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AI-Enabled Fraud Detection Readiness in Sarawak SMEs: A Quantitative TOE-UTAUT Model for Accounting Transformation

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ABSTRACT

This manuscript develops a quantitative research model for examining artificial intelligence (AI)-enabled fraud detection readiness among small and medium-sized enterprises (SMEs) in Sarawak, Malaysia. Rather than treating AI adoption solely as a general technology acceptance issue, the paper positions adoption readiness as a multi-layered condition shaped by technological fit, organizational mobilisation, institutional facilitation, and user-level acceptance. Drawing on the Technology-Organization-Environment (TOE) framework and the Unified Theory of Acceptance and Use of Technology (UTAUT), the proposed model explains how relative advantage, compatibility, cost, security, task-technology fit, business innovativeness, top management support, government support, effort expectancy, and social influence may affect SMEs' intention to adopt AI in accounting. Trust and firm size are incorporated as boundary conditions to capture behavioral uncertainty and resource asymmetry in regional SME settings. The manuscript further specifies a survey-based methodological protocol involving purposive sampling, a seven-point Likert-scale questionnaire, pilot testing, SPSS-based data screening, and Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS. By emphasizing readiness, measurement logic, and empirical testability, the paper offers a methodological contribution to AI accounting research and provides a replicable model for studying digitally underserved regional economies.

Keywords: artificial intelligence; fraud detection; accounting transformation; Sarawak SMEs; TOE; UTAUT; PLS-SEM; trust; firm size

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1.0 Introduction

Artificial intelligence (AI) is increasingly reshaping accounting work by automating repetitive procedures, enabling continuous monitoring, and improving the detection of unusual financial patterns. Machine learning, natural language processing, and robotic process automation are particularly relevant to accounting because they can strengthen data accuracy, reduce manual processing time, and support the early identification of fraud-related anomalies (Albahsh & Al-Anaswah, 2024; Rikhardsson et al., 2022; Shiyyab et al., 2023). These developments have made AI a salient mechanism for improving financial governance in both large firms and SMEs (OECD, 2022; Schönberger, 2023).

SMEs are important units of analysis because they frequently operate with limited accounting personnel, narrow financial margins, and less formalized internal control structures. Prior research on AI and digital accounting suggests that smaller firms may benefit from intelligent automation, but they also face barriers relating to cost, technical skills, data readiness, and implementation capacity (Lutfi et al., 2022; Rikhardsson et al., 2022; Schönberger, 2023). In Malaysia, the official SME definition is based on sales turnover or full-time employees, with different thresholds for manufacturing and services or other sectors (SME Corporation Malaysia, 2023).

Sarawak represents a particularly important setting because SME digital transformation is shaped by geographical dispersion, uneven digital infrastructure, and the need for targeted digital capacity development. The Sarawak Digital Economy Strategy 2030 emphasizes digital infrastructure, human capital, innovation, and entrepreneurship as foundations for regional digital transformation (Sarawak Digital Economy Corporation, 2021). These contextual conditions indicate that AI adoption in Sarawak should not be examined merely as a technology purchase decision, but as a broader question of organizational readiness and user acceptance (Lutfi et al., 2022; Tornatzky & Fleischer, 1990; Venkatesh et al., 2003).

This manuscript therefore develops a quantitatively testable readiness model for AI-enabled fraud detection in SME accounting. The argument advanced here is that readiness emerges when technological attributes, organizational capabilities, external support systems, and user perceptions are mutually aligned. The TOE framework captures structural readiness across technological, organizational, and environmental domains, whereas UTAUT explains behavioral acceptance among users who must work with AI systems in practice (Tornatzky & Fleischer, 1990; Venkatesh et al., 2003).

2. Research Setting and Publication Rationale

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Sarawak offers a theoretically meaningful setting for examining AI-enabled accounting transformation because its SMEs operate within a distinctive socio-technical environment. Malaysia has promoted digital transformation through national and state-level initiatives, yet the diffusion of advanced technologies across firms and regions remains uneven (OECD, 2022; SME Corporation Malaysia, 2023). In this context, Sarawak-based SMEs may face challenges associated with infrastructure, technical skills, trust in digital systems, and managerial readiness (Sarawak Digital Economy Corporation, 2021; Schönberger, 2023).

