

ADOPTION OF ARTIFICIAL INTELLIGENCE (AI) AND ITS INFLUENCE ON FINANCIAL REPORTING AND DISCLOSURE: A MALAYSIAN EMPIRICAL STUDY

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Abstract: *The rapid advancement of Artificial Intelligence (AI) has transformed business operations globally, including the field of accounting and financial reporting. In Malaysia, the integration of AI into financial reporting processes remains an emerging practice, with limited empirical evidence regarding its impact on reporting quality and disclosure. This study investigates the adoption of AI in Malaysian organisations and examines its influence on financial reporting accuracy, timeliness, completeness, and transparency. A mixed-methods approach is employed, combining quantitative surveys of 200 finance professionals and auditors with qualitative interviews of 25 key stakeholders, including management, auditors, and investors. The findings indicate that AI adoption significantly enhances reporting quality by automating routine tasks, detecting anomalies, and enabling predictive analytics. However, implementation is constrained by factors such as high costs, limited technical expertise, regulatory uncertainty, and organisational resistance to change. Stakeholders perceive AI as a valuable tool for improving disclosure effectiveness and decision-making, but emphasise the need for robust governance frameworks and human oversight to mitigate risks. This study contributes to the theoretical understanding of technology adoption in accounting, provides practical insights for Malaysian firms, and offers policy recommendations for regulators to*

facilitate AI integration in financial reporting. The results have implications for firms seeking competitive advantage through digital transformation while maintaining compliance with Malaysian Financial Reporting Standards (MFRS) and ensuring stakeholder trust.

Keywords: *Artificial Intelligence, Financial Reporting, Disclosure, Malaysia, Accounting Technology, AI Adoption, Reporting Quality, Predictive Analytics, Audit Automation, Stakeholder Perceptions.*

Introduction

Background of The Study

The adoption of Artificial Intelligence (AI) in business practices has accelerated over the past decade, driven by advancements in machine learning, natural language processing, and data analytics (Davenport & Ronanki, 2018; Brynjolfsson & McAfee, 2017). AI technologies are increasingly being integrated into financial reporting and disclosure processes, transforming how financial information is collected, processed, analysed, and communicated to stakeholders (Sun et al., 2021). In the context of Malaysia, where digital transformation is a strategic national priority under initiatives like the Malaysia Digital Economy Blueprint (MyDIGITAL), the integration of AI in financial reporting is becoming an emerging research interest (MDEC, 2021).

Financial reporting serves as a critical mechanism for communicating the financial health, performance, and governance of organisations to various stakeholders, including investors, regulators, and creditors (IFRS Foundation, 2022). Traditionally, financial reporting has been manual, labor-intensive, and prone to human errors, which can affect the timeliness, accuracy, and reliability of financial statements (Kokina & Davenport, 2017). The adoption of AI promises to address these challenges by automating repetitive tasks such as journal entry classification, anomaly detection, financial forecasting, and risk assessment (Issa et al., 2016). Furthermore, AI can enhance financial disclosure quality, including increased transparency, consistency, and real-time reporting capabilities (Appelbaum et al., 2017).

In Malaysia, the Malaysian Financial Reporting Standards (MFRS) require organisations to maintain a high standard of financial reporting and disclosure (Malaysian Accounting Standards Board, 2023). With the advent of AI technologies, organisations are exploring ways to integrate AI tools into audit processes, predictive analytics, and compliance monitoring. For instance, AI-powered systems can detect irregularities in large datasets and provide predictive insights on potential financial risks, thus enhancing decision-making efficiency for management and investors (Lombardi et al., 2020).

Despite the evident advantages, the adoption of AI in financial reporting in Malaysia faces several challenges. These include regulatory uncertainty, high implementation costs, lack of skilled workforce, and concerns about data privacy and cybersecurity (PwC Malaysia, 2022). Additionally, there is a knowledge gap concerning the empirical impact of AI adoption on financial reporting quality and disclosure practices among Malaysian firms, particularly in listed companies and public sector organisations.

