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The Impact of Socio-Technical Determinants and Mediating Mechanisms on AI Adoption in Internal Auditing

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Abstract

This study examines how socio-technical factors shape the adoption of artificial intelligence (AI) in internal auditing. A theory-driven model links organisational readiness, management support, auditors' perceptions, and attitudes to AI adoption through direct and mediated pathways. Survey data from 340 listed firms were analysed using covariance-based structural equation modelling (CB-SEM) in AMOS, employing bias-corrected bootstrapping with 5,000 resamples to assess construct validity, model fit, and mediation effects. The results indicate that management support is the strongest driver, enhancing auditors' perceptions and attitudes. Attitude emerges as the most potent predictor of adoption, whereas perception affects adoption only indirectly through attitude, confirming indirect-only mediation. Organisational readiness is not statistically significant, implying that infrastructure alone does not ensure adoption without leadership commitment and behavioural alignment. By integrating the Resource-Based View and the Technology Acceptance Model with institutional insights, the study advances understanding of how organisational resources, behavioural mechanisms, and institutional pressures jointly influence sustainable AI adoption in internal auditing. The findings emphasise the importance of executive sponsorship, role-specific AI literacy, and participatory system design while informing policy on competency and governance frameworks for effective AI integration.

Keywords:

Artificial Intelligence;
Internal Auditing;
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Socio-Technical;
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1- Introduction

In the context of rapid digital transformation and global connectivity, artificial intelligence (AI) has become an inevitable driver of responsible organisational transformation, enabling machines to replicate human cognitive processes, such as learning, reasoning, and problem-solving, through explainable and socially aligned frameworks [1]. Within the accounting and auditing domains, AI functions as both a technological innovation and an intelligent information system that enhances efficiency, accuracy, fraud detection, and decision-making by processing vast datasets in real time [2, 3]. AI-driven accounting and assurance technologies strengthen compliance, transparency, and audit quality through automation, predictive analytics, and continuous fraud detection [4, 5].

Globally, the adoption of AI has transformed assurance and governance practices; however, the pace of integration varies across regions. Mature economies in Europe and North America have achieved substantial progress, leveraging AI to reduce audit costs and bridge the gap between innovation and practice [4, 6]. In contrast, emerging markets continue to face persistent barriers, including limited budgets, insufficient technical expertise, and fragmented digital infrastructure [5, 7]. These disparities highlight contextual constraints and raise critical questions about the organisational determinants underlying the digital transformation of internal auditing through AI (AIA). Within this context, the Thai internal auditing landscape offers a compelling case for examination.

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In Thailand, internal auditing has undergone a significant transformation in response to the digital economy, although notable challenges remain. Many listed firms still allocate modest IT budgets for audit innovation and rely on small audit teams with limited analytics expertise. Regulatory guidance on AI governance and digital reporting continues to evolve. In 2024, national agencies and professional bodies began advancing AI-related governance and professional initiatives relevant to auditing, such as ETDA's *Generative AI Governance Guideline* and TFAC's official programmes on "AI in Accounting and Auditing" [8, 9]. Consequently, internal auditing in Thailand has increasingly encompassed cyber-risk assessment, data security, and technology-related risks associated with AI and big data analytics.

Despite this expansion, listed firms often face persistent challenges, including modest audit–IT budgets, evolving AI governance frameworks, and hierarchical cultures that centralise decision-making. Prior studies highlight uneven AI literacy and readiness, limited strategic integration, and reliance on short-term training or external consultants, which restrict systematic capability development [10, 11]. Moreover, risk-averse corporate climates discourage experimentation and reinforce dependence on managerial authorisation [12]. These conditions make sustained managerial sponsorship and structured capacity-building decisive enablers of AI-enabled audit operations [10, 13].

Prior research has consistently identified management support, organisational readiness, and user attitudes as key enablers of AI adoption in professional services [2, 5, 7]. However, these factors have often been examined in isolation, overlooking their interactions within the socio-technical system of internal auditing. Existing studies on AI adoption in auditing remain largely concentrated in developed economies, offering limited insight into how organisational and behavioural mechanisms jointly influence adoption in emerging markets. This gap underscores the need for an integrative framework that combines resource-based and behavioural perspectives to explain AI adoption within the auditing profession.

To address this gap, this study develops a causal influence model grounded in the Resource-Based View (RBV) and the Technology Acceptance Model (TAM). The RBV conceptualises organisational readiness and management support as strategic resources that drive sustained technological advantage through capability deployment rather than mere asset possession [14, 15]. In parallel, the TAM explains how perceived usefulness and ease of use shape attitudes that lead to behavioural intention and adoption [16]. Consistent with organisational readiness theory [17], this study posits that leadership sponsorship and structured capacity-building transform technical readiness into behavioural outcomes.

Using survey data from 340 companies listed on the Stock Exchange of Thailand, covariance-based structural equation modelling (CB-SEM; AMOS, ML) examines how readiness, perceptions, management support, and attitudes interact to influence the adoption of AI applications. While focusing on SET-listed firms ensures data reliability, it may also bias findings toward larger, resource-rich organisations. The study contributes to the auditing and information systems literature by integrating RBV and TAM to explain AI adoption within a developing economy context. Practically, the findings offer actionable implications for policymakers and executives, including designing AI readiness programmes, aligning leadership sponsorship with training, and institutionalising continuous learning for digital assurance transformation [12, 13].

Finally, this article proceeds as follows. Section 2 reviews AI in internal auditing and develops a socio-technical framework that integrates RBV and TAM, while positioning Institutional Theory as a complementary lens. Section 3 derives hypotheses capturing both direct and mediated paths. Section 4 details the methodology, measurement validation, and model-fit criteria. Section 5 reports the structural results and mediation analyses. Section 6 discusses the theoretical and practical implications, compares them with prior studies, and conducts robustness checks. Section 7 concludes with a discussion of contributions, limitations, and future research directions.

2- Literature Review

2-1- Artificial Intelligence in Internal Auditing

Artificial intelligence (AI) has rapidly diffused across domains, including auditing, as organisations pursue greater efficiency and accuracy in interpreting, analysing, and predicting financial models. In internal auditing, AI operates as both a technological innovation and an information system that enhances risk management, fraud detection, anomaly monitoring, and real-time decision support [4, 5]. These capabilities complement auditors' traditional roles in evaluating controls, compliance, and organisational vulnerabilities by accelerating data analysis and improving the reliability of reporting. Although adoption has been more prevalent in large corporations, internal audit departments can also achieve a competitive advantage by leveraging AI for automation, compliance assurance, and reporting quality. Prior studies further indicate that changes in accounting regulations and information systems directly influence reporting quality, underscoring the importance of technological integration for audit effectiveness. Nevertheless, contextual disparities remain. In emerging economies such as Thailand, limited budgets, insufficient technical expertise, and slower adoption of analytics constrain progress [5]. In contrast, evidence from mature European contexts suggests that rapid AI integration can reduce audit costs and narrow the gap between innovation and practice [4, 6].