The practical problem is anchored in the need for stronger fraud prevention mechanisms. The Fraud Triangle explains that fraudulent behavior may arise when pressure, opportunity, and rationalization interact, making internal control and monitoring mechanisms central to fraud prevention (Cressey, 1953). AI-enabled accounting systems may reduce opportunities for fraud by supporting anomaly detection, transaction screening, continuous monitoring, and automated audit trails (Rikhardsson et al., 2022; Shiyyab et al., 2023). However, these benefits are unlikely to materialize unless firms possess the technological capacity, managerial commitment, institutional assistance, and user confidence required for implementation (Lutfi et al., 2022; Schönberger, 2023).

The scholarly rationale for this manuscript lies in the limited integration of regional context, fraud-specific accounting applications, and measurement-oriented methodology in existing AI adoption studies. Prior research provides useful insights into AI auditing, cloud accounting, SME digitalization, and technology adoption, but many studies emphasize large firms, national-level patterns, or generalized digital transformation (Albahsh & Al-Anaswah, 2024; Lutfi et al., 2022; Rikhardsson et al., 2022). A Sarawak-focused readiness model can therefore extend the literature by explaining how AI-enabled fraud detection becomes feasible in digitally constrained SME environments (Sarawak Digital Economy Corporation, 2021; Schönberger, 2023).

3. Theoretical Positioning: From Adoption Factors to Readiness Mechanisms

The TOE framework explains organizational technology adoption through three domains: technological, organizational, and environmental contexts (Tornatzky & Fleischer, 1990). In this manuscript, these domains are interpreted as readiness mechanisms. The technological domain concerns whether AI is beneficial, compatible, secure, affordable, and aligned with accounting tasks; the organizational domain concerns whether the firm is innovative and whether management actively supports transformation; and the environmental domain concerns whether public-sector support, regulation, and digital infrastructure enable implementation (Lutfi et al., 2022; Thuan et al., 2022; Tornatzky & Fleischer, 1990).

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UTAUT complements TOE by explaining the behavioral side of readiness. The original UTAUT model identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as major determinants of technology acceptance and use (Venkatesh et al., 2003). In the present manuscript, effort expectancy and social influence are emphasized because employees and SME decision-makers must perceive AI as usable and socially legitimate before adoption intention can develop (Ikumoro & Jawad, 2019; Venkatesh et al., 2003).

Trust is treated as a moderator because digital accounting systems process sensitive financial information and may be resisted when users perceive algorithmic opacity, data misuse, or system unreliability. Trust has been widely discussed as a condition that reduces perceived risk and strengthens acceptance of digital systems, particularly in contexts where users lack deep technical expertise (Badghish & Soomro, 2024; Shiyyab et al., 2023). Firm size is included as a second moderator because SMEs differ substantially in financial capacity, staffing, absorptive capacity, and access to institutional support (SME Corporation Malaysia, 2023; Tang et al., 2024).

The theoretical contribution lies in connecting structural readiness and user acceptance. Rather than treating TOE and UTAUT as parallel frameworks, this manuscript conceptualizes them as interdependent. Technological compatibility may shape perceived ease of use, organizational support may strengthen implementation capacity, government initiatives may influence social legitimacy, and firm size may determine whether adoption drivers translate into actionable capability (Lutfi et al., 2022; Tornatzky & Fleischer, 1990; Venkatesh et al., 2003).

4. Research Model Development

The proposed model positions intention to adopt AI in accounting as the primary endogenous construct. The model is organized into four readiness domains and two moderating conditions: technological readiness, organizational mobilisation, institutional facilitation, user acceptance, trust, and firm size. This structure is consistent with TOE-based technology adoption research, UTAUT-based behavioral acceptance research, and SME digitalization studies emphasizing resource heterogeneity (Lutfi et al., 2022; SME Corporation Malaysia, 2023; Tornatzky & Fleischer, 1990; Venkatesh et al., 2003).

Table 1. Construct domains in the proposed AI-enabled fraud detection readiness model

Domain	**Constructs**	**Role in the readiness model**
Technological readiness	Relative advantage, compatibility, cost, security, task-technology fit	Explains whether AI is perceived as useful, feasible, affordable, safe,

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		and aligned with accounting fraud detection tasks.
Organizational mobilisation	Business innovativeness, top management support	Explains whether the firm has strategic openness and leadership commitment to support AI implementation.
Institutional facilitation	Government support	Explains whether public policy, grants, infrastructure, and training reduce adoption barriers.
User acceptance	Effort expectancy, social influence	Explains whether users perceive AI as easy to use and socially endorsed within their work environment.
Boundary conditions	Trust, firm size	Explains when and for whom the proposed relationships may be stronger or weaker.

