

Smart Financial Decisions and Business Sustainability: The Mediating Role of AI-Driven Financial Analytics

Kadek Wulandari Laksmi P ^{1*}, Komang Widhya Sedana Putra P ², IGN Oka Ariwangsa ³

^{1*,2,3} Management Study Program, Faculty of Economics and Business, Universitas Pendidikan Nasional, Denpasar City, Bali Province, Indonesia

Email: wulandarilaksmi@undiknas.ac.id ^{1*}, widhyasedana@undiknas.ac.id ², okaariwangsa@undiknas.ac.id ³

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Abstract

Artificial intelligence (AI) is increasingly embedded in corporate financial decision-making, reshaping how organisations pursue sustainability goals; nevertheless, many companies still find it difficult to convert their financial strategies into durable, sustainable results. Existing research offers mixed conclusions: some studies argue that financial choices strengthen sustainability performance, whereas others point to a disconnect caused by a focus on short-term gains, exposing a gap in the understanding of the mechanism connecting the two. This research addresses that gap by investigating whether AI-driven financial analytics mediates the link between financial decision-making and business sustainability. A quantitative design was used, drawing on survey responses from 200 MSME decision-makers in Indonesia. Partial Least Squares Structural Equation Modelling (PLS-SEM) was applied to examine both the direct and indirect pathways among the constructs. Results show that financial decisions have a markedly positive influence on sustainability and also meaningfully shape the extent to which firms adopt AI-driven financial analytics. AI-driven analytics, in turn, positively affects sustainability and partially mediates the main relationship, demonstrating that technological capability amplifies the value of sound financial decisions. Theoretically, the study broadens the Resource-Based View and Dynamic Capabilities perspective by framing AI-driven financial analytics as a strategic capability embedded in the finance function. From a practical standpoint, the findings point to the need for firms to weave AI into their financial workflows to secure sustainable outcomes, and for policymakers to encourage the development of digital capability among MSMEs. Subsequent research is encouraged to adopt longitudinal designs and cross-national comparisons to better capture how these dynamics evolve across contexts.

Keywords:

Financial Decisions; Business Sustainability; AI-Driven Financial Analytics; MSMEs; Digital Transformation.

1. INTRODUCTION

Businesses worldwide are experiencing a fundamental shift fuelled by the fast-paced spread of artificial intelligence (AI) and data-centric technologies (Ma et al., 2025). Organisations in nearly every sector are weaving AI deeper into their financial operations, from predictive tools that guide investment choices to automated systems for assessing risk (Gabelaia & Hendieh, 2025). This change goes beyond mere technology adoption—it signals a broader move toward decision-making anchored in data, occurring against a backdrop of uncertainty, market volatility, and mounting pressure to operate sustainably. Yet even as awareness of sustainable practice grows, numerous firms still find it hard to convert financial choices into lasting sustainability results (Sheng & An, 2024). The simultaneous presence of sophisticated financial tools and ongoing sustainability struggles implies that the link between financial decision-making and sustainability is more complicated than it first appears.

Grasping this relationship matters both academically and in practice. Choices around investment allocation, capital structure, and resource deployment sit at the heart of a firm's survival and expansion (Motylska-Kuzma, 2017). When such choices ignore long-term considerations, however, they can erode sustainability efforts and produce short-term thinking along with wasteful use of resources. Practitioners who overlook this risk strategic misalignment, poor capital deployment, and a weaker competitive position. Meanwhile, scholars are left questioning whether established theoretical models can still capture how decision-making actually unfolds in today's digitally driven organisations.

Theoretically, scholars have often approached the financial-decision-sustainability link through frameworks such as the Resource-Based View, which stresses that internally held capabilities are what generate lasting competitive advantage (Ristyan et al., 2023). More recent work has started to recognise how digital capability shapes financial results (Maycotte et al., 2025; Yavuz et al., 2025), yet the specific role of AI-driven analytics within these theoretical lenses has received comparatively little attention.

