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DETERMINANTS OF ARTIFICIAL INTELLIGENCE ADOPTION IN ACCOUNTANCY FOR FRAUD PREVENTION AMONG SARAWAK SMES: A TOE-UTAUT FRAMEWORK PERSPECTIVE

Asri Firdaus De Rozario[*1] and Dr. Rahmat Aidil Djubair[2]

[1]Student of School of Business and Management,
University of Technology Sarawak, No. 1, Jalan Universiti, 96000 Sibu
[2]School of Business and Management,
University of Technology Sarawak, No. 1, Jalan Universiti, 96000 Sibu

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ABSTRACT

Artificial Intelligence (AI) is increasingly positioned as a strategic technology for transforming accounting practice through automation, predictive analytics, continuous monitoring, and fraud detection (Rikhardsson et al., 2022; Hasan, 2022; Shiyyab et al., 2023). Although AI-enabled accounting systems may strengthen financial transparency and operational efficiency, adoption remains uneven among small and medium-sized enterprises (SMEs), particularly in regions with limited infrastructure, resource constraints, and lower digital maturity (Schönberger, 2023; Lutfi, Al-Debei, & Alshira'h, 2022; SME Corporation Malaysia, 2023). Within Sarawak, SMEs operate in a distinctive socio-technical environment characterized by geographical dispersion, uneven access to digital infrastructure, and limited exposure to advanced accounting technologies (Sarawak Digital Economy Corporation, 2021; Kamaruddin, Jamaludin, & Azmi, 2024). Accordingly, this manuscript develops a context-sensitive framework to examine the determinants of AI adoption in accountancy for fraud prevention among Sarawak SMEs. Drawing on the Technology-Organization-Environment (TOE) framework and the Unified Theory of Acceptance and Use of Technology (UTAUT), the study proposes that technological factors, organizational factors, environmental support, and individual-level perceptions influence AI adoption intention (Tornatzky & Fleischer, 1990; Venkatesh, Morris, Davis, & Davis, 2003). The model further incorporates trust and firm size as moderating variables to account for behavioral uncertainty and resource heterogeneity among SMEs (Badghish & Soomro, 2024; Tang, Lily, & Chew, 2024). Methodologically, the study is designed as a quantitative survey using structured questionnaires and Partial Least Squares Structural Equation Modelling (PLS-SEM), supported by SPSS for preliminary data screening and SmartPLS for measurement and structural model assessment (Hair et al., 2021; Sarstedt, Ringle, & Hair, 2022). The manuscript contributes to the technology adoption and accounting information systems literature by extending TOE-UTAUT integration to a digitally underserved regional context and by positioning AI adoption as a mechanism for strengthening fraud prevention in SME accounting practices.

KEYWORDS: Artificial intelligence; accounting; fraud prevention; SMEs; Sarawak; TOE; UTAUT; PLS-SEM.

1.0 INTRODUCTION

Artificial Intelligence (AI) has progressed from a predominantly theoretical concept to a practical driver of organizational transformation across finance, logistics, healthcare, and professional services (Sheikh, Prins, & Schrijvers, 2023; OECD, 2022). In accounting environments, AI technologies such as Machine Learning (ML), Natural Language Processing (NLP), and Robotic Process Automation (RPA) enable automated transaction processing, predictive analytics, anomaly recognition, document interpretation, and real-time decision support (Rikhardsson et al., 2022; Hasan, 2022; Mihai & Dutescu, 2024). These technologies are particularly relevant to accounting because they can reduce manual processing, improve the reliability of financial information, and strengthen fraud prevention mechanisms (Albahsh & Al-Anaswah, 2024; Shiyyab et al., 2023).

The relevance of AI in accounting is not confined to large corporations. SMEs may also benefit from intelligent automation because they often operate with limited accounting personnel, less formalized internal control systems, and high dependence on manual documentation (Schönberger, 2023; Elmegaard, Rikhardsson, & Rohde, 2021). In such contexts, AI-enabled accounting tools can support invoice verification, automated reconciliation, continuous monitoring, exception reporting, and early identification of suspicious transaction patterns (Rikhardsson et al., 2022; Skidmore & Smith, 2024). These functions are especially important in fraud-prone settings where conventional controls may be insufficient to detect increasingly sophisticated financial irregularities (Cressey, 1953; Ghani, Ariffin, & Sukmadilaga, 2022; Shiyyab et al., 2023).