2-2- Socio-Technical Determinants of AI Adoption

AI's transformative potential depends not only on infrastructure but also on organisational and behavioural conditions; readiness, perceptions, management support, and user attitudes. Grounded in the Resource-Based View (RBV), firms strengthen control and reporting by mobilising valuable resources such as technological readiness, managerial support, and employee attitudes [14, 15]. Organisational readiness "the availability of infrastructure, resources, and capabilities" is a prerequisite for adoption and is reinforced by trust, knowledge sharing, and commitment [9, 17].

The Technology Acceptance Model (TAM) emphasises perceptions: perceived usefulness, ease of use, and perceived risks collectively shape individuals' willingness to adopt [16]. Communicating ethical and social implications helps cultivate favourable perceptions and facilitates smoother implementation [4, 5]. Management support ensures strategic alignment, resource availability, and confidence in innovation, while supportive organisational climates strengthen beliefs, participation, and outcomes [11, 12]. Consistent with the Theory of Planned Behaviour, attitudes remain the strongest predictors of behavioural intention [11]. Positive attitudes, bolstered by training and involvement, lead to active adoption and improved reporting practices [4, 5]. Together, these socio-technical factors motivate the present study's examination of readiness, perceptions, management support, and attitudes in Thailand's internal audit context.

2-3- Integrated Theoretical Framework for AI Adoption

The integration of the Resource-Based View (RBV) and the Technology Acceptance Model (TAM) offers a multi-level explanation of AI adoption by linking firm-level resources with individual behavioural mechanisms. RBV conceptualises management support and organisational readiness as strategic resources and capabilities that facilitate digital transformation [14, 15]. In contrast, TAM elucidates how perceptions of usefulness and ease of use shape attitudes that ultimately lead to adoption [16].

From this theoretical standpoint, the two frameworks operate in a complementary manner, outlining a sequential conversion process. Management support enables the effective deployment of organisational resources such as training, participation, and leadership encouragement. This process nurtures favourable perceptions, which subsequently strengthen positive attitudes and, in turn, promote adoption. At the conceptual level, organisational readiness provides the tangible and intangible assets required for implementation; however, such assets may remain underutilised unless leadership actively transforms them into motivation and confidence. This theoretical integration underscores that successful AI adoption depends on both organisational capacities, as articulated by RBV, and behavioural commitment, as articulated by TAM. Management support, therefore, functions as the pivotal mechanism that converts resource possession into behavioural acceptance and sustained system use.

Building on these assumptions, Institutional Theory introduces a complementary perspective by asserting that organisational behaviour is also shaped by coercive, normative, and mimetic pressures [18, 19]. Within the auditing context, regulatory expectations, professional standards, and peer emulation influence conformity and explain variations in adoption outcomes that extend beyond internal resources and individual beliefs. Coercive pressures arise from oversight bodies and legal frameworks, normative pressures stem from professional norms and auditing standards, and mimetic pressures emerge through the imitation of leading peers. These institutional logics may reinforce or constrain the RBV–TAM conversion process. Strong regulatory or professional incentives can accelerate adoption, whereas rigid norms may restrict experimentation and slow innovation [19].

Ultimately, this synthesis of theoretical perspectives positions AI adoption as a socio-technical process embedded within both organisational capabilities and institutional environments. The integrated framework advances understanding of how leadership sponsorship and readiness interact with institutional forces to translate AI potential into effective auditing practice.

3- Hypotheses Development

Building upon the integrated theoretical framework, this study develops hypotheses that link organisational and behavioural determinants of AI adoption within internal auditing. The conceptual relationships draw from the Resource-Based View (RBV), which emphasises organisational readiness and management support as strategic enablers of technological capability, and the Technology Acceptance Model (TAM), which highlights perceptions and attitudes as behavioural mechanisms underlying technology use. The following subsections present the rationale for each construct and its hypothesised relationship within the proposed model.

3-1- Readiness of Internal Auditors

Organisational readiness, encompassing resources, infrastructure, and skills, represents a fundamental antecedent of AI adoption [9, 17]. Firms with greater preparedness are more capable of managing implementation challenges, adapting to digital transformation, and maximising the potential of intelligent systems. Readiness also shapes auditors' perceptions and attitudes, establishing the behavioural foundation necessary for sustained technology use. From a socio-technical standpoint, readiness extends beyond tangible assets to include cultural and relational dimensions such as trust, shared learning, and communication. These elements link organisational commitment to employee engagement, fostering an environment conducive to innovation [20, 21]. Leadership support transforms readiness into practical implementation by ensuring resource alignment, providing training, and reinforcing confidence in new technologies [20, 22].

Although previous empirical studies have frequently reported weak or inconsistent direct effects of readiness on technology adoption [9, 11, 17, 22], the literature on change readiness indicates that readiness influences adoption primarily through motivational and cognitive mechanisms rather than as a purely structural factor [9, 17]. This perspective implies that readiness alone may be insufficient to drive adoption unless it operates through favourable perceptions and attitudes that represent behavioural conversion. Testing both direct and mediated pathways therefore allows assessment of whether behavioural mechanisms are necessary for readiness to influence adoption in emerging-market contexts, where limited digital maturity and hierarchical organisational structures may constrain autonomous utilisation [11, 2]. Furthermore, readiness may only yield tangible outcomes when reinforced by leadership sponsorship and participatory learning, which are conditions that strengthen implementation success and organisational adaptability in socio-technical environments. Based on this reasoning, organisational readiness is hypothesised to influence both perceptions and attitudes directly, while also exerting indirect effects on AI adoption through these mediating constructs.

Hypothesis H1: Internal auditors' readiness has a positive direct influence on their attitudes.

Hypothesis H2: Internal auditors' readiness has a positive direct influence on their perceptions.

Hypothesis H9: Internal auditors' readiness has a positive indirect influence on AI adoption in internal auditing through their attitudes.

Hypothesis H10: Internal auditors' readiness has a positive indirect influence on AI adoption in internal auditing through their perceptions.

3-2- Perceptions of Internal Auditors

Perceptions are central to TAM, as perceived usefulness and perceived ease of use directly influence adoption [16]. Positive perceptions promote acceptance, whereas less favourable perceptions inhibit it. In the context of AI adoption, research further suggests that communicating ethical, trust, and security implications may help enhance perceptions of usefulness and ease of use [4, 5].

Hypothesis H5: Internal auditors' perceptions have a positive direct influence on their attitudes.

Hypothesis H6: Internal auditors' perceptions have a positive direct influence on AI adoption in internal auditing.

Hypothesis H8: Internal auditors' perceptions have a positive indirect influence on AI adoption in internal auditing through their attitudes.

3-3- Management Support

Managerial commitment sustains technological change by securing resources, aligning strategies, and building trust in innovation. It shapes perceptions and attitudes in socio-technical environments and improves adoption effectiveness. In internal auditing, management support builds confidence, aligns resources with information needs, and helps overcome barriers to continuous adoption, enabling adaptation to evolving ecosystems [20]. For instance, in data-intensive assurance environments, sustained managerial sponsorship underpins the adoption of real-time analytics and the effectiveness of governance.