A notable gap stems from conflicting evidence about how financial decisions shape sustainability. Some research finds that well-made financial choices support sustainability by promoting efficient resource use and long-horizon investment (Wang et al., 2022; Zhao et al., 2025), while other work shows that financial priorities can clash with sustainability aims, especially when firms chase short-term returns (Yiadom et al., 2025; Naseer et al., 2025). Such contradictions point to a missing link that could explain how financial choices actually get converted into sustainability performance within today's technology-driven settings. In particular, the literature has yet to clarify whether—and how—AI-driven financial analytics might mediate this connection. Closing this gap matters theoretically because it tests whether conventional models, which largely ignore intelligent systems, still hold up as adequate explanations of decision-making. Leaving AI-related mechanisms out risks an overly simplified account of how financial decisions translate into sustainability. On a practical level, this blind spot could lead organisations to pour resources into AI without truly capturing its potential to support sustainable outcomes—that is, firms might acquire sophisticated tools yet fail to achieve any real strategic payoff.

Motivated by this gap, the present study investigates the connection between financial decisions and business sustainability, giving particular attention to the mediating function of AI-driven financial analytics. The guiding research question is: how, and to what degree, does AI-driven financial analytics mediate the link between financial decision-making and business sustainability? A mediational framework is adopted here, one that treats AI-driven financial analytics as a strategic capability converting financial-decision inputs into sustainability-oriented results. This approach goes beyond simple direct-effect modelling, offering a richer account of the underlying mechanism. While earlier studies have typically treated digital tools as background or contextual factors, this research puts AI-driven analytics at the centre of the decision-making process.

This study makes three main contributions. Theoretically, it extends the Resource-Based View by framing AI-driven financial analytics as a vital organisational capability that boosts how effectively financial decisions translate into sustainability. Empirically, it supplies evidence regarding the mediating function within the financial-decision-sustainability nexus, helping resolve inconsistencies found in earlier work. Practically, it offers managers concrete guidance on aligning financial strategy with sustainability aims through the effective deployment of AI-driven analytics. By connecting financial decision-making, sustainability, and AI capability, the study aims to deepen understanding of how organisations can manage the complexity of contemporary business while pursuing long-term value.

1.1. Grand Theoretical Foundations

Two major theoretical perspectives anchor this study: the Resource-Based View (RBV) and Dynamic Capabilities Theory. Together, they offer a solid basis for understanding how financial decisions and AI capability jointly shape business sustainability. RBV holds that firms secure lasting competitive advantage by effectively deploying resources that are valuable, rare, difficult to imitate, and non-substitutable, or VRIN (Ristyan et al., 2023). Financial decision-making, in this view, is a strategic process governing how organisational resources are allocated. Yet simply having financial resources available is not enough to ensure sustainability; what truly matters is the firm's capacity to deploy those resources effectively, which is what ultimately shapes long-term results (Mailani et al., 2024). Financial decisions therefore need to be reinforced by capabilities that raise decision quality and strategic coherence.

Dynamic Capabilities Theory adds to this picture by highlighting a firm's capacity to integrate, build, and reshape both internal and external competencies as environments shift rapidly (Mushangai, 2023). Within the current wave of digital transformation, AI-driven financial analytics can be understood as precisely this kind of dynamic capability—one that helps firms detect opportunities, act on them through well-informed financial decisions, and reshape their resource base accordingly (Ayoub & Sopuru, 2026). This lens is especially useful for explaining how firms adjust their financial strategies to remain sustainable amid uncertainty and rapid technological change. Taken together, these two theories suggest that although financial decisions are essential, their ultimate effect on sustainability depends on whether advanced organisational capabilities—AI-driven financial analytics chief among them—are in place.

1.2. Financial Decisions and Business Sustainability

Financial decisions cover the core managerial choices tied to investment, financing, and resource allocation (Pea-Assounga et al., 2024). These choices shape a firm's operational efficiency, exposure to risk, and long-run strategic path. Viewed through a sustainability lens, well-considered financial decisions can open the door to investment in environmentally sound technologies, bolster social responsibility efforts, and strengthen economic resilience (Lina, 2024).