Despite these potential benefits, AI adoption remains uneven across countries, industries, firm sizes, and regions. Studies on SME digitalization have consistently shown that adoption decisions are influenced by implementation cost, digital literacy, organizational readiness, technical infrastructure, system compatibility, and cybersecurity concerns (Schönberger, 2023; Lutfi et al., 2022; Rawashdeh, Al-Nuaimi, & Harahsheh, 2023). Developed digital economies have promoted SME technology adoption through strong infrastructure, innovation ecosystems, and public-private cooperation, whereas many peripheral and developing regions continue to face slower uptake due to institutional and infrastructural constraints (OECD, 2022; Arfi, Hikkerova, & Sahut, 2021; Kamaruddin et al., 2024).

Malaysia has placed digital transformation and AI development within national economic policy agendas, including the Malaysia Digital Economy Blueprint and SME digitalization initiatives (SME Corporation Malaysia, 2023; Malaysian Institute of Accountants, 2023). However, Malaysian SMEs continue to face challenges related to high technology cost, limited expertise, cybersecurity exposure, and uneven access to digital infrastructure (SME Corporation Malaysia, 2023; Baharuden, Hasnan, & Azman, 2019; Nguyen, Sim, & Rajendran, 2022). These constraints are more pronounced in regions where firms are geographically dispersed and where specialized digital accounting training remains limited (Sarawak Digital Economy Corporation, 2021; Kamaruddin et al., 2024).

Sarawak provides a meaningful empirical setting for examining AI adoption in accountancy because its SMEs operate within a distinctive socio-technical environment shaped by regional infrastructure, geographical dispersion, and uneven digital readiness (Sarawak Digital Economy Corporation, 2021; Kamaruddin et al., 2024). Prior literature has often concentrated on large firms, urban enterprises, or general national-level digitalization, leaving limited empirical understanding of how Sarawak SMEs evaluate AI adoption for accounting and fraud prevention (Rikhardsson et al., 2022; Schönberger, 2023). This regional gap matters because technology adoption models developed in highly digitized urban contexts may not fully capture the resource limitations, trust concerns, and institutional support needs experienced by SMEs in Sarawak (Ikumoro & Jawad, 2019; Lutfi et al., 2022).

This manuscript therefore develops a TOE-UTAUT framework for examining the determinants of AI adoption in accountancy for fraud prevention among SMEs in Sarawak. The paper argues that AI adoption should not be explained solely through perceived technological usefulness or organizational readiness. Rather, it is shaped by the interaction of technological attributes, organizational capability, environmental support, user-level perceptions, trust in AI systems, and firm size (Tornatzky & Fleischer, 1990; Venkatesh et al., 2003; Badghish & Soomro, 2024). By integrating TOE and UTAUT, the manuscript offers a multi-level framework that is theoretically grounded and contextually suitable for digitally underserved SME environments.

2.0 PROBLEM STATEMENT AND RESEARCH GAP

Although AI technologies are increasingly recognized for their capacity to enhance accounting efficiency and fraud detection, their implementation among Sarawak SMEs remains sporadic and under-theorized (Rikhardsson et al., 2022; Schönberger, 2023; Kamaruddin et al., 2024). The problem is not merely technological; it is also organizational, institutional, and behavioral. SMEs frequently face limited financial resources, outdated accounting systems, weak digital infrastructure, and insufficient managerial readiness, all of which constrain the adoption of advanced accounting technologies (Baharuden et al., 2019; Lutfi et al., 2022; Nguyen et al., 2022).
Fraud risk further intensifies the need for AI-enabled accounting transformation. Financial irregularities such as invoice manipulation, unauthorized withdrawals, procurement fraud, payroll abuse, and falsified financial records may arise when internal controls are weak and manual accounting procedures dominate (Cressey, 1953; Ghani et al., 2022; Shiyyab et al., 2023). AI-based anomaly detection, continuous monitoring, and automated audit trails can assist SMEs in identifying unusual patterns earlier than traditional manual procedures (Rikhardsson et al., 2022; Aljarboa, 2024; Skidmore & Smith, 2024). Nevertheless, these systems are unlikely to be adopted if SMEs perceive them as costly, incompatible, insecure, technically complex, or unsupported by management and institutions (Schönberger, 2023; Rawashdeh et al., 2023).