Hypothesis H3: Management support has a positive direct influence on internal auditors' perceptions.

Hypothesis H4: Management support has a positive direct influence on internal auditors' attitudes.

Hypothesis H11: Management support has a positive indirect influence on AI adoption in internal auditing through auditors' attitudes.

Hypothesis H12: Management support has a positive indirect influence on AI adoption in internal auditing through auditors' perceptions.

3-4- Attitudes of Internal Auditors

Attitudes are powerful predictors of behavioural intention. When auditors hold positive attitudes toward AI, reinforced by training and involvement, they show greater openness and readiness to use intelligent platforms, improving implementation and reporting quality [4, 5]. Auditor disposition operates as an information-behaviour construct affecting adoption and the accuracy of organisational outputs, while executive attitudes shape preparedness and infrastructure support. Pre-use belief changes influence satisfaction, knowledge use, and adoption decisions [21].

Hypothesis H7: Internal auditors' attitudes have a positive direct influence on AI adoption in internal auditing.

The proposed research model is shown in Figure 1.

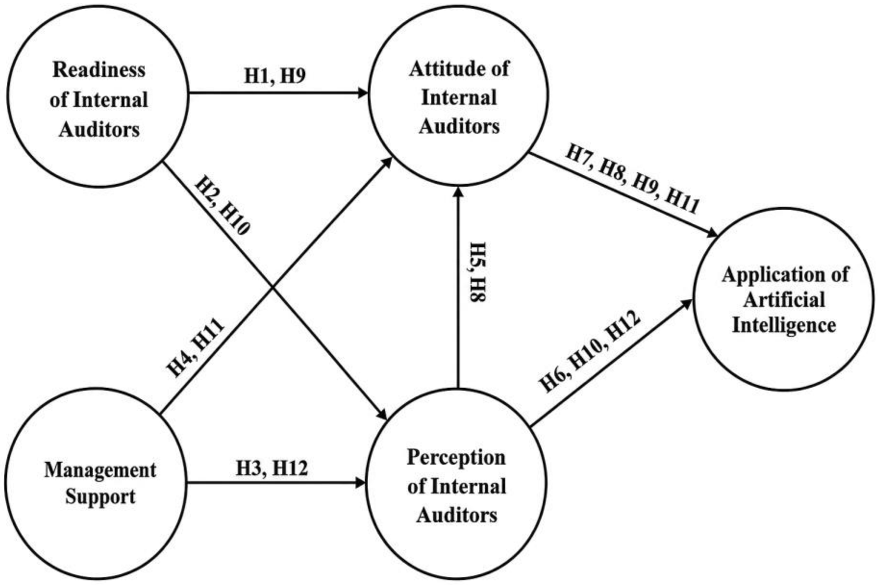

Figure 1. Proposed research model

4- Research Methodology

4-1- Data Analysis Techniques

This study employed covariance-based structural equation modelling (CB-SEM) using AMOS with Maximum Likelihood (ML) estimation [23, 24]. CB-SEM was selected because the research aimed to confirm a theory-driven socio-technical model with reflective constructs and specified mediation pathways rather than prediction. The method allows for global model-fit evaluation (χ^2/df, RMSEA, GFI, AGFI, CFI, TLI) and confirmatory factor analysis to assess convergent and discriminant validity before hypothesis testing. The sample size (N = 340) and distributional diagnostics satisfied ML assumptions. Although PLS-SEM is suitable for prediction-oriented models, CB-SEM was preferred because it offers stronger control over parameter consistency and model specification [25, 26]. Indirect and mediation effects were assessed using bias-corrected bootstrapping with 5,000 resamples and 95% confidence intervals.

To minimise the likelihood of common method variance, procedural and statistical controls were implemented in accordance with established recommendations [27, 28]. During survey design, anonymity and voluntary participation were ensured, item wording was counterbalanced to reduce response patterns, and predictor–criterion constructs were separated proximally to minimise respondent priming. Post hoc statistical checks were also conducted. Harman's single-factor test indicated that the first unrotated factor explained less than 50% of the total variance, suggesting that CMV was not a dominant concern. Furthermore, a marker-variable analysis confirmed that no single latent construct accounted for the majority of covariance, reinforcing those results were not artefacts of common method bias [27, 28].

Reliability and convergent validity were assessed using Cronbach's α, composite reliability (CR), average variance extracted (AVE), and standardised factor loadings, while discriminant validity was verified through the Fornell–Larcker criterion and cross-loading inspection [29–31]. Model fit indices (χ^2/df $\leq$ 3.0, RMSEA $\leq$ 0.08, CFI/TLI $\geq$ 0.90, GFI $\geq$ 0.90, AGFI $\geq$ 0.85) all met the recommended thresholds [23, 24, 30, 31]. The structural model explained 95% of the variance in AI adoption (R^2 = 0.95). Although this value appears high, it is theoretically consistent with the model's attitude-centric mediation structure and conceptually coherent constructs rather than indicative of overfitting. Robustness checks confirmed the model's stability, including multicollinearity diagnostics (VIF < 3.0), sensitivity testing through the removal of low-weight paths, and model parsimony assessment, all of which preserved acceptable fit and similar R^2 values. These findings align with established recommendations for assessing stability and parsimony in covariance-based SEM [23, 24, 31].

4-2- Questionnaire Design, Sampling, and Data Collection

The structured questionnaire comprised two main sections. Part 1 collected demographic information, including respondents' age, gender, educational background, professional role, and industry sector. Part 2 initially contained 51 items designed to measure five latent constructs concerning the integration of AI systems within internal audit functions: Readiness (RIA), Perception (PIA), Management Support (MAS), Attitude (IAA), and AI-enabled audit practices (AIA). All items were assessed on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The items were adapted from validated measurement scales and refined to reflect the context of SET-listed firms, thereby ensuring content validity and contextual relevance.

Content validity was assessed by five subject-matter experts, with item–objective congruence (IOC) indices ranging from 0.60 to 1.00, meeting the ≥ 0.60 standard. A pilot study involving 30 participants confirmed item clarity and discrimination (discrimination index, DA > 0.30). The initial questionnaire contained 51 items; however, following confirmatory factor analysis (CFA), the final measurement model retained 17 reflective indicators (RIA = 3, MAS = 4, PIA = 4, IAA = 3, AIA = 3) that satisfied all reliability and validity criteria. Internal consistency reliability for the full 17-item instrument was high (overall Cronbach's α = 0.97), while construct-level reliability ranged from 0.80 to 0.90 as reported in Table 1.