That said, the link between financial decisions and sustainability is not always straightforward. Firms frequently favour near-term profit over long-term sustainability, which can produce suboptimal results (Mansikkamäki, 2023). This tension illustrates a wider difficulty in reconciling financial goals with sustainability objectives. Some research points to a positive link between careful financial management and sustainable performance, while other findings are mixed, implying that financial decisions by themselves may not be enough to drive sustainability without additional supporting mechanisms.

H1: Financial decisions have a positive effect on business sustainability.

1.3. Financial Decisions and AI-Driven Financial Analytics

As financial environments grow more intricate, firms have turned increasingly to AI-driven financial analytics to strengthen their decision-making (Aldasoro et al., 2025). Such systems draw on big data, machine-learning algorithms, and predictive modelling to produce insights that sharpen the accuracy, speed, and strategic foresight of financial choices. Seen through RBV, AI-driven financial analytics can function as a strategic resource that raises the value generated by financial decisions. Dynamic Capabilities Theory, meanwhile, frames this technology as a capability enabling firms to keep adapting their decision-making in step with a changing environment. Firms that weave AI effectively into their finance functions are better equipped to spot risks, allocate resources efficiently, and anticipate emerging trends (Vuković et al., 2025). Financial decisions and the adoption of AI-driven analytics are thus becoming increasingly interconnected (Ünvan & Alsokhni, 2026): organisations that make more sophisticated financial choices also tend to invest more in advanced analytical tools, forming a self-reinforcing loop between decision quality and technological capability.

H2: Financial decisions have a positive effect on AI-driven financial analytics.

1.4. AI-Driven Financial Analytics and Business Sustainability

AI-driven financial analytics helps close the divide between financial decision-making and sustainability outcomes. Through real-time insight generation, scenario modelling, and predictive functionality, AI allows firms to weave long-term thinking into their financial strategies (Bessa & Barbosa, 2025). AI can, for example, support sustainability-oriented investment choices by assessing environmental, social, and governance (ESG) risk, streamlining resource use, and surfacing opportunities to improve efficiency. It also strengthens transparency and accountability—both crucial to sustainable business conduct. Theoretically, AI-driven analytics reinforces a firm's dynamic capabilities by supporting ongoing learning and adaptation (Chen et al., 2025), turning what were once static financial processes into intelligent systems that keep financial goals in step with sustainability aims. Firms that make good use of AI-driven analytics are consequently more likely to achieve stronger sustainability performance.

H3: AI-driven financial analytics has a positive effect on business sustainability.

1.5. The Mediating Role of AI-Driven Financial Analytics

Although the importance of both financial decisions and AI capability is well recognised, exactly how financial decisions come to influence sustainability is still not fully understood. This study proposes that AI-driven financial analytics functions as a key mediating factor in that relationship. When financial decisions are backed by AI-driven analytics, they become more grounded in data, more forward-looking, and more closely tied to sustainability objectives (Phalalum & Panmarerng, 2026). Put differently, AI serves as the mechanism that converts financial inputs into sustainable results. Absent such a mechanism, financial decisions risk staying reactive and short-term focused, which limits their contribution to sustainability (Zhang & Lucey, 2022). This mediating view fits comfortably within both RBV and Dynamic Capabilities Theory: from an RBV angle, AI raises the value drawn from financial resources, while from a dynamic-capabilities angle, it lets firms reshape their decision-making in ways that support sustainability over the long run.

H4: AI-driven financial analytics mediates the relationship between financial decisions and business sustainability. Example of an Introduction with Literature Review

2. RESEARCH METHOD

2.1. Research Design

A quantitative research design underpins this study, chosen to test the relationships among financial decisions, AI-driven financial analytics, and business sustainability within a mediation framework. Quantitative methods suit this purpose well because they allow causal relationships among latent constructs to

be tested statistically. Since the study aims to validate hypotheses grounded in theory and to assess both direct and indirect effects, this design supplies the methodological precision needed to produce results that are robust and generalisable. A structured survey instrument also makes it possible to systematically capture how respondents perceive and practise financial decision-making and AI usage—both of which are inherently multifaceted phenomena. This approach is consistent with prior strategic-management and finance research that favours hypothesis testing on large samples.