4.1 Technological Readiness Mechanisms

Relative advantage is central to AI readiness because SMEs are more likely to consider AI when it is expected to improve transaction accuracy, accelerate reporting, strengthen fraud detection, or reduce operational inefficiencies. This logic is consistent with diffusion theory, which argues that perceived superiority over existing practice increases adoption likelihood (Rogers, 2003). In accounting, AI can offer such superiority through automated analysis, anomaly recognition, and improved audit support (Albahsh & Al-Anaswah, 2024; Rikhardsson et al., 2022).

Compatibility is equally important because AI systems must align with existing accounting software, workflows, reporting routines, and organizational values. Technology adoption research indicates that innovations are more likely to be accepted when they fit existing practices and reduce disruption during implementation (Lutfi et al., 2022; Rogers, 2003). In SMEs with limited IT personnel, incompatible systems may increase resistance, training needs, and implementation cost (Schönberger, 2023).

Cost is treated as a constraining readiness mechanism because AI adoption may involve software subscriptions, infrastructure investment, training, data preparation, cybersecurity compliance, and external technical support. SME technology research has consistently emphasized that resource constraints and uncertainty over return on investment can delay adoption decisions (Lutfi et al., 2022; Rikhardsson et al., 2022; Schönberger, 2023). For Sarawak SMEs, these financial demands may be especially salient because digital capacity varies across locations and firm sizes (Sarawak Digital Economy Corporation, 2021).

Security is treated as an enabling condition because accounting data are sensitive and AI systems must protect financial records, transaction logs, customer information, and business confidentiality. Prior studies on AI and accounting emphasize that trust, data protection, and system reliability are essential for technology acceptance in financial domains (Shiyyab et al., 2023; Skidmore & Smith, 2024). A secure AI system may therefore reduce perceived risk and strengthen SMEs' willingness to use AI-enabled fraud detection tools (Badghish & Soomro, 2024).

Task-technology fit completes the technological domain by assessing whether AI functions correspond directly with accounting activities such as invoice verification, anomaly detection, audit-trail generation, and real-time transaction monitoring. The logic of task-technology fit suggests that technologies are more likely to improve performance when their features match the requirements of the task being performed (Goodhue & Thompson, 1995). In SME accounting, this implies that AI tools must be evaluated not only for technical sophistication but also for practical relevance to fraud detection tasks (Rikhardsson et al., 2022; Shiyyab et al., 2023).

4.2 Organizational Mobilisation Mechanisms

Business innovativeness captures the extent to which SMEs are willing to experiment with new digital solutions and redesign internal accounting routines. Innovation-oriented firms are more likely to treat AI as a strategic capability rather than merely as software expenditure, which aligns with broader research linking digital innovation to organizational agility and technology readiness (Arfi et al., 2021; Schönberger, 2023). In the Sarawak SME context, innovativeness may help firms overcome resource limitations by experimenting with scalable and task-specific AI solutions (Sarawak Digital Economy Corporation, 2021).

Top management support is also critical because SME decision-making is often concentrated among owners or senior managers. TOE-based adoption studies consistently identify managerial commitment as a key organizational condition because leaders allocate resources, communicate strategic direction, reduce employee uncertainty, and legitimize technology implementation (Lutfi et al., 2022; Tornatzky & Fleischer, 1990). In accounting transformation, leadership support may also be necessary to align AI adoption with internal controls, data governance, and fraud prevention objectives (Albahsh & Al-Anaswah, 2024; Shiyyab et al., 2023).

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4.3 Institutional Facilitation Mechanism

Government support is incorporated as the environmental mechanism in the model. Public policy, grants, training schemes, advisory services, infrastructure expansion, and regulatory guidance can reduce the uncertainty and cost associated with AI adoption among SMEs (OECD, 2022; SME Corporation Malaysia, 2023). In Sarawak, targeted support is particularly important because generic national digitalization initiatives may not fully address the operational realities of rural and semi-urban SMEs (Sarawak Digital Economy Corporation, 2021).

