

Critical Success Factors for AI Training Robot Adoption in Accounting SMEs: An Integrated Delphi–DEMATEL–ANP Approach

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Abstract

Artificial Intelligence (AI) and Robotic Process Automation (RPA) are transforming accounting services toward intelligent, data-driven professional services. However, small and medium-sized accounting firms (SMEs) face barriers to AI adoption, including limited resources, technological capabilities, employee skills, and regulatory uncertainty. This study identifies and prioritizes the critical success factors (CSFs) influencing AI training robot adoption in Taiwanese accounting SMEs. The framework integrates the Technology–Organization–Environment (TOE) framework, Task–Technology Fit (TTF), Technology Acceptance Model (TAM), Human–Computer Trust (HCT), and Explainable Artificial Intelligence (XAI). We used a two-round Delphi process with 15 experts to refine the CSFs, followed by DEMATEL to identify causal relationships and ANP to assess their relative priorities. The DEMATEL results indicate that the Technological dimension is the strongest causal driver ($D-R = 1.355$), followed by the Organizational dimension ($D-R = 0.435$), whereas Decision Making is the principal effect dimension ($D-R = -1.781$). The findings further emphasize task–technology alignment, AI maturity, regulatory conditions, top management support, employee AI competence, and human–computer trust. Overall, AI adoption represents an integrated organizational transformation rather than merely a technological investment. The proposed Delphi–DEMATEL–ANP framework provides systematic decision support for resource prioritization, organizational readiness, capability development, and sustainable AI-enabled digital transformation in accounting SMEs.

JEL classification numbers: M15, M41, O33, C44.

Keywords: Artificial Intelligence, AI Training Robots, Accounting SMEs, Task–Technology Fit, DEMATEL, Analytic Network Process, Digital Transformation.

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1. Introduction

The rapid development of the global digital economy and Artificial Intelligence (AI) is fundamentally transforming organizational structures, business processes, and competitive strategies. Digital transformation has evolved beyond conventional digitalization toward intelligentization, in which AI increasingly supports business model innovation, knowledge creation, operational optimization, and strategic decision-making. Under the Industry 5.0 paradigm, this transformation also reflects a shift from technology-centered automation toward a human-centric approach emphasizing collaboration between advanced technologies and human expertise, together with sustainability, resilience, and social value creation (Bukowski & Werbinska-Wojciechowska, 2025).

Organizations are consequently accelerating AI adoption to improve productivity and respond to increasingly complex business environments. In Taiwan, AI applications have expanded across intelligent manufacturing, professional services, knowledge management, and decision-support systems. Nevertheless, converting AI adoption into organizational value remains challenging because firms frequently encounter shortages of AI professionals, inadequate data governance, difficulties in cross-functional integration, and insufficient organizational learning capabilities. Successful AI transformation therefore requires more than acquiring technological tools; organizations must develop appropriate governance structures, management support, interdisciplinary capabilities, and learning mechanisms that enable AI to become a strategic resource for innovation and decision-making (Kaggwa et al., 2024).

Robotic Process Automation (RPA) represents an important component of this transformation. Traditional RPA automates repetitive, rule-based activities and standardized workflows, improving operational efficiency and reducing labor costs. However, its ability to address unstructured information and knowledge-intensive tasks remains limited. The emergence of Generative AI and Agentic AI has expanded these capabilities through natural language understanding, autonomous reasoning, multimodal analysis, and continuous learning (Alla, 2025). Consequently, integrating AI with RPA marks a shift from routine process automation to intelligent, knowledge-oriented automation.

This development is particularly relevant to the accounting profession, which is knowledge-intensive, highly regulated, and dependent on professional judgment and effective knowledge management. Accounting firms increasingly face labor shortages, heavy workloads, employee burnout, and talent attrition, while many activities—including document processing, bookkeeping, account reconciliation, and tax filing—remain labor-intensive (Liu-Lastres et al., 2023). AI and RPA therefore provide opportunities to automate routine activities while supporting professional knowledge and decision-making.