The existing literature provides useful theoretical insights into AI adoption and accounting digitalization, but much of it remains insufficiently localized for Sarawak. Prior studies commonly focus on large organizations, banking institutions, urban SMEs, or national-level digitalization trends, which may not adequately reflect the conditions faced by SMEs in East Malaysia (Albahsh & Al-Anaswah, 2024; Rikhardsson et al., 2022; Kamaruddin et al., 2024). This creates a contextual gap because Sarawak SMEs may experience different levels of infrastructure readiness, digital skills, government support access, and trust in emerging technologies (Sarawak Digital Economy Corporation, 2021; SME Corporation Malaysia, 2023).

There is also a theoretical gap. The TOE framework is useful for examining technological, organizational, and environmental conditions, but it does not sufficiently explain individual-level perceptions and behavioral intention (Tornatzky & Fleischer, 1990; Oliveira & Martins, 2011). Conversely, UTAUT explains user acceptance through constructs such as effort expectancy and social influence, but it provides less emphasis on organizational resources and external institutional constraints (Venkatesh et al., 2003; Dwivedi et al., 2023). Integrating TOE and UTAUT therefore offers a more comprehensive explanation of AI adoption in SMEs, particularly where organizational readiness and user acceptance interact with regional infrastructure and policy support (Ikumoro & Jawad, 2019; Lutfi et al., 2022).

The manuscript addresses these gaps by proposing an integrated framework that incorporates technological factors, organizational factors, government support, effort expectancy, social influence, trust, and firm size. Trust is included because AI adoption in accounting involves reliance on algorithmic outputs, data security, and system transparency (Badghish & Soomro, 2024; Frank et al., 2023). Firm size is included because SMEs differ in financial capacity, staffing, infrastructure, and ability to absorb innovation risk (Bayu, 2021; Tang et al., 2024). This framework is therefore expected to provide a more context-sensitive understanding of AI adoption in Sarawak SME accountancy practices.

3.0 LITERATURE REVIEW

3.1 AI Adoption in Accounting and Fraud Prevention

AI adoption in accounting refers to the integration of intelligent computational technologies into accounting tasks, financial reporting, audit support, internal control, and fraud detection (Rikhardsson et al., 2022; Hasan, 2022; Skidmore & Smith, 2024). In SME contexts, AI adoption is particularly valuable because intelligent tools can compensate for limited accounting personnel and reduce dependence on manual inspection (Schönberger, 2023; Elmegaard et al., 2021). ML algorithms can identify abnormal financial transactions, RPA can automate repetitive accounting procedures, and NLP can assist in extracting relevant information from unstructured documents (Hasan, 2022; Mihai & Dutescu, 2024).

Fraud prevention and detection represent critical application areas for AI in SME accounting. The Fraud Triangle explains that fraud risk emerges from the interaction of pressure, opportunity, and rationalization (Cressey, 1953). AI can reduce opportunity by strengthening continuous monitoring, automating alerts, improving transaction traceability, and enhancing audit-trail visibility (Ghani et al., 2022; Shiyyab et al., 2023). However, the adoption of AI-based fraud detection depends on whether SMEs perceive such systems as beneficial, compatible, secure, affordable, easy to use, and supported by internal and external stakeholders (Rikhardsson et al., 2022; Rawashdeh et al., 2023; Badghish & Soomro, 2024).

3.2 Technology-Organization-Environment Framework

The Technology-Organization-Environment (TOE) framework explains organizational technology adoption through three contextual dimensions: technological, organizational, and environmental (Tornatzky & Fleischer, 1990). The technological context captures innovation attributes such as relative advantage, compatibility, cost, security, and task-technology fit (Rogers, 2003; Nguyen et al., 2022). The organizational context concerns internal capabilities, including leadership support, business innovativeness, financial resources, and digital readiness (Baharuden et al., 2019; Lutfi et al., 2022). The environmental context includes external pressures and support mechanisms such as government initiatives, regulatory requirements, industry norms, and technology ecosystem support (Thuan, Rowe, & Loebbecke, 2022; Adnan, Yunus, & Jusoh, 2024).