2.2. Research Context and Sample

The empirical focus of this research is Micro, Small, and Medium Enterprises (MSMEs) operating in Indonesia. This setting is especially relevant given how central the MSME sector is to the national economy, coupled with growing pressure on firms to embrace digital tools while also advancing sustainability. Many Indonesian MSMEs continue to struggle with embedding advanced financial analytics into their decision processes, which makes this context well suited for testing the relationships proposed here. Respondents were drawn from business owners, financial managers, and other individuals responsible for financial and strategic decisions within their organisations, chosen as key informants because of their direct involvement in financial planning and operational practice. A purposive sampling approach ensured that participants met specific criteria—namely, active involvement in financial decision-making and prior exposure to digital or AI-based financial tools—so that the data collected would be both relevant and dependable for the study's objectives.

Because the precise population of AI-adopting MSMEs cannot be determined exactly, this study follows the sampling rule proposed by Hair (2021), which suggests a minimum sample of five to ten times the number of indicators used in structural equation modelling. With nine measurement indicators in this study, the corresponding minimum sample would be 90 respondents. To achieve greater statistical robustness and stronger generalisability, however, the study aimed for—and ultimately obtained—responses from 200 participants, well beyond the recommended floor.

2.3. Data Collection Procedure

A structured questionnaire, distributed through both online and offline channels, was used to gather data from eligible respondents. Online distribution relied on digital platforms such as email and professional networks, whereas offline collection involved direct outreach to MSME communities and business networks. Before the main survey was administered, a small-scale pilot test checked the instrument's clarity, readability, and relevance; feedback from that pilot informed subsequent refinements so that every item would be easily understood. To keep the process transparent, respondents were told the purpose of the study beforehand, and participation was entirely voluntary. Responses that failed to meet the study's predefined criteria, or that were incomplete, were dropped from the final dataset to preserve data quality.

2.4. Measurement and Instrument Development

Every construct in this study was measured with multi-item scales adapted from earlier literature, chosen to preserve content validity and theoretical fit. Items were adjusted where necessary to suit the MSME and AI-enabled financial context, without altering their underlying conceptual meaning. Financial decision-making was captured through items covering investment decisions, financing structure, and how efficiently resources are allocated—dimensions that reflect how firms manage capital, control financial risk, and prioritise strategic spending. Earlier work has shown that decisions concerning investment allocation, capital structuring, and resource optimisation play a central part in shaping firm performance and direction over time (Motylska-Kuzma, 2017; Pea-Assounga et al., 2024), and recent studies further point to the role financial decisions play in enabling sustainability initiatives such as green investment and long-range planning (Lina, 2024). Building on this, the indicators used were: (1) effectiveness of investment allocation, (2) appropriateness of financing decisions, and (3) efficiency in resource use.

AI-driven financial analytics was gauged by measuring how extensively firms apply AI technologies to their financial decision-making, including their use of predictive analytics, data-driven insight generation, and automated evaluation systems. The expanding use of AI in finance has been linked to sharper decision accuracy, better risk assessment, and improved strategic foresight (Aldasoro et al., 2025; Gabelaia & Hendieh, 2025), while AI capability more broadly reflects a firm's capacity to fold data analytics into its financial operations and adapt to complexity (Vuković et al., 2025; Ünvan & Alsokhni, 2026). The corresponding indicators were: (1) use of AI for financial forecasting, (2) integration of data analytics into decision-making, and (3) reliance on automated financial-analysis systems.

Business sustainability was assessed through a multidimensional lens covering economic, environmental, and social performance, in keeping with the broader sustainability literature's emphasis on financial resilience, environmental stewardship, and social contribution. Earlier studies suggest sustainability outcomes hinge on a firm's ability to link financial strategy with long-term value creation and responsible conduct (Sheng & An, 2024; Wang et al., 2022), while other work highlights how financial decisions support sustainable investment and operational resilience (Zhao et al., 2025; Yiadom et al., 2025). Drawing on these views, sustainability was captured through: (1) long-term financial sustainability, (2) environmental responsibility in operations, and (3) contribution to social and stakeholder well-being.