In this context, AI training robots integrate artificial intelligence, knowledge management, continuous learning, and intelligent automation. Through historical data analysis, knowledge extraction, scenario-based learning, and interactive

support, these systems can facilitate professional knowledge acquisition, standardize organizational processes, and strengthen employees' problem-solving capabilities. Their integration with RPA may enable accounting firms to transition from labor-intensive operations toward intelligent, data-driven, and knowledge-oriented professional services.

However, small and medium-sized accounting firms face greater implementation barriers than large accounting organizations because of limited financial resources, technological capabilities, specialized talent, and change-management capacity. Their adoption decisions consequently depend not only on technological characteristics but also on organizational readiness, management support, employee competencies, task requirements, and external environmental conditions (Shahadat et al., 2023). Identifying the critical success factors influencing AI training robot adoption and understanding their causal relationships and relative importance are therefore essential for supporting digital transformation in these firms.

Several theoretical perspectives are relevant to this issue. The Technology–Organization–Environment (TOE) framework explains technology adoption through technological conditions, organizational characteristics, and external environmental influences, demonstrating that AI adoption represents a systematic organizational decision rather than simply a technological choice. However, organizational adoption alone does not ensure operational value. Task–Technology Fit (TTF) theory suggests that technological effectiveness depends on the alignment between technological capabilities and task requirements. In accounting, AI systems must appropriately support activities such as auditing, taxation, financial reporting, document review, and professional decision-making (Adamek & Solarz, 2025).

At the individual level, the Technology Acceptance Model (TAM) emphasizes perceived usefulness (PU) and perceived ease of use (PEOU) as important determinants of technology acceptance. In professional accounting environments, however, Human–Computer Trust (HCT) is equally important because professionals must rely on AI-generated information while remaining accountable for their decisions. Lack of transparency, uncertainty regarding system performance, or resistance to technological change may weaken user acceptance (Lee & Cao, 2026). Moreover, as AI undertakes increasingly complex tasks, concerns involving explainability, privacy, perceived risk, ethical governance, and accountability become increasingly significant. Explainable Artificial Intelligence (XAI) and appropriate accountability mechanisms are therefore necessary to strengthen transparency, trustworthiness, and responsible AI adoption (Camilleri, 2024).

Despite growing research on AI, RPA, and digital transformation, several important gaps remain. First, previous studies frequently employ a single theoretical perspective, providing insufficient explanation of interactions among technological, task, organizational, environmental, and individual factors (Khanijahani et al., 2022). Second, conventional regression or Structural Equation Modeling approaches primarily examine predefined relationships and may not fully reveal the complex interdependencies and feedback structures among AI adoption factors.

Third, emerging concerns such as explainability, Human–Computer Trust, Perceived Risk, and accountability have not been sufficiently integrated with established technology-adoption frameworks. Fourth, empirical evidence concerning AI adoption among small and medium-sized accounting firms remains limited, although these firms face distinctive resource constraints, talent shortages, regulatory obligations, and technological challenges.

To address these gaps, this study integrates TOE, TTF, TAM, Human–Computer Trust, Perceived Risk, XAI, and cost–benefit considerations into a comprehensive analytical framework. This approach examines AI training robot adoption from technological, organizational, environmental, task, individual, trust, risk, governance, and economic perspectives. Incorporating cost–benefit considerations is particularly important for resource-constrained firms because technological desirability does not necessarily indicate economic feasibility (Sharabati et al., 2023).

Methodologically, the study combines the Delphi Method, Decision-Making Trial and Evaluation Laboratory (DEMATEL), and Analytic Network Process (ANP). Delphi is employed to establish expert consensus and refine the critical success factors identified from the literature. DEMATEL subsequently determines causal relationships, influence directions, and interaction intensity among these factors, while ANP evaluates their relative importance by considering interdependencies and feedback relationships. This integrated approach enables the study to identify not only important adoption factors but also the factors that serve as fundamental drivers within the overall decision system (Kiani & Andalib Ardakani, 2023; Pavlovic et al., 2024).

