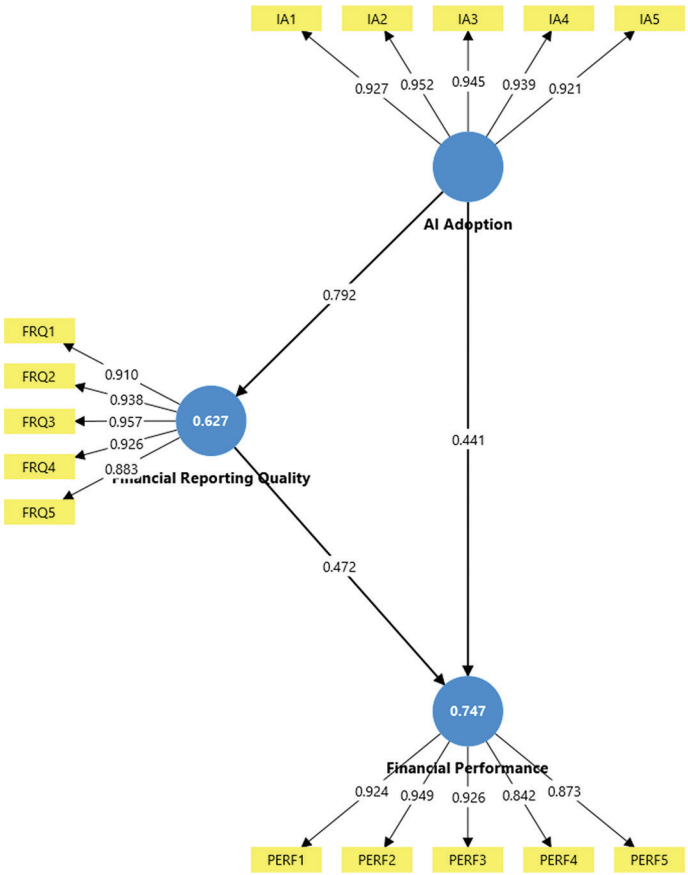
Table 11: Specific indirect effects (mediation analysis)

Indirect effect	Orig sam (O)	Sam mean (M)	Standard deviation	T-statistics	P-value
AI adoption -> Financial reporting quality -> Financial performance	0.373	0.371	0.081	4.615	0.000

Table 12: Total effects

Total effect	Orig sample (O)	Sam mean (M)	Standard deviation	T-statistics	P-value
AI adoption -> Financial performance	0.815	0.810	0.045	18.154	0.000
AI adoption -> Financial reporting quality	0.792	0.787	0.050	15.775	0.000
Financial reporting quality -> Financial performance	0.472	0.471	0.095	4.943	0.000

Figure 2: Structural equation model



much of the literature examines AI-related value in broad organizational settings, this study focuses on Moroccan startups and identifies financial reporting quality as an informational mechanism through which AI can enhance financial outcomes. The use of PLS-SEM allows the simultaneous examination of the direct and indirect relationships proposed in the conceptual model.

The results provide empirical support for the proposed model and underscore the importance of viewing financial information as a strategic resource rather than merely as administrative information.

In the context of Moroccan startups, which often face limited managerial resources, financing constraints, and information systems that are still poorly structured, the integration of AI-based tools can serve as a significant lever for strengthening internal capabilities. The following discussion examines the results for each hypothesis and situates them within the context of key theoretical and empirical literature.

First, the results support Hypothesis H_1, showing that financial reporting quality is positively and statistically significantly impacted by AI adoption ($\beta = 0.792$; $P < 0.001$). This findings suggest that incorporating AI tools into financial processes improves the timeliness, relevance, and dependability of financial data, especially through automation, sophisticated data analytics, and enhanced internal controls. AI can be viewed as a strategic technological resource that enhances startups' informational capacities from the perspective of the resource-based view (RBV). These results are consistent with earlier studies that highlight how digital technologies add value when they enhance the efficiency and caliber of information systems (DeLone and McLean, 2003; Rikhardsson and Yigitbasioglu, 2018). Strengthening informational capacity seems to be a crucial strategic lever in growing startup ecosystems that are marked by structural and financial constraints.

Second, financial reporting quality positively and significantly affects financial performance ($\beta = 0.472$; $P < 0.001$), supporting Hypothesis H_2. These results converge with those of prior accounting research showing that higher-quality financial reporting reduces information asymmetry and can improve investment efficiency and resource allocation (Biddle et al., 2009; Bushman and Smith, 2001). It also reinforces the rational decision-making perspective, according to which timely, reliable, and relevant financial information better supports better managerial decisions. Unlike many earlier studies based on listed firms and archival accounting data, the present research examines this relationship among Moroccan startups through managers' perceptions. These results therefore extend the prior evidence by suggesting that financial reporting quality remains a relevant performance lever even in younger firms operating under resource constraints and high uncertainty.