A five-point Likert scale, running from "strongly disagree" to "strongly agree," was used for all items. Relying on established, literature-backed constructs help the instrument maintain both validity and reliability while steering clear of conceptual ambiguity or plagiarism concerns. Small contextual tweaks were made so items would read clearly and stay relevant to respondents operating within the MSME and digital-transformation setting.

2.5. Data Analysis Technique

Partial Least Squares Structural Equation Modelling (PLS-SEM) was the chosen analytical method. Several considerations make PLS-SEM well suited to this research (Hair, 2022). It handles complex models involving multiple latent variables and mediating relationships effectively; it does not demand strict normality in the underlying data, which matters given that real-world business data are often non-normal; and it performs well for predictive and exploratory work, particularly in newer research areas such as AI-driven financial analytics. Analysis proceeded in two stages: first, evaluating the measurement model for validity and reliability, and second, examining the structural model to test the proposed hypotheses, including the mediation effect. Bootstrapping was used to establish whether path coefficients and indirect effects were statistically significant.

2.6. Validity and Reliability

Multiple validity and reliability checks were carried out to confirm the robustness of the measurement model. Convergent validity relied on factor loadings and Average Variance Extracted (AVE), against thresholds of 0.70 and 0.50 respectively. Discriminant validity was checked using the Fornell-Larcker criterion together with cross-loadings, confirming that each construct stood apart from the others. Reliability was verified through Cronbach's alpha and composite reliability (CR), with values above 0.70 taken as evidence of adequate internal consistency. Together, these checks help establish that the constructs are credible and that the instrument genuinely captures the intended variables.

2.7. Ethical Considerations

The study follows established ethical norms for academic research. Participants were given clear information about the study's purpose beforehand, and informed consent was secured prior to data collection. Respondents were assured that taking part was voluntary and that their answers would stay confidential and be used only for research purposes. No personal identifying information was gathered, and data were analysed only in aggregated form to protect anonymity. The study also took care to avoid plagiarism by adapting measurement items from earlier literature appropriately and crediting original sources. Throughout, the research process prioritised transparency, honest reporting, and analytical integrity in line with academic and ethical expectations.

3. RESULTS AND DISCUSSION

3.1. Results

3.1.1. Descriptive Analysis

Table 1. Descriptive Profile of the Respondents

Characteristics	Category	Frequency	Percentage (%)
Gender	Male	112	56.00%
	Female	88	44.00%
Age	< 25 years	28	14.00%
	25 – 34 years	76	38.00%
	35 – 44 years	62	31.00%
	> 44 years	34	17.00%
Education Level	High School	54	27.00%
	Bachelor's Degree	102	51.00%
	Postgraduate	44	22.00%
Business Experience	< 3 years	36	18.00%
	3 – 5 years	58	29.00%
	6 – 10 years	64	32.00%
	> 10 years	42	21.00%
Position	Owner	118	59.00%
	Financial Manager	46	23.00%
	Operational/Other Manager	36	18.00%
Use of AI in Finance	Yes	132	66.00%
	No / Limited Use	68	34.00%

The demographic profile in Table 1 shows a fairly even gender split, with a modest tilt toward male respondents—consistent with how MSME ownership and management tend to be structured in developing economies. Most respondents fall into the 25–44 age bracket, suggesting the sample largely consists of economically active people likely to be receptive to technological change. A majority hold a bachelor's degree, pointing to a reasonably solid level of formal education among decision-makers—relevant given that education is often tied to readiness in adopting technologies such as AI-driven analytics.

Business-experience figures show most respondents falling in the 3-to-10-year range, blending early-stage growth firms with more established operations. This spread strengthens the study by capturing views from firms across different developmental stages. Business owners make up the bulk of respondents, which reinforces data reliability given that strategic and financial decisions in MSMEs are typically concentrated at ownership level. A sizeable share of respondents also reports using AI in their financial activities, aligning the sample well with this study's focus on AI-driven financial analytics. Altogether, respondent characteristics suggest the data come from individuals who are relevant, well-informed, and capable of making decisions—strengthening the credibility and applicability of the findings.