Accordingly, the primary objective of this study is to identify and prioritize the critical success factors affecting the adoption of AI training robots integrated with RPA in Taiwanese small and medium-sized accounting firms. Specifically, it seeks to identify relevant factors across multiple theoretical dimensions, determine their causal relationships and relative importance, and develop an integrated decision-making framework to support resource allocation and digital transformation. Rather than examining only whether firms intend to adopt AI, the study investigates how adoption factors interact, which factors exert the greatest systemic influence, and where limited organizational resources should be prioritized.

This study makes theoretical, methodological, and practical contributions. Theoretically, it establishes a cross-level framework combining established technology-adoption theories with AI-specific concerns involving trust, explainability, perceived risk, governance, and economic feasibility. Methodologically, the Delphi–DEMATEL–ANP approach captures expert consensus, causal relationships, interdependencies, and decision priorities within a unified analytical process. Practically, the framework can assist small and medium-sized accounting firms in evaluating AI training robot adoption, strengthening organizational readiness, developing employee capabilities, allocating limited resources, reducing implementation risks, and establishing appropriate AI governance. Consistent with Industry 5.0, the study emphasizes a complementary

relationship between AI and professional expertise, whereby intelligent technologies enhance rather than merely replace human knowledge, judgment, and organizational learning.

2. Literature Review

2.1 AI Adoption and Organizational Challenges

Driven by digital transformation and growing demand for intelligent operations, organizations are shifting from traditional process-oriented models toward data-driven decision-making. Rising workloads, labor shortages, and operational complexity have accelerated the adoption of Artificial Intelligence (AI) and Robotic Process Automation (RPA) to improve efficiency, service quality, and decision effectiveness. AI applications have also expanded from standalone tools to integrated organizational solutions, particularly in professional services such as accounting automation, data analytics, knowledge management, and decision support (Pavlovic et al., 2024).

However, AI adoption is not merely a technological implementation issue; it is a complex organizational process involving individual, task-related, and organizational factors. Despite increasing technological maturity, organizations continue to encounter substantial implementation barriers, many of which arise from organizational and managerial rather than technical limitations. In Taiwan, although AI applications have expanded from manufacturing to professional services, structural and institutional barriers remain significant (Wang et al., 2024). The literature identifies three major challenges: talent capability, data governance, and organizational integration (Romeo & Lacko, 2026).

First, talent capability is critical because organizations often lack AI and data science professionals and employees with sufficient digital competencies. Effective AI implementation increasingly requires interdisciplinary expertise combining technological, analytical, and business knowledge. However, education and corporate training frequently lag behind rapidly evolving skill requirements, creating a persistent workforce capability gap.

Second, data governance determines the reliability and effectiveness of AI systems. Poor data quality, limited accessibility, and immature governance mechanisms can undermine AI-generated outcomes. Privacy, regulatory compliance, cybersecurity, and model explainability further increase governance complexity, making robust data governance essential for successful AI implementation (Romeo & Lacko, 2026).

Third, organizational integration enables AI initiatives to move beyond isolated pilot projects toward organization-wide applications. Information silos, inadequate cross-functional collaboration, and weak resource coordination can restrict scalability and long-term value creation. Successful AI adoption therefore requires stronger process integration, interdepartmental communication, and organizational learning capabilities.

Overall, realizing AI's strategic value requires coordinated investment in talent development, data governance, and cross-functional integration. Developing these complementary organizational capabilities enables firms to improve operational performance, strengthen strategic decision-making, and sustain competitive advantage (Mahabub et al., 2025).