4.4 User Acceptance Mechanisms

Effort expectancy and social influence represent the behavioral layer of the model. Effort expectancy is relevant because AI systems that are perceived as easy to learn and use are more likely to be accepted by accounting personnel with varied levels of digital literacy (Venkatesh et al., 2003). In SME contexts, ease of use is particularly important because employees may have limited access to formal digital training and technical support (Ikumoro & Jawad, 2019; Lutfi et al., 2022).

Social influence is relevant because SMEs often rely on peer learning, managerial endorsement, professional advice, and industry examples when deciding whether to adopt new systems. UTAUT proposes that perceived expectations from important others can shape behavioral intention, especially in organizational contexts where supervisors, colleagues, and professional networks influence technology use (Venkatesh et al., 2003). In Sarawak SMEs, social influence may be strengthened through local business associations, accounting bodies, and government-led digitalization programmes (Sarawak Digital Economy Corporation, 2021; SME Corporation Malaysia, 2023).

4.5 Boundary Conditions: Trust and Firm Size

Trust is proposed to moderate the relationships between effort expectancy, social influence, and AI adoption. When employees trust AI systems, perceived ease of use may have a stronger effect because users are less likely to fear system errors, data misuse, or opaque algorithmic decisions (Badghish & Soomro, 2024; Shiyyab et al., 2023). Trust may also strengthen social influence because endorsements from managers, peers, or professional bodies become more persuasive when the technology itself is perceived as reliable and secure (Venkatesh et al., 2003).

Firm size is proposed to moderate the relationships between TOE-based determinants and AI adoption. Larger SMEs may possess stronger financial resources, more developed digital infrastructure, and greater capacity to absorb training and implementation costs, while smaller SMEs may be more sensitive to affordability, external support, and task-level fit (SME

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Corporation Malaysia, 2023; Tang et al., 2024). Including firm size therefore allows the model to account for heterogeneity within the SME sector rather than treating all SMEs as structurally similar (Schönberger, 2023).

5. Proposed Hypotheses

The hypotheses are formulated from the theoretical arguments above and are intended for empirical testing using survey data from Sarawak SMEs. The hypothesized direct effects reflect technological, organizational, environmental, and individual-level readiness mechanisms, while the moderation hypotheses test whether trust and firm size condition the strength of selected relationships (Hair et al., 2021; Lutfi et al., 2022; Tornatzky & Fleischer, 1990; Venkatesh et al., 2003).

Table 2. Proposed hypotheses

Code	Hypothesis
H1	Relative advantage positively influences AI adoption intention in accounting among Sarawak SMEs.
H2	Compatibility positively influences AI adoption intention in accounting among Sarawak SMEs.
H3	Cost negatively influences AI adoption intention in accounting among Sarawak SMEs.
H4	Security positively influences AI adoption intention in accounting among Sarawak SMEs.
H5	Task-technology fit positively influences AI adoption intention in accounting among Sarawak SMEs.
H6	Business innovativeness positively influences AI adoption intention in accounting among Sarawak SMEs.
H7	Top management support positively influences AI adoption intention in accounting among Sarawak SMEs.
H8	Government support positively influences AI adoption intention in accounting among Sarawak SMEs.
H9	Effort expectancy positively influences AI adoption intention in accounting among Sarawak SMEs.
H10	Social influence positively influences AI adoption intention in accounting among Sarawak SMEs.
H11a	Trust moderates the relationship between effort expectancy and AI adoption intention.
H11b	Trust moderates the relationship between social influence and AI adoption intention.
H12a-H12h	Firm size moderates the relationships between TOE-based determinants and AI adoption intention.

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6. Proposed Research Method

The manuscript proposes a quantitative research design because the objective is to test hypothesized relationships among latent constructs and evaluate both direct and moderating effects. Quantitative survey designs are appropriate when researchers seek to measure perceptions systematically and test theory-derived relationships across a defined sample (Creswell & Creswell, 2023). In this study, the use of PLS-SEM is consistent with prediction-oriented research involving complex models, latent variables, and moderation effects (Hair et al., 2021; Sarstedt et al., 2022).