These demographic patterns also shed light on the structural results presented in Section 3.3. Since respondents are mostly owners with 3-to-10 years of experience, and a majority have already used AI-based financial tools, the sample skews toward MSMEs further along their digital-adoption path. This composition likely reinforces the strong direct effect of financial decisions on sustainability, since owner-respondents usually hold direct authority over both financial and technology decisions, letting the two moves in tandem rather than as separate, sequential steps. The relatively high share of respondents with a bachelor's degree or higher may similarly help explain the significant path running from financial decisions to AI-driven financial analytics, since formal education tends to correlate with greater readiness to interpret and act on data-driven insight. Conversely, the segment with limited or no AI usage (34 percent of the sample) may account for the comparatively modest—though still significant—direct effect of AI-driven financial analytics on sustainability, hinting that analytics' benefits are not yet spread evenly across the MSME population studied. These patterns suggest respondent characteristics are not simply descriptive background but plausibly influence the relative strength of the tested paths—something future research could probe more formally through subgroup or moderation analysis.

3.1.2. Research Context and Sample

Table 2. Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (ρ_a)	Composite reliability (ρ_c)	Average variance extracted (AVE)
AI-driven financial	0.812	0.888	0.835	0.508
Business sustainability	0.797	0.914	0.844	0.554
Financial decisions	0.767	0.884	0.859	0.593

Table 2 shows that every construct meets the recommended benchmarks for reliability and convergent validity. Cronbach's alpha values for AI-driven financial analytics, business sustainability, and financial decisions all clear the widely accepted 0.70 threshold, showing that items within each construct hold together with satisfactory internal consistency—meaning the indicators are stable enough to capture the underlying concepts they represent. Composite reliability figures (both ρ_a and ρ_c) likewise sit consistently above 0.80 across constructs, reinforcing the measurement model's reliability and indicating that constructs are measured with considerable precision; the composite reliability scores for business sustainability stand out as especially strong, pointing to a well-defined, cohesive construct. On convergent validity, every AVE value clears the recommended 0.50 floor, meaning each construct accounts for more than half the variance in its indicators—confirming that items converge well around their respective latent variables. Collectively, these results confirm that the measurement model is both reliable and valid, providing a sound basis for moving on to the structural model.

3.1.3. Hypothesis Test

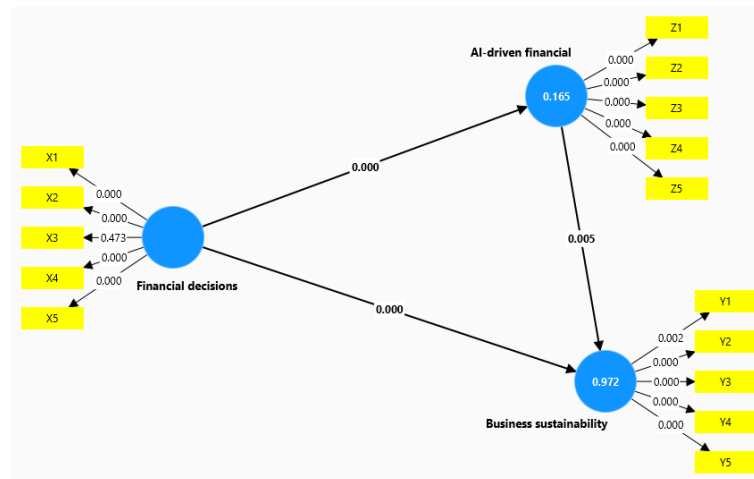


Figure 1. Structural Equation Model Testing

Table 3. Regression Weight Structural Equational Model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AI-driven financial -> Business sustainability	0.101	0.100	0.036	2.795	0.005
Financial decisions -> AI-driven financial	0.407	0.418	0.047	8.617	0.000
Financial decisions -> Business sustainability	0.941	0.939	0.024	38.710	0.000
Financial decisions -> AI-driven financial -> Business sustainability	0.041	0.042	0.017	2.442	0.015