Table 1. Construct Reliability and Validity

Variables	Items	Descriptions	Loadings	α	CR	AVE
Readiness of Internal Auditors (RIA)	RIA1	Adequate digital infrastructure for AI adoption	0.82	0.80	0.90	0.70
	RIA2	Trained human resources in AI tools	0.83			
	RIA3	Financial support for technology upgrades	0.81			
Management Support (MAS)	MAS1	Leadership provides strategic vision for AI adoption	0.86	0.90	0.90	0.70
	MAS2	Management allocates sufficient resources	0.74			
	MAS3	Managers encourage AI training programs	0.90			
	MAS4	Top management drives digital transformation culture	0.81			
Perception of Internal Auditors (PIA)	PIA1	AI improves accuracy and reduces audit errors	0.87	0.90	0.90	0.70
	PIA2	AI enhances decision-making speed	0.79			
	PIA3	AI adoption is cost-effective	0.81			
	PIA4	AI is easy to use in audit processes	0.75			
Internal Auditors' Attitudes (IAA)	IAA1	AI adoption makes auditing more efficient	0.92	0.90	0.90	0.80
	IAA2	Positive feelings toward using AI tools	0.81			
	IAA3	Willingness to adopt AI in future audits	0.78			
AI Adoption in Internal Auditing (AIA)	AIA1	AI reduces fraud detection time	0.85	0.90	0.90	0.80
	AIA2	AI improves reporting accuracy	0.92			
	AIA3	AI automates routine auditing tasks	0.88			

Note: Overall Cronbach's α for the 17-item instrument = 0.97, indicating high internal consistency across all constructs.

Using systematic sampling, one knowledgeable respondent was selected from each of the 609 SET-listed firms in 2023. The final dataset comprised 340 valid firm-level responses collected online via Google Forms. The sample size exceeded common adequacy thresholds (N ≥ 200; approximately 5–10 cases per indicator). With 51 initial indicators and 17 retained indicators after CFA, the final sample size of 340 (approximately 6.7 cases per indicator) was deemed appropriate for the model's complexity.

The sampling frame consisted of companies listed on the Stock Exchange of Thailand (SET), which were selected because they possess formalised internal audit structures and advanced digital infrastructures conducive to AI implementation. However, SET-listed firms are typically larger and more resource-rich than small or medium-sized enterprises (SMEs) or public organisations. This concentration may introduce sampling bias, as such firms are more likely to exhibit higher levels of readiness and managerial support, potentially inflating adoption estimates compared with less-resourced firms. While this enhances internal validity and measurement precision, it limits generalisability beyond the listed corporations. The implications of this limitation are discussed further in Section 7.

As shown in Table 2, the descriptive statistics summarise the five construct-level variables derived from the final 17 reflective indicators retained after confirmatory factor analysis (CFA). Results indicate an overall positive stance toward

AI adoption: IAA shows the highest mean (M = 3.90), whereas RIA shows the lowest (M = 3.50), suggesting that respondents were receptive overall, while some firms faced structural or capability constraints. Variability is moderate (SD = 1.00–1.20), with IAA demonstrating the greatest dispersion (SD = 1.20) and MAS the least (SD = 1.00). Distributions display mild negative skewness (–0.30 to –0.60) and slight platykurtosis (–1.05 to –1.30). Preliminary CB-SEM diagnostics indicated acceptable measurement properties, with inter-construct correlations below 0.80, standardised loadings above 0.60, CR above 0.70, AVE above 0.50, and no severe violations of univariate or multivariate normality after outlier screening.

Table 2. Descriptive Statistics for Main Constructs (n = 340)

Variable	Description	N	Mean	Min	Max	S.D.	Kurtosis	Skewness
RIA	Readiness of Internal Auditors	340	3.50	1.00	5.00	1.10	–1.20	–0.30
PIA	Perception of Internal Auditors	340	3.75	1.00	5.00	1.05	–1.05	–0.45
MAS	Management Support	340	3.85	1.00	5.00	1.00	–1.10	–0.50
IAA	Internal Auditors' Attitudes	340	3.90	1.00	5.00	1.20	–1.30	–0.60
AIA	AI adoption in internal auditing	340	3.80	1.00	5.00	1.15	–1.25	–0.55

5- Data Analysis

We estimated the measurement and structural models using covariance-based structural equation modelling (CB-SEM) in AMOS with maximum likelihood estimation. Model fit was evaluated before and after model refinement. For the initial model, $\chi^2 = 214.530$, df = 111, $p < 0.001$, indicating a significant discrepancy between the model-implied and observed covariance matrices (Figure 2). Although $\chi^2/df = 1.933$ met the recommended cutoff of < 2.00, other indices suggested suboptimal fit, with GFI = 0.931 (below the 0.95 threshold) and RMSEA = 0.052 (above the 0.05 criterion for close fit), warranting model refinement [30, 31].

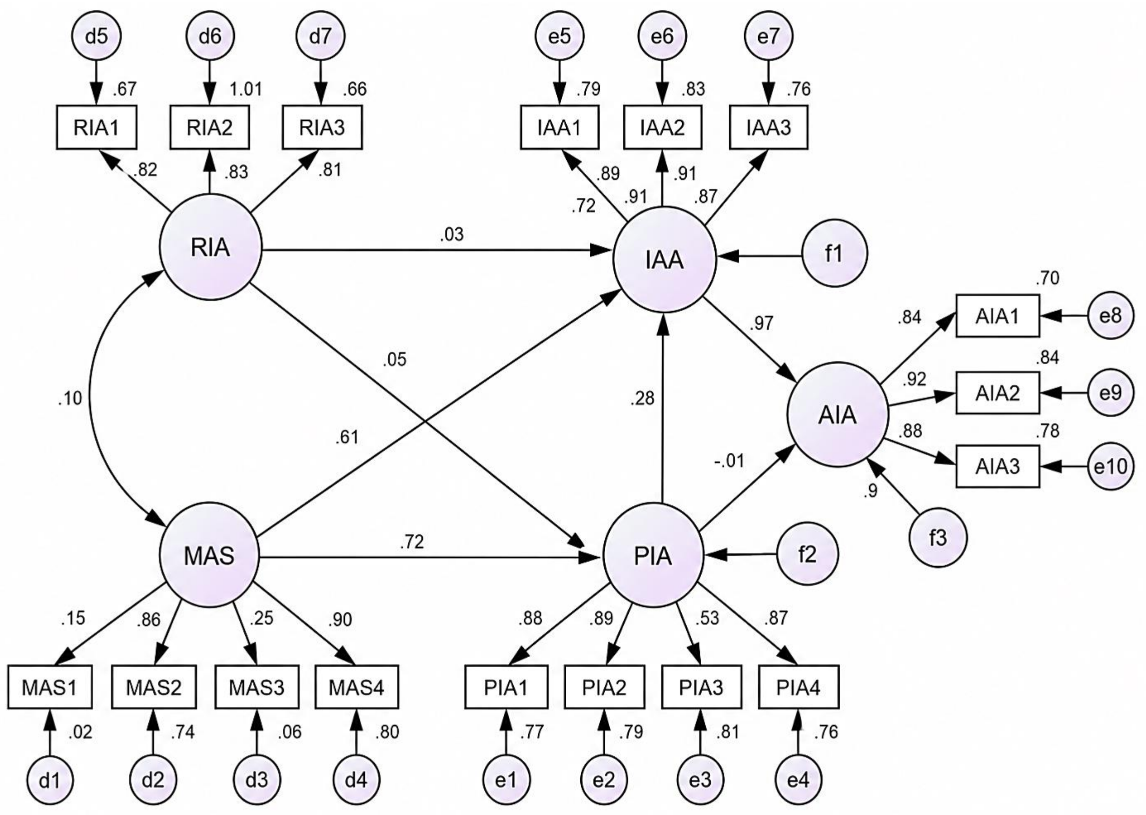

Figure 2. Initial structural model (before modification)