6.1 Research Design and Sampling Frame

The target population consists of SME owners, managers, accountants, finance personnel, and employees involved in accounting or digital financial processes in Sarawak. A purposive sampling strategy is appropriate because the study requires respondents who are familiar with accounting practices, digital systems, or AI-related decision-making (Creswell & Creswell, 2023; Taherdoost, 2022). SME Corp Malaysia, the Sarawak Chamber of Commerce and Industry, and the Malaysian Institute of Accountants may serve as practical sources for identifying eligible respondents, provided that respondent eligibility is verified before survey participation (SME Corporation Malaysia, 2023).

6.2 Instrument Development and Pilot Testing

The research instrument should consist of demographic items and construct-based measurement items adapted from prior technology adoption, accounting information systems, AI accounting, and SME digitalization literature. A seven-point Likert scale is proposed because it allows respondents to express more nuanced perceptions than shorter scales and is commonly used in behavioral and organizational survey research (Taherdoost, 2022). Each construct should be measured using multiple items to support internal consistency and latent variable modelling (Hair et al., 2021).

A pilot test involving approximately 30 eligible respondents is recommended to assess wording clarity, face validity, response burden, and early reliability before full deployment. Pilot testing is important because it helps identify ambiguous items, improves respondent comprehension, and reduces measurement error before large-scale data collection (Creswell & Creswell, 2023; Taherdoost, 2022). Where necessary, items should be revised based on expert review, pilot feedback, and reliability diagnostics (Hair et al., 2021).

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6.3 Data Collection and Data Screening

Data collection may be conducted through Google Forms accompanied by a cover letter explaining the research objectives, confidentiality, voluntariness, and respondent rights. Online surveys are suitable for geographically dispersed respondents when the target population is difficult to access physically, although researchers must implement screening procedures to reduce duplicate submissions, inattentive responses, and incomplete data (Creswell & Creswell, 2023; Taherdoost, 2022). Ethical practice also requires that respondents understand the purpose of the study and their right to withdraw without penalty (Creswell & Creswell, 2023).

After collection, responses should be exported to Excel and imported into SPSS for screening. The screening process should identify incomplete responses, duplicate submissions, straight-lining, response irregularities, and multivariate outliers. Mahalanobis distance may be used to detect multivariate anomalies because it accounts for the joint distribution of variables and is widely recommended in multivariate analysis (Tabachnick & Fidell, 2019). Observations flagged as potential outliers should be reviewed carefully before exclusion to avoid removing theoretically meaningful cases (Hair et al., 2019; Tabachnick & Fidell, 2019).

6.4 Measurement and Structural Model Assessment

SmartPLS is proposed for PLS-SEM analysis because the model contains multiple latent constructs, moderation effects, and prediction-oriented relationships. The measurement model should be assessed using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted, cross-loadings, Fornell-Larcker criterion, and the heterotrait-monotrait ratio (HTMT) (Hair et al., 2021; Henseler et al., 2015). Indicator loadings of 0.70 or higher, composite reliability above 0.70, and AVE values of 0.50 or higher are commonly used as criteria for reflective measurement models (Hair et al., 2021).

The structural model should be evaluated using variance inflation factor, path coefficients, t-values, p-values, confidence intervals, effect sizes, coefficient of determination, and predictive relevance. Bootstrapping with 5,000 subsamples is recommended to test the statistical significance of direct and moderating effects because it provides non-parametric estimates of standard errors and confidence intervals in PLS-SEM (Hair et al., 2021; Sarstedt et al., 2022). Multicollinearity should be assessed before interpreting path relationships, and the substantive significance of paths should be interpreted alongside effect sizes and explanatory power (Hair et al., 2021).

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Table 3. Proposed empirical protocol

Stage	Main procedure	Purpose
Pilot test	Administer preliminary questionnaire to eligible respondents.	Assess wording, clarity, timing, face validity, and early reliability.
Data screening	Check missing data, duplicates, response patterns, and multivariate outliers in SPSS.	Ensure clean and usable survey data.
Reliability assessment	Use Cronbach's alpha and composite reliability.	Confirm internal consistency of constructs.
Convergent validity	Assess indicator loadings and AVE.	Confirm that items represent their intended constructs.
Discriminant validity	Assess HTMT, cross-loadings, and Fornell-Larcker criterion.	Confirm empirical distinctiveness among constructs.
Structural model	Assess VIF, path coefficients, t-values, p-values, R2, f2, Q2, and moderation paths.	Test hypotheses and predictive capability.