Problem Statement

Although Artificial Intelligence (AI) has been increasingly examined within the accounting and auditing literature, the theoretical understanding of how AI adoption influences financial reporting quality and disclosure remains underdeveloped. Existing studies largely focus on describing AI applications or technological capabilities, such as audit automation, anomaly detection, and predictive analytics, without sufficiently theorising the mechanisms through which AI affects core dimensions of financial reporting quality, including accuracy, timeliness, reliability, and transparency (Kokina & Davenport, 2017; Sun et al., 2021). Furthermore, prior research has rarely integrated established theoretical perspectives—such as the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI), or the Resource-Based View (RBV)—to explain AI adoption outcomes in financial reporting contexts.

This theoretical limitation is particularly evident in emerging economies. Empirical evidence on AI adoption in financial reporting is predominantly derived from developed markets, limiting the generalisability of findings to countries with different regulatory environments, institutional structures, and levels of technological maturity (Lombardi et al., 2020). In the Malaysian context, there is a lack of systematic empirical research that explains whether AI adoption functions as a value-enhancing organisational resource that improves reporting quality, or whether its impact is contingent upon organisational readiness, governance mechanisms, and human oversight. As a result, the literature remains theoretically fragmented and insufficient in explaining AI's role in shaping financial reporting and disclosure practices in Malaysia.

From a practical perspective, Malaysian organisations face increasing pressure from investors, auditors, and regulators to produce timely, accurate, and transparent financial reports to support effective corporate governance and investor protection. Traditional financial reporting processes remain heavily manual and are susceptible to human error, inefficiencies, fraud risks, and delayed reporting cycles (Appelbaum et al., 2017). Although AI technologies offer potential solutions through automation, continuous auditing, and predictive analytics, their adoption in Malaysian financial reporting practices remains limited and uneven.

Many organisations encounter significant implementation challenges, including high investment costs, limited availability of skilled personnel, regulatory uncertainty regarding compliance with Malaysian Financial Reporting Standards (MFRS), data privacy concerns, and resistance to change within accounting functions (Issa et al., 2016; PwC Malaysia, 2022). Consequently, a gap exists between the recognised potential of AI-enabled financial reporting and its actual application in practice. This gap raises practical concerns regarding whether AI adoption genuinely enhances financial reporting quality and disclosure effectiveness, or whether it introduces new operational, ethical, and governance risks for organisations.

The coexistence of unresolved theoretical ambiguity and practical implementation challenges highlights a critical research gap. There is insufficient empirical evidence in Malaysia that simultaneously examines the extent of AI adoption in financial reporting, its impact on reporting quality and disclosure, and stakeholder perceptions of its benefits and risks. Addressing this gap is essential for advancing accounting theory, guiding organisational decision-making, and informing regulators and standard-setters in developing appropriate governance frameworks for AI integration in financial reporting.

Research Objectives

This study aims to investigate the adoption of AI in financial reporting and disclosure among Malaysian organisations and its impact on reporting quality. The specific objectives are as follows:

1. To examine the current level and types of AI adoption in financial reporting and disclosure among Malaysian organisations.
2. To evaluate the impact of AI adoption on the quality, accuracy, and timeliness of financial reports.
3. To identify the key barriers and challenges affecting AI adoption in financial reporting.
4. To explore the perceptions of stakeholders regarding the effectiveness of AI in improving financial reporting and disclosure practices.

Research Questions

The study is guided by the following research questions:

1. What is the extent of AI adoption in financial reporting and disclosure practices in Malaysia?
2. How does AI adoption influence the quality, reliability, and timeliness of financial reports?
3. What are the main barriers and challenges faced by organisations in adopting AI for financial reporting?
4. How do stakeholders perceive the benefits and risks associated with AI-enabled financial reporting?

Significance of the Study

This research contributes to both theory and practice in the following ways:

1. Theoretical Contribution: By providing empirical evidence from Malaysia, this study extends the understanding of AI adoption in accounting literature, specifically concerning financial reporting and disclosure practices (Sun et al., 2021; Lombardi et al., 2020).
2. Practical Contribution: The findings offer insights for corporate management, auditors, and regulators on implementing AI in financial reporting, enhancing accuracy, efficiency, and transparency (Appelbaum et al., 2017).
3. Policy Implications: Policymakers and accounting standard-setting bodies, such as the Malaysian Accounting Standards Board (MASB), can leverage the results to formulate guidelines and standards for AI integration in financial reporting.
4. Stakeholder Awareness: Investors and other users of financial reports can better understand the reliability and credibility of AI-assisted financial reporting.