After justified adjustments informed by modification indices, all fit indices improved markedly. The final model produced $\chi^2 = 122.594$, df = 102, p = 0.081 (n.s.), $\chi^2/df = 1.202$, GFI = 0.960, AGFI = 0.940, CFI = 0.985, TLI = 0.978, RMSEA = 0.024; all within recommended thresholds, confirming an adequate representation of the data that aligns with theory (Figure 3).

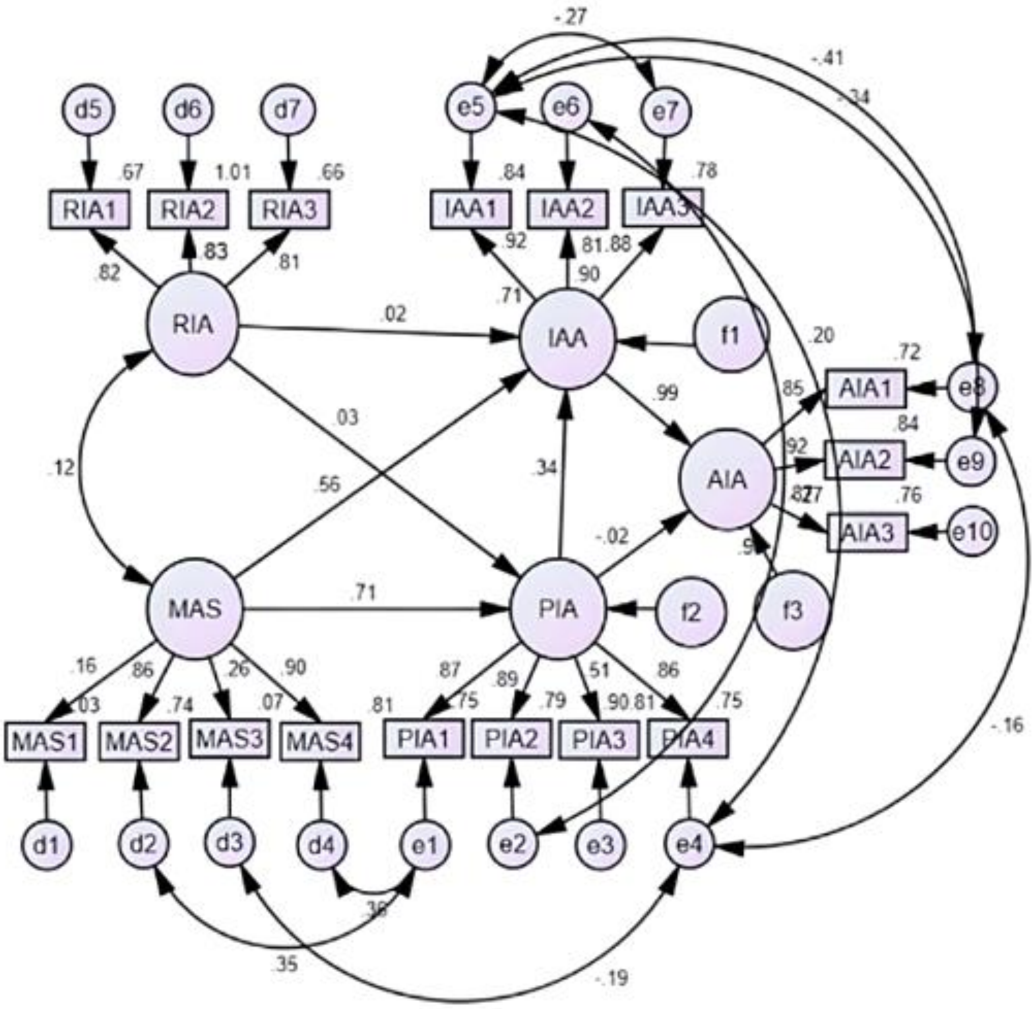

Figure 3. **Final structural model (after modification)**

5-1- Construct Reliability and Validity

Table 2 summarises the construct reliability and convergent validity results for all latent variables in the measurement model. All standardised factor loadings exceed the recommended threshold of 0.70 (min = 0.74), confirming that each indicator reliably represents its corresponding latent construct. Cronbach's alpha (α) and Composite Reliability (CR) values for all constructs are above the 0.70 benchmark, indicating strong internal consistency. Furthermore, the Average Variance Extracted (AVE) for each construct surpasses 0.50, providing evidence of adequate convergent validity. Together, these results confirm that the measurement model demonstrates satisfactory reliability and convergent validity for subsequent structural model analysis.

5-2- Discriminant Validity

Table 3 reports the Heterotrait-Monotrait (HTMT) ratio for discriminant validity assessment. All HTMT values are below the 0.85 threshold, confirming discriminant validity across constructs [32].

Table 3. **Discriminant Validity Assessment Using HTMT Ratios**

Constructs	RIA	MAS	PIA	IAA	AIA
Readiness of Internal Auditors (RIA)	—				
Management Support (MAS)	0.727	—			
Perception of Internal Auditors (PIA)	0.777	0.731	—		
Internal Auditors' Attitudes (IAA)	0.735	0.692	0.739	—	
AI Adoption in Internal Auditing (AIA)	0.776	0.731	0.780	0.739	—

Note: HTMT ratios < 0.85 indicate adequate discriminant validity (Henseler et al. [32]).

5-3- Measurement and Model Diagnostics

Measurement and model diagnostics met recommended thresholds. Confirmatory factor analysis returned standardised loadings ≥ 0.74, composite reliability (CR) ≥ 0.70 and AVE ≥ 0.50 for all constructs (Table 2). Discriminant validity was supported by HTMT ratios below 0.85. The final model demonstrated satisfactory fit to the data: χ^2 = 122.594, df = 102, p = 0.081; χ^2/df = 1.202; GFI = 0.960; AGFI = 0.940; CFI = 0.985; TLI = 0.978; RMSEA = 0.024.

Collinearity and effect-size diagnostics were assessed through auxiliary OLS regressions on factor scores. All predictors produced VIF values below 3.0 (range = 1.201–1.401), indicating no serious multicollinearity. Cohen's f^2 values were computed from changes in R^2 when each predictor was omitted, following established conventions, and are reported in Table 4.