TOE is suitable for examining AI adoption among Sarawak SMEs because adoption decisions are shaped by both firm-level capabilities and the external regional environment (Kamaruddin et al., 2024; Sarawak Digital Economy Corporation, 2021). Nevertheless, TOE alone may be insufficient because it does not fully capture employee perceptions, ease of use, peer influence, and behavioral intention (Ikumoro & Jawad, 2019). This limitation supports the integration of TOE with a user-acceptance theory such as UTAUT (Venkatesh et al., 2003; Dwivedi et al., 2023).

3.3 Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) explain technology acceptance through performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). In this manuscript, effort expectancy and social influence are emphasized because the adoption of AI in SME accounting depends not only on organizational decisions but also on the perceptions of employees, owners, managers, and accounting personnel who are expected to use or support the technology (Baharuden et al., 2019; Rikhardsson et al., 2022).

Effort expectancy reflects the degree to which users perceive that a technology is easy to learn and operate (Venkatesh et al., 2003). This construct is important in Sarawak SMEs because digital literacy and exposure to advanced accounting technologies may vary across firms and locations (Kamaruddin et al., 2024; Ikumoro & Jawad, 2019). Social influence reflects the degree to which important others encourage technology use, including managers, peers, industry associations, government agencies, and professional bodies (Venkatesh et al., 2003; Dash, Ramli, & Mahadzir, 2023). In closely connected SME networks, such normative influence may legitimize AI adoption and reduce uncertainty (Rikhardsson et al., 2022; Frank et al., 2023).

3.4 Integrated TOE-UTAUT Framework

The integration of TOE and UTAUT provides a more complete explanation of AI adoption by combining macro-level contextual conditions with micro-level behavioral perceptions (Ikumoro & Jawad, 2019; Lutfi et al., 2022). TOE accounts for technological readiness, organizational capability, and environmental support, whereas UTAUT captures user-level acceptance and behavioral intention (Tornatzky & Fleischer, 1990; Venkatesh et al., 2003). This dual-framework perspective is appropriate for Sarawak SMEs because adoption is influenced by infrastructure, resources, leadership, policy support, trust, and user confidence (Kamaruddin et al., 2024; Badghish & Soomro, 2024).

The proposed framework conceptualizes TOE and UTAUT constructs as interrelated rather than isolated. Compatibility may improve effort expectancy because users are more likely to perceive AI as easy to use when it aligns with existing accounting software and workflows (Nguyen et al., 2022; Rawashdeh et al., 2023). Top management support may strengthen adoption by providing resources, training, and organizational legitimacy (Tan & Lee, 2024; Schwaeke, Tan, & Goh, 2024). Government support may reduce cost barriers and signal external legitimacy through grants, infrastructure programs, and training initiatives (Adnan et al., 2024; SME Corporation Malaysia, 2023). Trust and firm size are therefore incorporated as moderating variables to reflect behavioral uncertainty and resource heterogeneity (Badghish & Soomro, 2024; Tang et al., 2024).

3.5 Technological Factors

3.5.1 Relative Advantage

Relative advantage refers to the degree to which an innovation is perceived as superior to the system or practice it replaces (Rogers, 2003). In accounting, AI may provide relative advantage by automating repetitive tasks, improving reporting accuracy, accelerating transaction analysis, and detecting fraud patterns that may not be visible through manual review (Rikhardsson et al., 2022; Hasan, 2022; Aljarboa, 2024). SMEs are more likely to adopt AI when decision-makers believe that intelligent accounting systems can improve efficiency, reduce human error, and enhance fraud prevention outcomes (Schönberger, 2023; Albahsh & Al-Anaswah, 2024).

H1: Relative advantage positively influences the adoption of AI in accounting practices among SMEs in Sarawak.