The structural model from Figure 1 and Table 3 shows that every hypothesised path is statistically significant, lending strong support to the proposed framework. AI-driven financial analytics has a positive, significant effect on business sustainability ($\beta = 0.101$; $p = 0.005$). While the coefficient itself is fairly modest, it still indicates that AI-based financial tools make a meaningful contribution to sustainability outcomes—suggesting that data-driven insight and predictive capability can support more forward-looking, responsible financial strategy.

Financial decisions exert a strong, significant effect on AI-driven financial analytics ($\beta = 0.407$; $p < 0.001$), indicating that firms with more disciplined, strategic financial decision-making are more inclined to adopt and use AI-driven analytics. Put another way, stronger financial governance appears to smooth the path for integrating advanced technological tools into organisational processes. The direct link between financial decisions and business sustainability is especially strong ($\beta = 0.941$; $p < 0.001$), underscoring how central financial decision-making is to sustainability outcomes—how firms allocate resources, manage investment, and structure financing has a decisive bearing on their long-term sustainability performance.

The indirect effect of financial decisions on business sustainability, channelled through AI-driven financial analytics, is also significant ($\beta = 0.041$; $p = 0.015$), confirming a mediating effect—though a smaller one than the direct effect. This indicates that AI-driven financial analytics partially mediates the relationship: financial decisions shape sustainability both directly and indirectly, with the indirect route running through strengthened analytical capability. Taken together, these results suggest that while financial decisions remain the main driver of business sustainability, AI-driven financial analytics reinforces this relationship by sharpening the quality and strategic direction of decision-making.

3.2. Discussion

These findings deepen the understanding of how financial decisions feed into sustainability outcomes within increasingly digitalised business settings. Rather than functioning solely as a direct driver, financial decision-making appears to work through both an immediate channel and a capability-building one. The strong direct effect confirms that decisions around resource allocation, financing structure, and investment priorities remain foundational to sustainability performance, while the significant indirect effect shows that the quality and orientation of these decisions is further shaped by how well AI-driven financial analytics is integrated. These results broadly echo prior work highlighting the positive contribution of financial decisions to long-term

sustainability through efficient resource allocation and strategic investment (Pea-Assounga et al., 2024; Lina, 2024), while also helping to reconcile conflicting findings elsewhere in the literature, where short-term pressures have sometimes been shown to erode sustainability (Mansikkamäki, 2023). By treating AI-driven financial analytics as a mediating mechanism, this study offers an explanation for those inconsistencies: financial decisions are not inherently aligned or misaligned with sustainability, but their ultimate impact depends on whether they are backed by analytical capabilities that support long-term, data-driven thinking.

The positive link found between financial decisions and AI-driven financial analytics is consistent with earlier research emphasising the deepening integration of advanced technology into financial processes (Aldasoro et al., 2025; Ünvan & Alsokhni, 2026). Firms with more structured, strategic financial decision-making appear better positioned to adopt AI tools, having the organisational readiness and resource commitment such investments require—supporting the idea that technology adoption is not a random occurrence but is embedded within broader managerial practice. Meanwhile, the significant effect of AI-driven financial analytics on sustainability reinforces the argument that digital capability can sharpen decision quality and strategic alignment (Bessa & Barbosa, 2025; Chen et al., 2025). Rather than substituting for managerial judgement, AI appears to augment it—offering deeper insight, cutting uncertainty, and enabling better-informed trade-offs between short-term performance and long-term sustainability.

Theoretically, these results broaden the explanatory reach of the Resource-Based View by showing that financial resources alone are not sufficient to generate sustainable outcomes unless paired with higher-order capabilities such as AI-driven analytics; AI capability, in this sense, functions as a strategic asset that amplifies the value-creating potential of financial decisions. The results also lend empirical weight to Dynamic Capabilities Theory, particularly by showing how firms use technology to reshape their decision-making in response to environmental complexity. The mediating role identified here suggests that dynamic capabilities operate not just at the operational level but within core financial functions as well.