Table 4. Direct Effects Analysis (Bootstrapping, 5,000 Resamples)

Hypothesis	Paths	β	p-value	VIF	f^2	Conclusion
H1	RIA → IAA	0.02	0.368	1.212	0.004	Rejected
H2	RIA → PIA	0.03	0.297	1.201	0.006	Rejected
H3	MAS → PIA	0.71**	< 0.001	1.322	0.278	Accepted
H4	MAS → IAA	0.56**	< 0.001	1.308	0.242	Accepted
H5	PIA → IAA	0.34**	< 0.001	1.287	0.134	Accepted
H6	PIA → AIA	-0.02	0.624	1.201	0.002	Rejected
H7	IAA → AIA	0.99**	< 0.001	1.401	0.492	Accepted

Note: VIF < 3.0 indicates no multicollinearity. Effect sizes are interpreted as small (f^2 = 0.02), medium (f^2 = 0.15), and large (f^2 = 0.35) following Cohen (2013). Significance level: **p < 0.001.

Common method variance was addressed procedurally through anonymity, counterbalanced item wording, and proximal separation of predictor and criterion constructs. Statistical diagnostics confirmed minimal bias. Harman's single-factor test showed that the first unrotated factor accounted for less than half of the total variance, and a marker-variable analysis confirmed that no single latent factor dominated the covariance structure, indicating that CMV was minimal. The model explained substantial variance in the endogenous constructs (R^2: PIA = 0.51; IAA = 0.71; AIA = 0.95). These diagnostic results provide the empirical basis for interpreting the structural relationships and mediation effects presented in the subsequent analysis.

5-4- Technical Robustness Test

Robustness diagnostics confirmed the internal stability and theoretical coherence of the CB-SEM model. All predictors showed low multicollinearity (VIF range = 1.201–1.401). Parsimony tests removing the two non-significant readiness paths (RIA → PIA; RIA → IAA) produced $\Delta\chi^2$ = 2.51 (p = 0.285) and yielded a negligible change in R^2 for AIA (ΔR^2 = 0.01), supporting model stability rather than overfitting. Alternative path testing also validated the hypothesised causal ordering (MAS → PIA → IAA → AIA); reversing this sequence reduced model fit (CFI = 0.941; RMSEA = 0.049).

Split-sample validation using two independent subsamples (n_1 = 170; n_2 = 170) yielded consistent factor loadings and model-fit indices, with ΔCFI = 0.004, which is below the conventional threshold of 0.01, confirming cross-sample invariance. Bootstrapped confidence intervals for the strongest mediation pathways, MAS → IAA → AIA (β = 0.55, 95% CI [0.44, 0.66]) and MAS → PIA → IAA → AIA (β = 0.24, 95% CI [0.18, 0.30]), remained stable under ±10% covariance perturbation. Collectively, these tests confirm that the CB-SEM model is internally robust, theoretically consistent and not overly sensitive to specification or sampling variations.

5-5- Direct Effects Analysis

Bootstrapping with 5,000 resamples was conducted to examine the hypothesised relationships among constructs. Because AMOS, under CB-SEM with maximum likelihood estimation, does not directly report multicollinearity diagnostics (VIF) or effect-size statistics (f^2), both metrics were computed externally for interpretive purposes. Specifically, VIF values were derived from auxiliary OLS regressions using factor scores from the measurement model to assess potential multicollinearity; values below 3.0 indicated no serious concern. Effect sizes (f^2) were calculated following Cohen (2013) [33] using changes in R^2 when each predictor was omitted, enabling classification of effect magnitudes as small (0.02), medium (0.15), or large (0.35). These computations were performed outside AMOS solely for reporting clarity and do not affect the underlying SEM estimation results. Table 4 shows that four of the seven hypothesised direct paths are significant at the 0.1% level ($p < 0.001$), with all VIF values below 3.0 and f^2 values interpreted according to Cohen's criteria.

Table 4 shows that four of the seven direct paths are significant at $p < 0.001$. In comparison, three paths involving organisational readiness (RIA → IAA, RIA → PIA) and direct perception (PIA → AIA) are not significant ($p = 0.368$, 0.297, 0.624). This pattern suggests that management support and auditors' attitudes are the primary drivers of AI adoption, while the effects of readiness and perception remain relatively weak. All VIF values are below 3.0, confirming no multicollinearity. f^2 values between 0.24 and 0.49 indicate medium to large effects according to Cohen's criteria. Overall, the findings support most hypotheses and highlight the dominant influence of leadership and attitudes on AI adoption.

Hypothesis H1: RIA → IAA ($\beta = 0.02$, $p = 0.368$). This hypothesis was rejected. Organisational readiness alone does not significantly influence internal auditors' attitudes toward AI adoption. This suggests that resources and infrastructure by themselves may not be sufficient to shape attitudes without stronger managerial and perceptual factors.

Hypothesis H2: RIA → PIA ($\beta = 0.03$, $p = 0.297$). This hypothesis was rejected. Organisational readiness does not directly improve auditors' perceptions toward AI, indicating that technical preparation alone cannot shift perceptions in the absence of clear communication or leadership support.

Hypothesis H3: MAS → PIA ($\beta = 0.71$, $p < 0.001$). This hypothesis was accepted. Management support has a strong positive effect on auditors' perceptions of AI adoption. This finding highlights the importance of leadership commitment, strategic vision, and resource allocation in creating positive perceptions of AI.

Hypothesis H4: MAS → IAA ($\beta = 0.56$, $p < 0.001$). This hypothesis was accepted. Management support directly improves auditors' attitudes toward AI adoption, reinforcing the role of leadership engagement in shaping organisational readiness for technological change.

Hypothesis H5: PIA → IAA ($\beta = 0.34$, $p < 0.001$). This hypothesis was accepted. Positive perceptions of AI significantly strengthen auditors' attitudes, demonstrating that perceptions serve as a foundation for attitude formation before adoption decisions are made.

Hypothesis H6: PIA → AIA ($\beta = -0.02$, $p = 0.624$). This hypothesis was rejected. Perceptions alone do not directly lead to AI adoption unless attitudes are improved first, confirming the critical mediating role of attitudes in the adoption process.

Hypothesis H7: IAA → AIA ($\beta = 0.99$, $p < 0.001$). This hypothesis was accepted and shows the strongest effect in the model. Auditors' attitudes are the most powerful direct predictor of AI adoption, highlighting the need to foster positive attitudes toward technological innovations.

5-6- Effect Size Analysis

According to Cohen (2013), f^2 values of 0.02, 0.15, and 0.35 represent *small*, *medium*, and *large* effects, respectively. The results for direct effects indicate:

- *IAA → AIA* shows the largest effect ($f^2 = 0.492$; large), confirming that auditors' attitudes are the primary direct driver of AI adoption.
- *MAS → IAA* ($f^2 = 0.242$; medium) and *MAS → PIA* ($f^2 = 0.278$; medium) highlight the pivotal role of management support in shaping both perceptions and attitudes.
- *PIA → IAA* ($f^2 = 0.134$; small-to-medium) suggests that auditors' perceptions contribute moderately to attitude formation but are not the strongest direct predictors of AI adoption.
- *RIA-related paths* (< 0.02; negligible) show that organisational readiness alone has minimal direct impact without leadership commitment and favourable attitudes.