2.2 Theoretical Foundations and Integrated Framework

2.2.1 Organizational-Level Theories: TOE Framework and Dynamic Capabilities

The Technology–Organization–Environment (TOE) framework, proposed by Tornatzky (1990), is widely used to explain organizational adoption of innovative technologies. It suggests that adoption decisions are shaped by three contexts: technological, organizational, and environmental (Sun et al., 2024). In AI adoption, the technological context includes AI maturity, vendor support, system integration, and data quality; the organizational context encompasses top management support, employee competencies, organizational readiness, and culture; and the environmental context includes competitive pressure, government policies, industry regulations, and market conditions. Thus, TOE provides a systematic framework for examining the organizational drivers and barriers associated with AI adoption and digital transformation (Hirtranusi et al., 2026).

Within the environmental context, several factors are particularly important. Government policies and subsidies can encourage AI adoption by reducing technological uncertainty and implementation costs through financial support, regulatory incentives, and policy guidance. Industry standards and regulatory pressures also influence adoption, particularly in highly regulated sectors where organizations must comply with requirements concerning data privacy, cybersecurity, and ethical governance (Jørgensen et al., 2025). In addition, market uncertainty may encourage organizations to adopt AI to enhance decision-making, operational flexibility, and responsiveness, although excessive uncertainty can simultaneously increase investment risks and implementation concerns (Sánchez-Rodríguez et al., 2025). Finally, cost–benefit considerations affect organizational willingness to invest in AI, as firms must balance implementation and maintenance costs against expected operational and strategic benefits.

Although TOE effectively identifies the contextual conditions influencing technology adoption, it provides a relatively static explanation and offers limited insight into how organizations continuously adapt their resources and capabilities after adoption. Therefore, this study complements TOE with the Dynamic Capabilities perspective. Dynamic Capabilities theory emphasizes an organization's ability to integrate, build, and reconfigure internal and external resources in response to changing environments (Teece et al., 1997; Teece, 2007). It highlights three core capabilities: sensing opportunities and threats, seizing opportunities through strategic actions, and reconfiguring organizational resources to sustain competitive advantage (Sun, Chen, & Mei, 2024).

In AI adoption, dynamic capabilities enable organizations to continuously adjust resource allocation, redesign business processes, and strengthen technological integration. Accordingly, integrating TOE with Dynamic Capabilities provides a more comprehensive organizational-level explanation: TOE identifies the contextual conditions that shape AI adoption, whereas Dynamic Capabilities explain how organizations mobilize and reconfigure resources to transform AI adoption into sustained organizational value (Hirtranusi et al., 2026).

2.2.2 Task-Level Theory: Task–Technology Fit (TTF)

Task–Technology Fit (TTF) theory, proposed by Goodhue and Thompson (1995), suggests that information technology improves individual performance when its functionalities effectively support task requirements. Rather than emphasizing technological sophistication alone, TTF argues that performance outcomes depend primarily on the alignment between technology characteristics and the tasks being performed. Thus, even advanced technologies may fail to generate expected benefits when they do not adequately match users' task needs.

In the context of Artificial Intelligence (AI), TTF provides a useful framework for evaluating whether AI capabilities effectively support professional accounting activities, including transaction processing, audit sampling, financial analysis, tax planning, regulatory compliance, and decision support. AI technologies offering automation, data analytics, and intelligent decision-support functions can enhance the efficiency and accuracy of these activities when their capabilities correspond closely to specific task requirements (Narne et al., 2024).

Different AI technologies may also exhibit varying levels of fit across accounting tasks. For example, document recognition and data extraction systems are particularly applicable to bookkeeping and invoice processing, whereas machine learning models may better support risk assessment, fraud detection, and predictive analytics. Therefore, the alignment between AI functionalities and specific accounting tasks directly affects user performance, operational efficiency, and decision quality (Johri, 2025).