3.5.2 Compatibility

Compatibility refers to the extent to which an innovation aligns with existing values, needs, technological infrastructure, and work practices (Rogers, 2003; Ma, Yang, & Zhang, 2021). In SME accounting, compatibility is important because systems that require major restructuring or complex customization may increase resistance and implementation risk (Nguyen et al., 2022; Rawashdeh et al., 2023). AI tools that integrate with existing accounting software and require limited disruption are therefore more likely to be adopted by resource-constrained SMEs (Abubakar, Bala, & Bakar, 2021).

H2: Compatibility positively influences the adoption of AI in accounting practices among SMEs in Sarawak.

3.5.3 Cost

Cost is frequently identified as a major barrier to technology adoption among SMEs because smaller firms often operate with constrained financial resources and limited risk tolerance

(Schönberger, 2023; Barkley & Jokonya, 2024). AI implementation may require software acquisition, infrastructure upgrades, cybersecurity protection, technical consultancy, data preparation, staff training, and ongoing maintenance (Nguyen et al., 2022; Tan & Lee, 2024). In Sarawak SMEs, high perceived cost may therefore discourage AI adoption even when potential long-term benefits are recognized (Kamaruddin et al., 2024).

H3: Cost negatively influences the adoption of AI in accounting practices among SMEs in Sarawak.

3.5.4 Security

Security refers to the perceived ability of AI systems to protect sensitive accounting data, financial records, and confidential business information (Chittipaka, Rahman, & Hanapi, 2023). SMEs may hesitate to adopt AI when they perceive risks related to cyberattacks, data breaches, unauthorized access, or algorithmic manipulation (Alrfai, Rahman, & Hanapi, 2023; Arabo & Abu Bakar, 2022). Conversely, secure systems can increase confidence in AI adoption because accounting functions require data integrity, confidentiality, and compliance with data protection expectations (Vijayakumar, 2021; Tan & Lee, 2024).

H4: Security positively influences the adoption of AI in accounting practices among SMEs in Sarawak.

3.5.5 Task-Technology Fit

Task-technology fit refers to the degree to which the functions of a technology match the requirements of users' tasks (Goodhue & Thompson, 1995; Al-Rahmi et al., 2023). In accounting, AI systems are more likely to be adopted when their capabilities fit practical tasks such as anomaly detection, invoice classification, automated reconciliation, audit-trail analysis, budgeting, and compliance monitoring (Sun, Dedahanov, Li, & Shin, 2024; Muchenje & Seppänen, 2023). High task-technology fit reduces operational friction and demonstrates practical relevance to SME users (Alyoubi & Yamin, 2019).

H5: Task-technology fit positively influences the adoption of AI in accounting practices among SMEs in Sarawak.

3.6 Organizational Factors

3.6.1 Business Innovativeness

Business innovativeness reflects a firm's willingness to adopt new ideas, technologies, and operational practices (Abaddi, 2024; Yang, Chan, & Lim, 2024). Innovative SMEs are more likely to view AI as a strategic capability that can strengthen data analytics, financial reporting, and fraud detection rather than as a purely technical cost (Abaddi, 2023; Karim Zadeh, Yaghoubi, & Bohlouli, 2024). In Sarawak, business innovativeness may help SMEs overcome resource constraints by encouraging experimentation with scalable and task-specific AI solutions (Badghish & Soomro, 2024).

H6: Business innovativeness positively influences the adoption of AI in accounting practices among SMEs in Sarawak.

3.6.2 Top Management Support

Top management support refers to the commitment of senior leaders to provide resources, strategic direction, and encouragement for technology adoption (Tan & Lee, 2024; Schwaeke et al., 2024). In SMEs, owners and managers often have substantial influence over digital investment decisions, employee training, and organizational change (Baharuden et al., 2019; Ghani et al., 2022). Strong leadership support can reduce resistance, allocate funding, legitimize AI adoption, and align AI implementation with accounting and fraud prevention objectives (Prakasa & Fauzan, 2024; Oghuma, Lwoga, & Nwokedi, 2023).

H7: Top management support positively influences the adoption of AI in accounting practices among SMEs in Sarawak.