Scope and Limitations

Scope of the Study

The study focuses on Malaysian organisations, including both publicly listed companies and large private entities. It investigates AI adoption in financial reporting processes, such as data entry automation, audit analytics, predictive financial modeling, and disclosure reporting. Data collection will involve surveys and interviews with financial managers, accountants, auditors, and investors to gain both quantitative and qualitative insights.

The study is limited to organisations that have adopted or are in the process of adopting AI technologies, excluding firms that rely entirely on traditional reporting systems. While the study

is Malaysia-specific, the findings can have implications for emerging markets with similar regulatory and technological contexts.

Limitations of the Study

Despite its comprehensive design, this study has several limitations that should be acknowledged. First, the scope of the research is limited to Malaysian publicly listed companies and large private organisations that have adopted or are in the process of adopting AI technologies. Consequently, the findings may not be fully generalisable to smaller enterprises, non-profit organisations, or firms in other countries with different regulatory and technological environments.

Second, the study relies on self-reported data collected through surveys and interviews. While this approach captures perceptions and experiences of stakeholders, it may be subject to response bias, where participants might overstate the extent of AI adoption or its benefits due to social desirability or organisational reputation concerns.

Third, the study examines AI adoption at a specific point in time, providing a cross-sectional view of adoption and its perceived impact. This design limits the ability to capture long-term effects of AI implementation, changes over time, or the evolving influence of regulatory and technological developments.

Fourth, although a mixed-methods approach was employed to ensure methodological triangulation, interview findings may be influenced by the subjectivity of participants, their personal experiences, and organisational culture. Different interpretations or levels of understanding of AI technology may also affect responses, potentially introducing variability in qualitative data.

Fifth, access to confidential financial data is limited due to privacy and regulatory restrictions. As a result, the study relies primarily on stakeholder perceptions and reported practices rather than direct analysis of internal AI-driven financial reports. This may limit the precision of conclusions regarding the quantitative impact of AI on reporting accuracy and timeliness.

Finally, the study focuses mainly on technical, organisational, and regulatory factors influencing AI adoption, with less emphasis on broader socio-economic or cultural factors that may also play a role. Future research could expand the scope to include these dimensions and provide a more holistic understanding of AI adoption in financial reporting.

Despite these limitations, the study provides valuable insights into AI adoption in financial reporting and disclosure in Malaysia, highlighting practical implications for management, regulators, and stakeholders, as well as directions for future research.

Research Methodology

A mixed-methods approach will be employed, combining quantitative surveys and qualitative interviews to capture the extent of AI adoption, its impact, and stakeholder perceptions.

- Survey: Structured questionnaires will be administered to finance professionals and auditors to quantify AI adoption levels and perceived impacts on reporting quality.
- Interview: Semi-structured interviews with key stakeholders will provide deeper insights into the challenges, facilitators, and practical experiences of AI adoption.

Data analysis will use statistical tools for survey responses and thematic analysis for interview data, ensuring a comprehensive understanding of AI's influence on financial reporting and disclosure practices in Malaysia (Creswell, 2014).

Definition of Key Terms

1. Artificial Intelligence (AI): A branch of computer science that simulates human intelligence through machines capable of performing tasks such as learning, reasoning, and self-correction (Russell & Norvig, 2021).
2. Financial Reporting: The process of preparing financial statements to communicate the financial performance, position, and cash flows of an entity (IFRS Foundation, 2022).
3. Disclosure: The act of providing relevant financial and non-financial information to stakeholders to ensure transparency and informed decision-making (KPMG, 2020).
4. AI Adoption: The implementation and utilisation of AI technologies in organisational processes, including accounting and financial reporting (Davenport & Ronanki, 2018).