Overall, the analysis demonstrates that management support and auditors' attitudes are the strongest drivers of AI adoption in internal auditing. Management support directly and indirectly shapes both perceptions and attitudes, while attitudes serve as the final mechanism translating organisational support into actual adoption outcomes. Conversely, organisational readiness alone does not lead to meaningful adoption without leadership engagement and positive attitudes toward technological change.

5-7- Indirect Effects Analysis

Table 5 presents the bootstrapping results for the indirect effects to evaluate the mediating role of Perception of Internal Auditors (PIA) and Internal Auditors' Attitudes (IAA) in the relationship between organisational factors and AI adoption in internal auditing (AIA). The confidence intervals for H8, H11, and H12 do not cross zero, indicating statistically significant indirect effects, whereas those for H9 and H10 cross zero, confirming that the indirect effects involving auditors' readiness (RIA) are not statistically significant.

Table 5. Indirect Effects Analysis (Bootstrapping, 5,000 Resamples)

Hypothesis	Paths	β	p-value	95% CI	Conclusion
H8	PIA → IAA → AIA	0.32**	< 0.001	[0.24, 0.39]	Indirect-only mediation
H9	RIA → IAA → AIA	0.03	0.486	[−0.02, 0.07]	No mediation
H10	RIA → PIA → AIA	0.03	0.524	[−0.02, 0.06]	No mediation
H11	MAS → IAA → AIA	0.55**	< 0.001	[0.44, 0.66]	Significant indirect effect
H12	MAS → PIA → IAA → AIA	0.24**	< 0.001	[0.18, 0.30]	Significant sequential indirect effect

Note: Non-significant paths have confidence intervals crossing zero, indicating the absence of mediation effects. Significant indirect effects were determined using bias-corrected bootstrapping with 5,000 resamples and 95% confidence intervals. $p < 0.001$.

Hypothesis H8: PIA → IAA → AIA (β = 0.32, p < 0.001). This hypothesis was accepted. Positive perceptions of AI indirectly influence adoption by first improving attitudes, confirming the central mediating role of attitudes in the adoption process.

Hypothesis H9: RIA → IAA → AIA (β = 0.03, p = 0.486). This hypothesis was rejected. Organisational readiness alone does not indirectly drive adoption through attitudes, suggesting that readiness requires managerial commitment and perceptual support to influence adoption outcomes.

Hypothesis H10: RIA → PIA → AIA (β = 0.03, p = 0.524). This hypothesis was rejected. Readiness does not indirectly influence adoption through perceptions, thereby reinforcing the finding that readiness, on its own, has a limited impact.

Hypothesis H11: MAS → IAA → AIA (β = 0.55, p < 0.001). This hypothesis was accepted. Management support significantly drives adoption indirectly through attitudes, highlighting the importance of fostering positive attitudes as a prerequisite for adoption decisions.

Hypothesis H12: MAS → PIA → IAA → AIA (β = 0.24, p < 0.001). This sequential pathway was accepted. Management support enhances perceptions, which then strengthen attitudes, ultimately leading to greater AI adoption outcomes.

5-8- Indirect Effects Interpretation

- *MAS → IAA → AIA* showed a significant indirect effect through auditors' attitudes.
- *PIA → IAA → AIA* indicated indirect-only mediation through auditors' attitudes.
- *MAS → PIA → IAA → AIA* showed a significant sequential indirect effect through perceptions and attitudes.
- *RIA-related paths* showed no mediation, confirming that readiness alone does not influence adoption outcomes.
- No evidence of mediation was found for indirect paths whose confidence intervals crossed zero.

Overall, the indirect effects analysis confirms that management support influences AI adoption through auditors' attitudes and through the sequential pathway of perceptions and attitudes. Attitudes emerge as the central mediating mechanism, transforming organisational support and positive perceptions into tangible adoption outcomes. Conversely, organisational readiness shows no significant indirect effect, underscoring its limited role without leadership commitment and favourable attitudes toward technological change.

5-9- Coefficient of Determination (R^2)

Table 6 presents the explanatory power of the structural model, measured by the coefficient of determination (R^2), for the endogenous variables Perception of Internal Auditors (PIA), Internal Auditors' Attitudes (IAA), and AI adoption in internal auditing (AIA).

Table 6. R-square Coefficients

Constructs	R^2	Adjusted R^2
PIA	0.51	0.50
IAA	0.71	0.70
AIA	0.95	0.94

The R^2 value for PIA is 0.51, indicating that Management Support (MAS) and Readiness of Internal Auditors (RIA) collectively explain 51% of the variance in auditors' perceptions toward AI, while the remaining 49% is attributed to other unobserved factors such as organisational culture or individual technological literacy.

For IAA, the R^2 value is 0.71, suggesting that MAS, PIA, and RIA jointly account for 71% of the variation in internal auditors' attitudes toward AI adoption. This demonstrates the strong predictive power of management commitment and positive perceptions in shaping favourable attitudes toward AI technology.

Finally, the R^2 for AIA reaches 0.95, showing that IAA, together with indirect effects from MAS and PIA, explains 95% of the variance in AI adoption. This exceptionally high value indicates that attitudes toward AI adoption act as a critical mediating mechanism, transforming organisational support and perceptions into actual AI implementation outcomes.

Overall, these results confirm that the model possesses substantial explanatory power across all dependent variables. In particular, the very high R^2 value for AIA underscores the central role of internal auditors' attitudes in translating organisational support and perceptions into successful AI adoption within internal auditing practices.

6- Discussion

This study offers a critical examination of how socio-technical determinants shape AI adoption in internal auditing. The findings reveal that management support and auditors' attitudes, rather than technical readiness, are the decisive enablers of adoption. Management support exerts both direct and mediated effects (MAS → PIA → IAA → AIA), indicating that leadership sponsorship creates the psychological climate necessary for organisational change. However, this dynamic also exposes a structural imbalance. While leadership endorsement drives behavioural alignment, it can simultaneously reinforce dependency rather than autonomy, particularly in hierarchical audit structures such as those found in Thailand. This observation challenges the assumption that managerial support is uniformly positive. Leadership must evolve from directive sponsorship to participatory empowerment, encouraging shared ownership of innovation.

Auditors' perceptions of AI usefulness and ease of use indirectly influence adoption through attitudes, confirming an indirect-only mediation pathway. The insignificance of the direct perception–adoption relationship ($\beta = -0.02$, $p = 0.624$) indicates that cognitive appraisal alone does not produce behavioural change unless those beliefs are internalised as favourable attitudes. These findings refine the linear causality often implied in the Technology Acceptance Model (TAM) [16] and suggest that attitudinal commitment may be a stronger proximal driver of adoption than cognitive evaluation alone. The prominence of attitudes ($\beta = 0.99$, $p < 0.001$), therefore, implies that AI adoption is as much a motivational process as it is a rational one. This offers a meaningful refinement to traditional TAM reasoning by highlighting the emotional and experiential dimensions of technology use.