The Indonesian MSME context offers an important contextual insight. Unlike large corporations, MSMEs typically work with limited resources, informal structures, and constrained access to advanced technology. Within such conditions, adopting AI-driven financial analytics reflects more than technological sophistication—it signals a strategic shift in how decisions get made. The relatively strong direct effect of financial decisions on sustainability may indicate that, in resource-constrained settings, managerial judgement still carries the most weight. Yet the presence of a significant mediating effect shows that even incremental AI adoption can meaningfully improve decision quality—a duality that may explain why the indirect effect, while significant, is smaller than the direct one.

Practically, these findings carry clear implications for managers and policymakers alike. Business leaders should recognise that sound financial decisions need to be paired with investment in analytical capability; simply adopting AI technology is unlikely to pay off unless it is woven into core financial processes. Policymakers, particularly in developing economies, should note the importance of expanding access to digital tools and building capacity among MSMEs—initiatives that improve digital literacy and offer affordable AI solutions could meaningfully strengthen both financial performance and sustainability outcomes. Overall, this study reframes the conversation from whether financial decisions matter for sustainability to how they matter, showing that the effectiveness of financial decision-making increasingly depends on a firm's ability to build intelligence into its processes. In doing so, it offers a fuller account of the financial-decision–sustainability nexus and opens further avenues for research into how finance, technology, and long-term value creation interact.

4. CONCLUSION

This study set out to examine how financial decisions shape business sustainability, and whether AI-driven financial analytics mediates that relationship. The evidence points to a clear answer: financial decisions meaningfully strengthen business sustainability both directly and indirectly, with AI-driven financial analytics serving as a genuine, if partial, mediator. This suggests that while financial decision-making remains the primary engine of sustainability outcomes, its impact grows stronger when reinforced by data-driven analytical capability.

Three key insights follow. First, financial decisions exert a dominant, positive influence on sustainability, confirming their central place in shaping long-term organisational outcomes. Second, firms with more structured financial decision-making are more likely to integrate AI-driven analytics into their processes. Third, AI-driven financial analytics contributes positively to sustainability and partially mediates the link between financial decisions and sustainability—indicating that technology enhances, rather than displaces, the strategic value of managerial judgement. Theoretically, these findings extend the Resource-Based View and Dynamic Capabilities perspectives by positioning AI-driven financial analytics as a key capability embedded within the finance function. Practically, they underline the need for managers to align financial strategy with technology investment, and for policymakers to help MSMEs access and use digital financial tools.

Despite its contributions, several limitations should be acknowledged. The cross-sectional design captures relationships at a single point in time, limiting the ability to draw causal conclusions or observe how financial

decisions, AI-driven analytics, and sustainability outcomes evolve together as MSMEs mature or deepen their AI adoption. Focusing on MSMEs within a single national context—Indonesia—also limits how far the findings can be generalised to other institutional, regulatory, or cultural settings, since dynamics may play out differently in more digitally advanced economies or markets with different MSME support systems. Additionally, although the measurement model showed satisfactory validity and reliability, the study did not incorporate potentially influential contextual variables such as organisational culture, digital maturity, firm size, or industry sector, which could further explain variation in how financial decisions translate into sustainability.

These limitations suggest several directions for future work. Longitudinal or panel designs would let researchers trace how the relationship between financial decisions, AI-driven analytics, and sustainability shifts as MSMEs gain more experience with digital tools. Cross-country or multi-context studies could test whether the comparatively strong direct effect observed among Indonesian MSMEs holds elsewhere, or whether it is specific to resource constraints typical of emerging markets. Future research might also build on the present model by explicitly incorporating organisational culture and digital maturity as moderating or additional mediating variables, and by examining differences across firm size and industry—including comparisons between SMEs and larger firms. Such extensions would help clarify the boundary conditions under which AI-driven financial analytics most effectively strengthens the link between financial decision-making and sustainable business outcomes.

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