A high level of task–technology fit can enable organizations to achieve greater productivity, improved decision-making, fewer operational errors, and enhanced service quality. Conversely, inadequate fit may result in implementation difficulties, user resistance, and suboptimal performance. TTF therefore provides an important task-level perspective for explaining how AI generates organizational value. In this study, TTF is employed to assess how effectively AI training robots support professional accounting tasks in small and medium-sized accounting firms. Specifically, it explains how the alignment between AI functionalities and accounting task requirements facilitates effective AI utilization and translates technological adoption into improved performance and digital transformation.

2.2.3 Individual-Level Theoretical Foundations: TAM, Human–Computer Trust, and Explainability

The Technology Acceptance Model (TAM), proposed by Davis (1989), is widely used to explain individuals' acceptance and use of information systems. TAM identifies two central beliefs: Perceived Usefulness (PU), the extent to which users believe a system enhances job performance, and Perceived Ease of Use (PEOU), the extent to which using the system requires minimal effort. These perceptions shape users' attitudes, behavioral intentions, and subsequent technology adoption. In the context of Artificial Intelligence (AI), TAM can be extended by incorporating factors reflecting the distinctive characteristics of intelligent and increasingly autonomous systems. Human–Computer Trust (HCT) is particularly important because users must be willing to rely on AI-generated recommendations and incorporate them into professional decisions. HCT reflects users' beliefs regarding the reliability, competence, and dependability of an AI system and can substantially influence their willingness to accept and use it (Xu, Murthy, & Jia, 2025).

Trust is closely associated with Explainable Artificial Intelligence (XAI). AI systems frequently present a “black-box” problem in which users cannot easily understand how particular recommendations or decisions are generated. This opacity can create uncertainty and weaken confidence in AI outputs. XAI addresses this limitation by enhancing system transparency and interpretability and providing understandable explanations for AI-generated outcomes. Greater explainability can therefore strengthen trust, reduce perceived uncertainty, and facilitate user acceptance.

Accordingly, trust may serve as an important psychological mechanism linking AI system characteristics, particularly transparency and explainability, to adoption behavior. When users understand how an AI system generates its recommendations, they are more likely to perceive the system as reliable and incorporate its outputs into their work. Therefore, TAM provides the foundation for explaining users' perceptions of usefulness and ease of use, while HCT and XAI capture the trust and transparency mechanisms that are particularly relevant to AI. Integrating these perspectives provides a more comprehensive individual-level explanation of how accounting professionals evaluate, trust, and adopt AI training robots in small and medium-sized accounting firms.

2.3 Research Framework

Building on the theoretical foundations discussed above, this study proposes a multi-level integrated framework to systematically examine the critical factors influencing the adoption of AI training robots in small and medium-sized accounting firms (SMEs). The theoretical foundations and their contributions to the proposed framework are summarized in Table 1. At the organizational level, the Technology–Organization–Environment (TOE) framework explains the technological, organizational, and environmental conditions influencing AI adoption. At the task level, Task–Technology Fit (TTF) theory evaluates the

alignment between AI functionalities and accounting task requirements. At the individual level, the Technology Acceptance Model (TAM) and Human–Computer Trust (HCT) explain users' perceptions, acceptance behavior, and trust formation. Explainable Artificial Intelligence (XAI) further addresses transparency, interpretability, and accountability, strengthening the explanation of trust and responsible AI adoption.

Integrating these perspectives provides a comprehensive theoretical foundation for identifying the critical success factors (CSFs) associated with AI training robot implementation across organizational, task, and individual levels. These theoretically derived factors subsequently provide the basis for the empirical evaluation and prioritization process (Table 2).

Following the literature review and theoretical integration, an initial set of CSFs is identified and refined using the Delphi Method to establish expert consensus. The validated factors are then analyzed using an integrated DEMATEL–ANP approach. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) identifies causal relationships and influence intensity among the factors, distinguishing driving factors from affected factors. Subsequently, the Analytic Network Process (ANP) evaluates their relative importance and priorities while accounting for interdependencies and feedback relationships.