7. Anticipated Contributions

This manuscript is designed as a conceptual and methodological article that prepares the basis for future empirical testing. Its claims should therefore be interpreted as theoretically grounded propositions rather than completed empirical findings. This positioning is appropriate for a journal article that aims to develop a model, justify hypotheses, and provide a replicable empirical protocol before survey results are available (Creswell & Creswell, 2023; Hair et al., 2021).

7.1 Theoretical Contribution

The manuscript contributes theoretically by reframing AI adoption in SME accounting as a readiness phenomenon that integrates structural, behavioral, and contextual mechanisms. It extends TOE by incorporating user acceptance factors from UTAUT and strengthens UTAUT by situating user perceptions within organizational and regional constraints (Tornatzky & Fleischer, 1990; Venkatesh et al., 2003). The inclusion of trust and firm size further advances the model by explaining why adoption drivers may operate differently across SMEs with different resources and different levels of confidence in AI systems (Badghish & Soomro, 2024; SME Corporation Malaysia, 2023).

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7.2 Methodological Contribution

The manuscript provides a clear empirical protocol for testing AI-enabled fraud detection readiness using PLS-SEM. This methodological orientation distinguishes the paper from broader conceptual discussions of AI in accounting by specifying sampling logic, measurement procedures, pilot testing, data screening, reliability and validity criteria, and structural model assessment (Hair et al., 2021; Henseler et al., 2015; Sarstedt et al., 2022). The protocol may be adapted by future researchers examining AI readiness in other digitally underserved regions.

7.3 Practical and Policy Contribution

For SME practitioners, the model provides a diagnostic tool for assessing whether AI adoption is practically feasible. It highlights the need to evaluate expected benefits, compatibility with existing accounting systems, affordability, cybersecurity, task alignment, managerial support, and user acceptance before investing in AI-enabled fraud detection systems (Rikhardsson et al., 2022; Schönberger, 2023; Shiyyab et al., 2023). For policymakers, the model identifies areas where intervention may be most needed, including cost reduction, infrastructure expansion, AI literacy, cybersecurity support, and size-sensitive SME assistance (OECD, 2022; Sarawak Digital Economy Corporation, 2021; SME Corporation Malaysia, 2023).

8. Boundary Conditions and Future Empirical Testing

This manuscript is not a results-based empirical paper because survey data have not yet been collected and analyzed. Future research should validate the model using survey data from Sarawak SMEs and may extend the framework by comparing urban and semi-urban firms, industry sectors, or SMEs with different levels of digital maturity (Creswell & Creswell, 2023; Hair et al., 2021). Longitudinal research would also be useful for examining whether readiness translates into actual AI usage and measurable fraud detection performance over time (Rikhardsson et al., 2022; Shiyyab et al., 2023).

A further boundary condition concerns respondent eligibility. Because purposive sampling focuses on individuals with relevant accounting or digital-system exposure, future empirical findings may be most applicable to SMEs that are already considering or beginning digital transformation. Future studies may incorporate probability sampling or mixed methods to include SMEs with no AI exposure and to capture deeper qualitative explanations for resistance, trust concerns, and implementation barriers (Creswell & Creswell, 2023; Taherdoost, 2022).

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9. Conclusion

This manuscript proposes a quantitative TOE-UTAUT model for examining AI-enabled fraud detection readiness among Sarawak SMEs. The paper differs from general AI adoption manuscripts by emphasizing readiness, measurement logic, and empirical testability. It argues that AI adoption in SME accounting depends on the alignment of technological benefits, compatibility, affordability, security, task fit, managerial commitment, innovation orientation, institutional support, user effort perceptions, and social endorsement (Lutfi et al., 2022; Rikhardsson et al., 2022; Tornatzky & Fleischer, 1990; Venkatesh et al., 2003). Trust and firm size are positioned as boundary conditions that explain how behavioral confidence and resource capacity shape adoption outcomes (Badghish & Soomro, 2024; SME Corporation Malaysia, 2023).

By focusing on Sarawak, the manuscript contributes a context-sensitive foundation for future empirical research and policy design aimed at strengthening accounting transparency and fraud prevention in regional SME settings. The proposed framework may assist scholars, policymakers, professional accounting bodies, and SME stakeholders in understanding how AI readiness can be developed before full implementation of AI-enabled fraud detection systems (OECD, 2022; Sarawak Digital Economy Corporation, 2021; Schönberger, 2023).

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