Third, the findings confirm the mediating role of financial reporting quality in the relationship between AI adoption and financial performance. The positive and significant indirect effect indicates that part of the value generated by AI adoption is transmitted through improvements in the quality of financial information. These results are consistent with studies suggesting that AI capabilities create organizational value through intermediate mechanisms, including analytical capabilities, information-processing improvements, and complementary organizational resources (Mikalef and Gupta, 2021; Enholm et al., 2022). However, the persistence of a significant direct effect of AI adoption on financial performance indicates that financial reporting quality is not the only explanatory channel. These findings are consistent with the automation–augmentation perspective, according to which AI can simultaneously improve operational efficiency and strengthen managerial decision-making capabilities (Raisch and Krakowski, 2021). Thus, the present study extends previous research by identifying financial reporting quality as a specific mediating mechanism in the context of Moroccan startups.

Taken together, these results contribute to the literature by providing empirical evidence that AI adoption is associated with financial performance through both direct and indirect pathways in Moroccan startups. These findings are consistent with those of prior studies emphasizing that AI creates business value when it is integrated into organizational processes and supported by complementary technological, managerial, and data-related capabilities (Mikalef and Gupta, 2021; Enholm et al., 2022). Moreover, the results indicate that AI adoption alone is not sufficient to improve financial outcomes, as its value also depends on its effective integration into financial information systems, internal controls, and managerial decision-making processes (Raisch and Krakowski, 2021). By identifying financial reporting quality as a specific informational mechanism, this study contributes to ongoing discussions on how digital technologies translate into financial outcomes in emerging-economy startup contexts.

6. CONCLUSION

This study aimed to examine the contribution of AI adoption to the financial performance of Moroccan startups, emphasizing the mediating role of financial reporting quality. The empirical findings demonstrate that AI adoption significantly enhances financial reporting quality and that financial reporting quality positively influences financial performance. Furthermore, the results confirm that AI adoption improves financial performance both directly and indirectly through improvements in reporting quality, supporting the presence of a complementary partial mediation mechanism.

From a theoretical perspective, this research contributes to the literature by integrating the resource-based view and rational decision-making theory into a coherent explanatory framework that links AI adoption, financial information quality, and organizational performance. The findings confirm that AI constitutes a strategic value-creating resource when it strengthens internal informational capabilities. By identifying financial reporting quality as a key mediating mechanism, the study refines the understanding of how technological innovation translates into measurable financial outcomes.

From a managerial standpoint, the results suggest that AI adoption should not be viewed merely as a technological investment but rather as a strategic lever for enhancing financial information systems. Startup managers should prioritize the effective integration of AI tools into financial reporting and decision-support processes to maximize performance gains. Investments in AI must therefore be accompanied by improvements in governance structures, data management practices, and internal control systems to fully realize their economic potential.

Despite its contributions, this research has certain limitations. The sample is limited to Moroccan startups, which could limit the generalizability of the results to other sectors or institutional contexts. Moreover, the cross-sectional design calls for caution when interpreting causal relationships. Longitudinal designs may be used in future studies to capture the dynamic effects of AI adoption over time or conduct comparative analyses across countries and industries to further explore contextual contingencies in technology-driven performance enhancement.

7. ETHICAL CONSIDERATIONS

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki. It was based on an anonymous online questionnaire voluntarily distributed to professionals working in Moroccan startups through personal and professional networks. No sensitive personal data were collected. Before completing the questionnaire, the respondents were informed about the purpose of the study, the voluntary nature of their participation, and the anonymous and confidential treatment of their responses. Free and informed consent was obtained from all participants prior to data collection. No formal ethical approval or official exemption from ethical review was obtained before the study was conducted.

REFERENCES

Appelbaum, D., Kogan, A., Vasarhelyi, M.A., Yan, Z. (2017), Impact of business analytics and enterprise systems on managerial accounting. International Journal of Accounting Information Systems, 25, 29-44.

Barney, J. (1991), Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120.

Barney, J.B. (2001), Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. Journal of Management, 27(6), 643-650.

Barth, M.E., Konchitchki, Y., Landsman, W.R. (2013), Cost of capital and financial statement transparency. Journal of Accounting and Economics, 55(2-3), 206-224.

Bharadwaj, A., El Sawy, O.A., Pavlou, P.A., Venkatraman, N. (2013), Digital business strategy: Toward a next generation of insights. MIS Quarterly, 37(2), 471-482.

Bharadwaj, A.S. (2000), A resource-based perspective on information technology capability and firm performance: An empirical investigation. MIS Quarterly, 24(1), 169-196.

Bhimani, A., Willcocks, L. (2014), Digitisation, “big data” and the transformation of accounting information. Accounting and Business Research, 44(4), 469-490.

Biddle, G.C., Hilary, G., Verdi, R.S. (2009), How does financial reporting quality relate to investment efficiency? Journal of Accounting and Economics, 48(2-3), 112-131.

Brynjolfsson, E., Hitt, L.M. (2000), Beyond computation: Information technology, organizational transformation and business performance. Journal of Economic Perspectives, 14(4), 23-48.

Bushman, R.M., Smith, A.J. (2001), Financial accounting information and corporate governance. Journal of Accounting and Economics, 32(1-3), 237-333.