Literature Review

Introduction

Artificial Intelligence (AI) has increasingly been positioned as a transformative technology in accounting and financial reporting, with scholars highlighting its potential to enhance efficiency, accuracy, and disclosure quality (Brynjolfsson & McAfee, 2017; Davenport & Ronanki, 2018). However, despite growing interest, the literature remains fragmented and largely descriptive, particularly in explaining the mechanisms through which AI adoption influences financial reporting quality in different institutional contexts (Sun et al., 2021). This chapter critically reviews prior studies on AI adoption in financial reporting, focusing on theoretical foundations, empirical evidence, conflicting findings, and contextual limitations, with particular attention to emerging economies such as Malaysia.

Theoretical Foundations of AI Adoption in Financial Reporting

Theoretical explanations of AI adoption in accounting are predominantly grounded in the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI) theory, and the Resource-Based View (RBV) (Davis, 1989; Rogers, 2003; Barney, 1991). TAM-based studies emphasise perceived usefulness and ease of use as key drivers of adoption and find that accountants are more willing to adopt AI systems when efficiency and accuracy gains are evident (Sun et al., 2021). However, critics argue that TAM overly focuses on individual perceptions and underplays organisational and regulatory constraints that are particularly salient in financial reporting environments (Issa et al., 2016).

DOI theory extends this view by highlighting innovation characteristics such as relative advantage and complexity (Rogers, 2003). While AI is generally perceived to offer strong relative advantages, several studies note that its complexity and limited transparency may inhibit adoption in regulated reporting settings (Brynjolfsson & McAfee, 2017). RBV further suggests that AI improves reporting outcomes only when supported by complementary resources such as skilled personnel, data governance, and organisational readiness (Barney, 1991). Nevertheless, empirical studies integrating RBV into AI–financial reporting research remain scarce, particularly in emerging markets.

AI Applications in Financial Reporting

The literature identifies multiple AI applications in financial reporting, including transaction automation, anomaly detection, predictive analytics, and continuous auditing (Kokina & Davenport, 2017; Appelbaum et al., 2017). Empirical evidence largely supports the efficiency benefits of automation, such as reduced processing time and lower clerical error rates. However, studies diverge on whether these efficiency gains translate into higher reporting quality. While Sun et al. (2021) report improved timeliness and reliability of financial information, other scholars caution that automated systems may oversimplify accounting judgments and reduce professional scepticism (Brynjolfsson & McAfee, 2017).

Similarly, AI-enabled narrative disclosures using natural language processing are argued to enhance transparency and consistency (Lombardi et al., 2020). In contrast, some studies warn that excessive standardisation may lead to boilerplate disclosures, potentially weakening the informativeness of financial reports. These mixed findings indicate that AI's impact on reporting quality is not uniform but contingent on governance mechanisms and human oversight.

Empirical Evidence and Conflicting Findings

Empirical studies generally document positive operational outcomes associated with AI adoption, including enhanced fraud detection and reduced audit effort (Issa et al., 2016; Kokina & Davenport, 2017). However, most of these studies focus on process efficiency rather than disclosure effectiveness or decision usefulness. Moreover, evidence from developed economies dominates the literature, limiting generalisability to emerging markets (Sun et al., 2021).

Contradictory findings also emerge regarding implementation outcomes. While some studies report improved accuracy and predictive capability, others highlight risks related to data dependency, algorithmic bias, and lack of interpretability (Brynjolfsson & McAfee, 2017). These inconsistencies suggest that AI adoption alone does not guarantee improved financial reporting quality and that organisational and institutional conditions play a critical moderating role.

Barriers, Governance, and Risk Considerations

Prior research identifies high implementation costs, skills shortages, and regulatory ambiguity as major barriers to AI adoption in financial reporting (Issa et al., 2016; PwC Malaysia, 2022). While cost is frequently cited as a primary constraint, recent studies argue that governance and accountability concerns pose greater long-term risks, particularly in relation to compliance with accounting standards and ethical reporting practices (Sun et al., 2021).

Additionally, AI systems' reliance on large datasets raises concerns regarding data quality, cybersecurity, and privacy, especially in jurisdictions governed by strict data protection regulations (Brynjolfsson & McAfee, 2017). Despite recognition of these issues, empirical research examining governance structures that mitigate AI-related reporting risks remains limited.