3.7 Environmental Factor

3.7.1 Government Support

Government support includes grants, incentives, regulatory guidance, infrastructure programs, training schemes, and advisory services that facilitate technology adoption (Adnan et al., 2024; Badghish & Soomro, 2024). In Sarawak, government support is particularly important because SMEs may lack the financial and technical capacity to implement AI independently (Sarawak Digital Economy Corporation, 2021; Kamaruddin et al., 2024). Public-sector support can reduce adoption cost, increase legitimacy, improve access to training, and encourage participation in digital transformation initiatives (SME Corporation Malaysia, 2023; Komathi & Sim, 2024).

H8: Government support positively influences the adoption of AI in accounting practices among SMEs in Sarawak.

3.8 Individual-Level Factors

3.8.1 Effort Expectancy

Effort expectancy refers to the perceived ease of learning and using a technology (Venkatesh et al., 2003). Employees and SME owners are more likely to adopt AI when systems are intuitive, require limited technical expertise, and support existing accounting workflows (Baharuden et al., 2019; Ikumoro & Jawad, 2019). In Sarawak SMEs, where digital literacy may vary across firms and districts, ease of use is expected to be an important determinant of adoption intention (Kamaruddin et al., 2024; Rawashdeh et al., 2023).

H9: Effort expectancy positively influences the adoption of AI in accounting practices among SMEs in Sarawak.

3.8.2 Social Influence

Social influence refers to the perceived pressure or encouragement from important others to use a technology (Venkatesh et al., 2003). In SME environments, adoption decisions may be shaped by owners, managers, accountants, peers, industry associations, government programs, and successful local examples (Dash et al., 2023; Shahril, Rahman, & Alias, 2022). When trusted actors endorse AI adoption, SMEs may perceive AI as more legitimate, credible, and useful for accounting transformation (Rikhardsson et al., 2022; Frank et al., 2023).

H10: Social influence positively influences the adoption of AI in accounting practices among SMEs in Sarawak.

3.9 Moderating Effects

3.9.1 Trust

Trust is conceptualized as confidence in the reliability, security, transparency, and functional adequacy of AI systems (Badghish & Soomro, 2024; Frank et al., 2023). Trust may strengthen the relationship between effort expectancy and adoption because users are more likely to perceive AI as manageable when they believe the system is dependable and secure (Jirawuttigul & Thammakorn, 2025). Trust may also strengthen the influence of social endorsement because recommendations from managers, peers, and institutions become more persuasive when AI systems are regarded as credible and safe (Frank et al., 2023; Badghish & Soomro, 2024).

H11a: Trust moderates the relationship between effort expectancy and AI adoption in accounting practices among SMEs in Sarawak.

H11b: Trust moderates the relationship between social influence and AI adoption in accounting practices among SMEs in Sarawak.

3.9.2 Firm Size

Firm size is included as a structural moderator because SMEs differ substantially in financial capacity, staffing, technological infrastructure, governance maturity, and ability to absorb innovation risk (Bayu, 2021; Tang et al., 2024). Larger SMEs may be better positioned to adopt AI because they can allocate resources, access skilled personnel, engage consultants, and participate in government-supported technology programs (Na et al., 2023; Chuen & Topimin, 2023). Smaller SMEs may respond differently because they face greater resource constraints and higher perceived implementation risk (Schönberger, 2023; Kamaruddin et al., 2024).

H12a: Firm size moderates the relationship between relative advantage and AI adoption in accounting practices among SMEs in Sarawak.
H12b: Firm size moderates the relationship between compatibility and AI adoption in accounting practices among SMEs in Sarawak.
H12c: Firm size moderates the relationship between security and AI adoption in accounting practices among SMEs in Sarawak.
H12d: Firm size moderates the relationship between cost and AI adoption in accounting practices among SMEs in Sarawak.
H12e: Firm size moderates the relationship between task-technology fit and AI adoption in accounting practices among SMEs in Sarawak.
H12f: Firm size moderates the relationship between business innovativeness and AI adoption in accounting practices among SMEs in Sarawak.
H12g: Firm size moderates the relationship between top management support and AI adoption in accounting practices among SMEs in Sarawak.
H12h: Firm size moderates the relationship between government support and AI adoption in accounting practices among SMEs in Sarawak.