Accordingly, the research process follows four sequential stages: Literature Review and Theoretical Integration → Delphi Consensus Process → DEMATEL Causal Analysis → ANP Priority Evaluation (Table 3). This multi-stage design connects theoretical identification with expert validation, causal analysis, and priority assessment, providing a systematic approach for determining not only which factors are critical to AI adoption, but also how they influence one another and which factors should receive greater managerial attention in small and medium-sized accounting firms.

Table 1: Research Framework and Theoretical Foundations

Level	Theoretical Foundation	Dimension	Key Factors
Organizational Level	Technology–Organization–Environment (TOE) Framework	Technology Context	AI Technology Maturity, Data Capability, System Integration Capability, Explainability
		Organization Context	Top Management Support, Employee AI Competence, Organizational Readiness, Human–Computer Trust, Business Process Reengineering
		Environment Context	External Support, Regulatory Environment, Competitive Pressure
Task Level	Task–Technology Fit (TTF) Theory	Task–Technology Fit	Task–Technology Fit
Individual Level	Technology Acceptance Model (TAM)	User Perception	Perceived Usefulness (PU), Perceived Ease of Use (PEOU)
	Human–Computer Trust (HCT)	Trust Mechanism	Trust in AI Systems
	Explainable Artificial Intelligence (XAI)	Transparency and Governance	Transparency, Explainability, Accountability
Expert Validation Stage	Delphi Method	Expert Consensus	Identification and Refinement of Critical Success Factors (CSFs)
Causal Analysis Stage	DEMATEL	Cause–Effect Analysis	Identification of Driving and Dependent Factors
Priority Evaluation Stage	ANP	Weight Evaluation	Relative Weight and Priority Ranking of CSFs
Research Outcome	AI Adoption Decision Framework	Decision Support	AI Training Robot Adoption Framework for Small and Medium-Sized Accounting Firms (SEMs)

Table 2: Mapping between Theories and Critical Success Factors

Theory	Corresponding Factors
TOE	AI Technology Maturity, Data Capability, System Integration Capability, Top Management Support, Employee AI Competence, Organizational Readiness, Business Process Reengineering, External Support, Regulatory Environment, Competitive Pressure
TTF	Task–Technology Fit
TAM	Perceived Usefulness, Perceived Ease of Use
HCT	Human–Computer Trust
XAI	Explainability, Transparency, Accountability
MCDM Methods	Delphi, DEMATEL, ANP

Table 3: Overall Research Process

Stage	Method	Purpose	Output
Stage 1	Literature Review	Identify potential factors	Initial factor pool
Stage 2	Delphi Method	Expert consensus	Critical Success Factors (CSFs)
Stage 3	DEMATEL	Analyze causal relationships	Cause–effect network
Stage 4	ANP	Evaluate relative importance	Factor weights and rankings
Stage 5	Framework Development	Integrate findings	AI Training Robot Adoption Decision Framework

3. Research Method

3.1 Research Procedure

The research procedure consists of four stages: identification of critical success factors, expert consensus building, causal relationship analysis, and priority evaluation. By integrating theoretical foundations with Multi-Criteria Decision-Making (MCDM) methods, this study systematically examines the critical success factors (CSFs) and their interrelationships influencing the adoption of AI training robots in small and medium-sized accounting firms (SMEs).

First, a systematic literature review integrates relevant theoretical perspectives, including the Technology–Organization–Environment (TOE) framework, Task–Technology Fit (TTF) theory, Technology Acceptance Model (TAM), Human–Computer Trust (HCT), and Explainable Artificial Intelligence (XAI). Based on these foundations, an initial pool of CSFs is identified for subsequent evaluation.

Second, the Delphi Method is employed to enhance the content validity and practical relevance of the proposed factors. Experts with experience in accounting, information systems, digital transformation, and AI participate in multiple rounds of evaluation and feedback. Through this consensus-building process, the CSFs are refined and validated to establish an evaluation framework specifically for AI training robot adoption in accounting SMEs.