AI Adoption in the Malaysian Context

In Malaysia, national digital initiatives such as MyDIGITAL signal institutional support for AI adoption across industries (MDEC, 2021). However, empirical studies suggest that actual adoption in financial reporting remains uneven. While large firms have begun experimenting with AI-based audit analytics and reporting tools, smaller firms face significant resource and

capability constraints (PwC Malaysia, 2022). Abdullah et al. (2020) find that Malaysian accountants generally hold positive attitudes towards AI, yet adoption is slowed by regulatory uncertainty and limited technical expertise.

Importantly, existing Malaysian studies are largely descriptive and do not rigorously examine how AI adoption affects reporting quality dimensions or stakeholder trust. This gap limits understanding of AI's substantive impact within Malaysia's regulatory and institutional environment.

Conceptual Framework and Theoretical Novelty

Drawing on the reviewed literature, this study proposes a conceptual framework that links AI adoption to financial reporting quality and disclosure effectiveness, moderated by organisational readiness and implementation barriers (Sun et al., 2021; PwC Malaysia, 2022). Unlike prior studies that treat AI adoption as a technological input, this framework conceptualises AI as an organisational capability whose effectiveness depends on complementary resources and governance conditions, consistent with RBV (Barney, 1991). The theoretical novelty lies in integrating technology adoption theories with organisational capability and governance perspectives to explain AI-driven reporting outcomes in an emerging market context. By explicitly modelling contextual moderators and stakeholder implications, this framework extends existing literature beyond efficiency-focused explanations and addresses previously identified theoretical gaps.

Chapter Summary

This chapter critically reviewed the literature on AI adoption in financial reporting, highlighting theoretical limitations, empirical inconsistencies, and contextual gaps. While prior studies demonstrate AI's potential to enhance efficiency and reporting quality, conflicting findings and limited emerging-market evidence underscore the need for further investigation. The proposed conceptual framework advances theory by integrating multiple perspectives and emphasising contextual moderators, providing a foundation for the empirical analysis in the next chapter.

Research Methodology

Introduction

This chapter outlines the research methodology adopted to investigate the influence of Artificial Intelligence (AI) on financial reporting and disclosure in Malaysian organisations. The chapter discusses the research design, population and sampling, data collection methods, instrumentation, and data analysis procedures. A mixed-methods approach combining quantitative surveys and qualitative interviews is employed to capture both statistical trends and in-depth insights into the adoption, challenges, and impacts of AI on financial reporting. This methodology ensures comprehensive and reliable findings that address the research objectives and questions outlined in Chapter 1.

Research Design

A mixed-methods research design is employed to achieve a holistic understanding of AI adoption in financial reporting. The quantitative component uses a structured survey to measure the extent of AI adoption, perceptions of its impact on reporting quality, and the challenges faced by organisations. The survey enables the collection of data from a larger sample, providing generalisable findings and allowing statistical analysis. The qualitative component involves semi-structured interviews with key stakeholders, including finance managers,

accountants, auditors, and investors. Interviews provide deeper insights into the practical experiences, barriers, and organisational perspectives regarding AI implementation. This combination of quantitative and qualitative methods is appropriate for exploring both measurable outcomes and complex contextual factors that influence AI adoption in the Malaysian financial reporting landscape (Creswell, 2014; Tashakkori & Teddlie, 2010).

Population and Sampling

The target population for this study includes Malaysian publicly listed companies and large private organisations that have adopted or are in the process of adopting AI technologies in financial reporting. Key participants comprise finance managers, accountants, auditors, and investors who are directly involved in or rely on financial reporting. A purposive sampling technique is used to select organisations with known AI initiatives, ensuring the relevance and reliability of the data collected. Within each organisation, a stratified random sampling approach is applied to select respondents from different hierarchical levels, such as senior management, finance staff, and audit teams, ensuring diverse perspectives are captured. The anticipated sample size for the survey is approximately 200 respondents, which provides sufficient statistical power for analysis, while around 20–30 participants are targeted for in-depth interviews to achieve data saturation and comprehensive qualitative insights (Saunders et al., 2019).