Chin, W.W. (1998), The partial least squares approach to structural equation modeling. In: Marcoulides, A.G., editor. Modern Methods for Business Research. France: Lawrence Erlbaum Associates. p295-336.

Cohen, J. (1988), Statistical Power Analysis for the Behavioral Sciences. 2nd ed. France: Lawrence Erlbaum Associates.

Croutsche, J.J. (2002), Étude des relations de causalité: Utilisation des modèles d'équations structurelles. La Revue des Sciences de Gestion, 198, 81-97.

Davenport, T.H., Ronanki, R. (2018), Artificial intelligence for the real world. Harvard Business Review, 96(1), 108-116.

Davila, A., Foster, G. (2007), Management control systems in early-stage startup companies. The Accounting Review, 82(4), 907-937.

Davila, A., Foster, G., Gupta, M. (2003), Venture capital financing and the growth of startup firms. Journal of Business Venturing, 18(6), 689-708.

Dechow, P., Ge, W., Schrand, C. (2010), Understanding earnings quality: A review of the proxies, their determinants and their consequences. Journal of Accounting and Economics, 50(2-3), 344-401.

DeLone, W.H., McLean, E.R. (2003), The DeLone and McLean model of information systems success: A ten-year update. Journal of Management Information Systems, 19(4), 9-30.

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., (2021), Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994.

Eisenhardt, K.M. (1989), Agency theory: An assessment and review. Academy of Management Review, 14(1), 57-74.

Eisenhardt, K.M., Zbaracki, M.J. (1992), Strategic decision making. Strategic Management Journal, 13(S2), 17-37.

Enholm, I.M., Papagiannidis, E., Mikalef, P., Krogstie, J. (2022), Artificial intelligence and business value: A literature review. Information Systems Frontiers, 24(5), 1709-1734.

Evrard, Y., Pras, B., Roux, E. (2003), Market: Études et Recherches en Marketing. 3rd éd. Delhi: Dunod.

Fornell, C., Larcker, D.F. (1981), Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.

Francis, J., LaFond, R., Olsson, P., Schipper, K. (2004), Costs of equity and earnings attributes. The Accounting Review, 79(4), 967-1010.

Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M. (2017), A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). 2nd ed. London: SAGE.

Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M. (2019), When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2-24.

Healy, P.M., Palepu, K.G. (2001), Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. Journal of Accounting and Economics, 31(1-3), 405-440.

International Accounting Standards Board. (2018), Conceptual Framework for Financial Reporting. United States: IFRS Foundation.

Jarrahi, M.H. (2018), Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577-586.

Kaplan, R.S., Atkinson, A.A. (2014), Advanced Management Accounting. 3rd ed. London: Pearson.

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.

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.

Mikalef, P., Krogstie, J., Pappas, I.O., Pavlou, P.A. (2020), Investigating the effects of big data analytics capabilities on firm performance: The mediating role of dynamic capabilities. Information Management, 57(2), 103169.

Moll, J., Yigitbasioglu, O. (2019), The role of internet-related technologies in shaping the work of accountants: New directions for accounting research. The British Accounting Review, 51(6), 100833.

Olan, F., Arakpogun, E.O., Suklan, J., Nakpodia, F., Damij, N., Jayawickrama, U. (2022), Artificial intelligence and knowledge sharing: Contributing factors to organizational performance. Journal of Business Research, 145, 605-615.

Otley, D.T. (2016), The contingency theory of management accounting and control: 1980-2014. Management Accounting Research, 31, 45-62.

Raisch, S., Krakowski, S. (2021), Artificial intelligence and management: The automation-augmentation paradox. Academy of Management Review, 46(1), 192-210.

Richard, P.J., Devinney, T.M., Yip, G.S., Johnson, G. (2009), Measuring organizational performance: Towards methodological best practice. Journal of Management, 35(3), 718-804.

Rikhardsson, P., Yigitbasioglu, O. (2018), Business intelligence and analytics in management accounting research: Status and future focus. International Journal of Accounting Information Systems, 29, 37-58.

Russell, S.J., Norvig, P. (2021), Artificial Intelligence: A Modern Approach. 4th ed. London: Pearson.

Simon, H.A. (1977), The New Science of Management Decision. United States: Prentice-Hall.

Sutton, S.G., Holt, M., Arnold, V. (2016), "The reports of my death are greatly exaggerated"-artificial intelligence research in accounting. International Journal of Accounting Information Systems, 22, 60-73.

Tenenhaus, M., Vinzi, V.E., Chatelin, Y.M., Lauro, C. (2005), PLS path modeling. Computational Statistics Data Analysis, 48(1), 159-205.

Venkatraman, N., Ramanujam, V. (1986), Measurement of business performance in strategy research: A comparison of approaches. Academy of Management Review, 11(4), 801-814.

Wade, M., Hulland, J. (2004), The resource-based view and information systems research: Review, extension, and suggestions for future research. MIS Quarterly, 28(1), 107-142.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R., Childe S.J. (2017), Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356-365.