4.0 RESEARCH METHODOLOGY

4.1. Conceptual Framework

The proposed conceptual framework positions AI adoption in accounting practices as the dependent variable. The independent variables are organized into four groups: technological factors, organizational factors, environmental factor, and individual-level factors. This classification is consistent with TOE and UTAUT, which jointly explain adoption through structural readiness and user acceptance (Tornatzky & Fleischer, 1990; Venkatesh et al., 2003; Ikumoro & Jawad, 2019).

Technological factors comprise relative advantage, compatibility, cost, security, and task-technology fit, while organizational factors comprise business innovativeness and top management support (Rogers, 2003; Nguyen et al., 2022; Tan & Lee, 2024). The environmental factor is government support, which reflects policy, infrastructure, and institutional assistance (Adnan et al., 2024; SME Corporation Malaysia, 2023). Individual-level factors comprise effort expectancy and social influence, both of which explain the behavioral dimension of AI acceptance (Venkatesh et al., 2003; Dwivedi et al., 2023). Trust moderates the relationships between individual-level factors and AI adoption, while firm size moderates the relationships between TOE factors and AI adoption (Badghish & Soomro, 2024; Tang et al., 2024).

Table 1. Summary of Proposed Hypotheses

H1	Relative advantage -> AI adoption	Positive
H2	Compatibility -> AI adoption	Positive
H3	Cost -> AI adoption	Negative
H4	Security -> AI adoption	Positive
H5	Task-technology fit -> AI adoption	Positive
H6	Business innovativeness -> AI adoption	Positive
H7	Top management support -> AI adoption	Positive
H8	Government support -> AI adoption	Positive
H9	Effort expectancy -> AI adoption	Positive
H10	Social influence -> AI adoption	Positive
H11a	Trust moderates effort expectancy -> AI adoption	Moderating
H11b	Trust moderates social influence -> AI adoption	Moderating
H12a-H12h	Firm size moderates TOE factors -> AI adoption	Moderating

5.0 RESEARCH METHODOLOGY

This study adopts a quantitative research design to examine the determinants of AI adoption in accounting practices among SMEs in Sarawak. A quantitative approach is appropriate because the study seeks to test theoretically derived relationships among latent constructs and to evaluate direct and moderating effects within an integrated TOE-UTAUT framework (Creswell & Creswell, 2023; Hair et al., 2021).

The target respondents comprise SME owners, managers, accountants, finance officers, and accounting-related personnel involved in financial decision-making or accounting system use. The study focuses on SMEs operating in Sarawak because the regional context presents distinct infrastructural and digital-readiness challenges (Sarawak Digital Economy Corporation, 2021; Kamaruddin et al., 2024). A purposive sampling strategy is appropriate because the study requires respondents who possess relevant knowledge of accounting practices, technology use, or AI-related decisions within their firms (Campbell, Hansen, & Walker, 2020; Wong & Topimin, 2023).

Data collection should be conducted using a structured questionnaire adapted from prior technology adoption, accounting information systems, and AI adoption studies (Baharuden et al., 2019; Lutfi et al., 2022; Rawashdeh et al., 2023). The questionnaire should include demographic information, firm characteristics, and measurement items for each construct in the conceptual framework. A seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree is recommended because it provides greater response sensitivity and is suitable for latent construct measurement in structural equation modelling (Kusmaryono et al., 2022; Taherdoost, 2022).

Prior to full data collection, a pilot test should be conducted to assess the clarity, reliability, and suitability of the questionnaire items. Pilot testing helps identify ambiguous wording, respondent fatigue, and construct measurement problems before the main survey is administered (Oben, 2021; Taherdoost, 2022). Cronbach's alpha may be used during pilot testing to assess preliminary internal consistency, with values of 0.70 or above generally considered acceptable in exploratory research (Taber, 2018; Hair et al., 2021).

The proposed data analysis procedure involves SPSS and SmartPLS. SPSS may be used for data screening, missing value inspection, duplicate response checking, descriptive statistics, reliability analysis, and respondent profiling (Pallant, 2020; George & Mallery, 2019). Outlier analysis may be conducted using Mahalanobis distance to identify multivariate anomalies that could distort subsequent modelling results (Tabachnick & Fidell, 2019; Kline, 2016).