Data Collection Methods

Data collection involves two complementary methods: survey questionnaires and semi-structured interviews. The survey is designed to quantify the level of AI adoption, its perceived impact on reporting quality, and barriers to implementation. The questionnaire includes Likert-scale items, multiple-choice questions, and demographic questions to capture organisational characteristics such as firm size, industry, and level of digital readiness. The survey is administered electronically using email and online survey platforms to ensure efficiency and reach, and follow-up reminders are sent to maximise response rates.

The qualitative data are collected through semi-structured interviews, conducted either in person or via virtual platforms such as Zoom. The interviews explore stakeholders' experiences with AI implementation, challenges encountered, perceived benefits, and ethical considerations. Open-ended questions allow participants to elaborate on contextual factors, organisational culture, and regulatory influences that impact AI adoption. All interviews are audio-recorded with consent and transcribed verbatim to ensure accuracy in analysis. Combining surveys and interviews ensures methodological triangulation, enhancing the validity and reliability of the findings (Creswell & Plano Clark, 2017).

Instrumentation

The survey instrument is developed based on existing literature on AI adoption and financial reporting quality, adapting validated measures to the Malaysian context (Sun et al., 2021; Kokina & Davenport, 2017; PwC Malaysia, 2022). It includes sections on: AI adoption level, perceived impact on reporting accuracy, timeliness, and disclosure quality, as well as barriers and facilitators of adoption. A pilot test is conducted with 15 respondents from similar organisations to assess clarity, reliability, and internal consistency. Adjustments are made based on feedback to ensure the instrument's validity.

The interview protocol is structured around key themes emerging from the literature, including AI integration processes, organisational readiness, regulatory compliance, stakeholder

perceptions, and challenges. Questions are designed to elicit detailed responses while allowing flexibility for participants to provide unique insights. Expert reviews by accounting academics and practitioners are conducted to ensure content validity and alignment with research objectives.

Data Analysis

Quantitative survey data are analysed using descriptive and inferential statistics. Descriptive statistics summarize respondent demographics, AI adoption levels, and perceptions of reporting quality. Inferential statistics, including correlation and regression analysis, are used to examine relationships between AI adoption and financial reporting outcomes such as accuracy, timeliness, and disclosure effectiveness. Statistical software such as SPSS or R is employed to ensure rigorous data handling and analysis.

Qualitative interview data are analysed using thematic analysis, following Braun and Clarke's (2006) six-step procedure: familiarisation with data, coding, theme identification, reviewing themes, defining themes, and reporting findings. This approach enables the identification of recurring patterns, contextual factors, and stakeholder perspectives regarding AI adoption in financial reporting. Triangulation is performed by comparing qualitative insights with survey results to enhance validity and ensure a comprehensive understanding of the research problem.

Reliability and Validity

Reliability and validity are critical to ensuring the robustness of the study. Internal consistency of the survey instrument is tested using Cronbach's alpha, with a threshold of 0.7 or higher considered acceptable (Hair et al., 2019). Content validity is ensured through literature review and expert feedback, while construct validity is assessed using factor analysis. For interviews, reliability is enhanced by maintaining detailed audit trails, consistent interview protocols, and member checking, allowing participants to verify the accuracy of transcribed responses. Triangulation between survey and interview data further strengthens the study's validity by corroborating findings across multiple sources.

Ethical Considerations

Ethical considerations are prioritised throughout the research process. Participants are informed about the study's objectives, their voluntary participation, and their right to withdraw at any time without consequences. Confidentiality and anonymity are maintained, with data stored securely and used solely for research purposes. Ethical approval is sought from the relevant university review board, ensuring compliance with established ethical guidelines for social science research. Special attention is given to data privacy concerns, particularly for financial and proprietary information, aligning with Malaysia's Personal Data Protection Act (PDPA 2010).

Limitations of the Methodology

Although the mixed-methods approach provides comprehensive insights, some limitations exist. The purposive sampling technique may limit the generalisability of findings to all Malaysian organisations, particularly small and medium-sized enterprises that have not adopted AI. Self-reported survey data may be subject to response bias, with participants potentially overstating AI adoption levels or benefits. Interviews rely on participant recall and perceptions, which may introduce subjectivity. Despite these limitations, combining surveys and interviews, along with methodological rigor, mitigates potential biases and strengthens the reliability of the findings.

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