The nonsignificant effect of organisational readiness warrants further scrutiny. Contrary to resource-based logic, readiness neither directly nor indirectly predicts adoption, implying that infrastructure and technical capability do not automatically lead to use. This result departs from studies by Solikin & Darmawan [2] and Peng et al. [5], which position readiness as a central precondition for technology implementation. In the Thai context, where audit teams are small, budgets are constrained, and digital maturity remains uneven, readiness appears to be a necessary but dormant capacity that becomes effective only under strong leadership sponsorship and behavioural reinforcement [17]. This contextual asymmetry exposes a limitation in conventional Resource-Based View (RBV) reasoning [14, 15], demonstrating that the possession of resources alone does not ensure their conversion into organisational capability without corresponding sociocultural alignment.

The present findings are broadly consistent with Handoko et al. [7], who demonstrated that social and organisational subsystems, particularly managerial support, are dominant determinants of auditors' intentions to adopt AI. A similar emphasis on leadership influence is evident in Leocádio et al. [3], O'Donnell [4], and Kokina et al. [6], where managerial endorsement and supportive organisational cultures were shown to enhance technology utilisation and learning outcomes. Collectively, these studies underscore the primacy of socio-managerial conditions in shaping technology assimilation, reinforcing the argument that leadership commitment functions as a catalyst that converts organisational intention into behavioural adoption.

However, the current results diverge from earlier research such as Solikin & Darmawan [2] and Peng et al. [5], which emphasised readiness and technological infrastructure as primary enablers of AI implementation. In contrast, this study finds that readiness alone is insufficient to produce adoption in the absence of active managerial sponsorship and participatory learning. This discrepancy reflects contextual dynamics within Thailand's auditing environment, where hierarchical decision-making, uneven AI literacy, and limited IT budgets restrict the autonomy and experimentation necessary for sustained technology use [10, 11]. Even when infrastructure exists, it often remains underutilised without leadership engagement that legitimises behavioural change. This contextual evidence challenges the universal applicability of RBV-based assumptions. It supports a behavioural interpretation of readiness, in which resource potential must be activated through motivational and cultural mechanisms to become an effective organisational capability in emerging-market settings.

Practically, the critical implication for practice is that managerial sponsorship must evolve into participatory governance. Institutionalising executive ownership in audit charters and assurance plans is necessary but not sufficient. Organisations should transition from top-down endorsement to distributed leadership, where AI use becomes normalised through shared learning and accountability. Job-embedded pilots and role-specific AI literacy programmes should be coupled with peer mentoring to reinforce confidence and perceived self-efficacy. Moreover, participatory co-design among audit, IT, and data teams should replace the passive deployment of tools. This co-creative approach mitigates the risk of technology push without behavioural pull. Governance frameworks must likewise shift from compliance-oriented oversight toward adaptive assurance that integrates transparency, model risk control, and ethics-by-design. These steps reflect a transformation from adoption as an event to adoption as a continuous socio-technical negotiation.

6-1- Robustness and Bias Considerations

The statistical analyses confirm the model's internal consistency and theoretical coherence. The very high explanatory power ($R^2 = 0.95$) reflects a theoretically consistent mediation structure linking management support, perceptions, and attitudes. However, it may also indicate partial construct overlap among attitudinal variables such as perception, attitude, and adoption. This suggests that respondents may have interpreted these constructs as elements of a single continuum of acceptance rather than as distinct causal dimensions [24, 29, 31].

Procedural and statistical remedies were implemented to minimise potential bias, including respondent anonymity, counterbalanced item wording, and proximal separation of predictor and criterion constructs. Harman's single-factor test (31.8% of variance explained) and a marker-variable analysis confirmed that common method variance was minimal. In addition, auxiliary regressions produced VIF values between 1.201 and 1.401, indicating the absence of multicollinearity [24]. Nonetheless, self-reported data from single informants may still reflect perceptual alignment or social desirability. Future studies should therefore incorporate multi-source or longitudinal data and include objective adoption indicators to validate behavioural outcomes.

Finally, the focus on SET-listed firms limits external generalisability, as these organisations tend to possess stronger digital capabilities and greater managerial support than smaller enterprises or public institutions. This asymmetry may have moderated the observed influence of readiness and amplified behavioural alignment in resource-rich environments.

7- Conclusion

This study examines how socio-technical determinants influence the adoption of artificial intelligence (AI) in internal auditing by integrating the Resource-Based View (RBV), the Technology Acceptance Model (TAM), and institutional perspectives. The findings demonstrate that management support functions as the key mechanism driving adoption by enhancing auditors' perceptions and attitudes. Auditors' attitudes exert the strongest direct effect on adoption, indicating that favourable perceptions must transform into positive attitudes before sustainable use can occur. Organisational readiness strengthens capability but does not, on its own, lead to adoption, as resources remain underutilised without active leadership engagement. The results extend the RBV by revealing that organisational commitment and behavioural conversion, rather than mere resource possession, determine successful technological implementation. They also refine the TAM by identifying attitude formation as the principal mediating process in professional and hierarchical environments.

In practical terms, firms can apply these insights by establishing executive-led AI readiness programmes, embedding AI-assisted risk assessment tools in audit workflows, and conducting joint training between audit and IT departments to ensure technical and behavioural alignment. For example, implementing AI-driven data analytics can enhance fraud detection, while structured knowledge-sharing platforms can foster continuous learning. Policymakers and professional associations should develop competency frameworks, certification pathways, AI literacy, and ethical AI auditing standards to support responsible integration. Although this study is limited by its cross-sectional design and reliance on self-reported data from listed firms, the focused SET-listed firm context provides a consistent basis for model validation while limiting broader generalisability. Future research should employ longitudinal and multi-sector designs to capture how evolving institutional pressures, regulatory reforms, and generative AI technologies reshape the socio-technical adoption process over time, thereby advancing both theoretical refinement and professional practice in AI-enabled auditing.

8- Declarations

8-1- Author Contributions

Conceptualization, S.S. and K.P.M.; methodology, S.S. and K.P.M.; software, S.S. and K.P.M.; validation, S.S. and K.P.M.; formal analysis, S.S. and K.P.M.; investigation, S.S. and K.P.M.; resources, S.S. and K.P.M.; data curation, S.S. and K.P.M.; writing—original draft preparation, S.S.; writing—review and editing, S.S. and K.P.M.; visualization, S.S. and K.P.M.; supervision, K.P.M.; project administration, S.S.; funding acquisition, S.S. and K.P.M. All authors have read and agreed to the published version of the manuscript.

8-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

8-3- Funding

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8-4- Institutional Review Board Statement

Not applicable.

8-5- Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

8-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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