SmartPLS may be used to assess the measurement and structural models through PLS-SEM. PLS-SEM is appropriate because it is suitable for complex models, prediction-oriented research, small-to-medium sample sizes, and non-normal data conditions (Hair et al., 2021; Sarstedt et al., 2022). The measurement model should be evaluated using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and discriminant validity through HTMT (Henseler, Ringle, & Sarstedt, 2015; Hair et al., 2021).

The structural model should be evaluated using variance inflation factor (VIF), path coefficients, t-values, p-values, confidence intervals, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) (Hair et al., 2021; Sarstedt et al., 2022; Ramayah et al., 2023). Bootstrapping with 5,000 subsamples is recommended to test the statistical significance of direct and moderating relationships (Hair et al., 2021; Cheah, Ting, Lim, Ahmad, & Rahman, 2023). Because this manuscript does not report completed empirical data, the methodology is presented as a proposed empirical protocol rather than as completed findings.

6.0 EXPECTED CONTRIBUTIONS

6.1 Theoretical Contributions

This manuscript contributes to technology adoption literature by integrating TOE and UTAUT in the context of AI-enabled accounting and fraud prevention among SMEs. The model extends existing adoption frameworks by demonstrating how structural conditions and user-level perceptions jointly shape AI adoption intention (Tornatzky & Fleischer, 1990; Venkatesh et al., 2003; Ikumoro & Jawad, 2019). The inclusion of trust and firm size further advances theory by accounting for behavioral uncertainty and resource heterogeneity in digitally underserved regions (Badghish & Soomro, 2024; Tang et al., 2024).

The study also contributes to accounting information systems research by positioning AI adoption as a mechanism for strengthening fraud prevention rather than only improving efficiency. This focus broadens the scholarly conversation on AI in accounting by connecting adoption determinants to governance, internal control, financial transparency, and fraud resilience (Rikhardsson et al., 2022; Ghani et al., 2022; Shiyyab et al., 2023).

6.2 Practical Contributions

From a practical standpoint, the framework can help SME owners and managers identify the conditions that facilitate AI adoption in accounting. By understanding the roles of relative advantage, compatibility, cost, security, task-technology fit, innovativeness, leadership, government support, ease of use, and social influence, SMEs can develop more informed digital transformation strategies (Schönberger, 2023; Nguyen et al., 2022; Tan & Lee, 2024).

The study also provides insights for policymakers, regulators, and professional bodies. In Sarawak, targeted interventions such as AI training programs, digital advisory services, cybersecurity support, tax incentives, and infrastructure investment may be necessary to reduce adoption barriers (Sarawak Digital Economy Corporation, 2021; SME Corporation Malaysia, 2023; Kamaruddin et al., 2024). Professional bodies may use the framework to design capacity-building initiatives that prepare accountants and SME stakeholders for AI-enabled financial management (Malaysian Institute of Accountants, 2023; Skidmore & Smith, 2024).

7.0 CONCLUSION

This manuscript develops a TOE-UTAUT framework for examining the determinants of AI adoption in accounting practices for fraud prevention among SMEs in Sarawak. The proposed model recognizes that AI adoption is shaped by multiple interacting factors, including technological attributes, organizational readiness, environmental support, individual perceptions, trust, and firm size (Tornatzky & Fleischer, 1990; Venkatesh et al., 2003; Badghish & Soomro, 2024).

By focusing on Sarawak, the manuscript responds to the need for region-specific evidence in digitally underserved contexts. The framework is suitable for empirical testing using quantitative survey data and PLS-SEM, particularly because it involves multiple latent constructs and moderating relationships (Hair et al., 2021; Sarstedt et al., 2022). Future research may extend the model by incorporating actual AI usage, fraud detection performance, longitudinal adoption patterns, or comparative analyses between Sarawak and other Malaysian states (Rikhardsson et al., 2022; Schönberger, 2023). Overall, the manuscript offers a theoretically grounded and practically relevant foundation for understanding how AI can strengthen accounting practices and fraud prevention among SMEs in Sarawak.

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