Third, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method analyzes the causal relationships and influence intensity among the validated factors. The total-relation matrix enables factors to be classified into cause and effect groups, thereby identifying key drivers and constructing their causal network structure.

Finally, the Analytic Network Process (ANP) evaluates the relative importance and priorities of the CSFs. Unlike AHP, ANP accommodates interdependencies and feedback relationships among factors, making it suitable for complex AI adoption decisions involving interconnected determinants (Wang et al., 2023).

Accordingly, the research procedure follows: Literature Review and Theoretical Integration → Delphi Method → DEMATEL Analysis → ANP Evaluation. This four-stage process integrates theoretical identification, expert validation, causal analysis, and priority evaluation, providing a systematic decision-making framework and practical guidance for accounting SMEs pursuing AI-enabled digital transformation and intelligent service innovation (Namdarzadegan & Bozorgi-Amiri, 2025).

3.2 Expert Panel and Questionnaire Design

To ensure the validity and practical relevance of the identified critical success factors (CSFs), this study employed the Delphi Method, inviting experts from small and medium-sized accounting firms (SMEs) and related industries in Taiwan. The panel primarily consisted of Certified Public Accountants (CPAs), IT managers, and software development professionals with experience in accounting, information systems, digital transformation, and process automation (Table 4). All participants had been involved in RPA implementation planning, evaluation, or decision-making, enabling them to provide informed judgments regarding AI training robot adoption.

To ensure expert suitability, three selection criteria were established. First, participants were required to have at least five years of professional experience in accounting, information systems, digital transformation, or process automation. Second, they must have participated in at least one digital transformation or RPA-related project involving planning, evaluation, or decision-making rather than merely serving as system users (Doan, 2025). Third, participants were required to possess sufficient knowledge of AI and process automation to evaluate their organizational implications. These criteria ensured that the panel represented experienced decision-making professionals rather than general technology users.

As two to three Delphi rounds are generally sufficient to achieve stable consensus (Hsu & Sandford, 2007), this study adopted a two-round Delphi process. In the first round, experts evaluated 29 preliminary CSFs using a five-point Likert scale ranging from 1 (“Very Unimportant”) to 5 (“Very Important”). The mean, standard deviation, median, and interquartile range (IQR) were calculated to assess factor importance and consensus.

In the second round, experts received the first-round statistical summaries and group feedback and were asked to reconsider their assessments. This iterative process facilitated convergence of expert judgments. The IQR was used as the primary consensus criterion, with $IQR \leq 1$ indicating a high level of agreement among panel members. The resulting factors formed the validated CSF framework for subsequent DEMATEL and ANP analyses.

Table 4: Profile of Delphi Experts

Expert	Affiliation	Years of Experience	Position	Gender
Expert 01	Academic University	12	Professor; CPA	Male
Expert 02	SEM Accounting Firm	12	Managing Partner; CPA	Female
Expert 03	SEM Accounting Firm	12	Managing Partner; CPA	Male
Expert 04	SEM Accounting Firm	12	Managing Partner; CPA	Female
Expert 05	SEM Accounting Firm	11	Managing Partner; CPA	Female
Expert 06	SEM Accounting Firm	11	Managing Partner; CPA	Female
Expert 07	SEM Accounting Firm	11	Managing Partner; CPA	Female
Expert 08	SEM Accounting Firm	11	Managing Partner; CPA	Female
Expert 09	SEM Accounting Firm	11	Managing Partner; CPA	Female
Expert 10	SEM Accounting Firm	11	Managing Partner; CPA	Female
Expert 11	SEM Accounting Firm	10	Audit Team Leader	Female
Expert 12	SEM Accounting Firm	9	Audit Team Leader	Female
Expert 13	Software Development Company	10	Product Software Designer	Male
Expert 14	Software Development Company	9	Associate Project Manager	Female
Expert 15	Software Development Company	10	Product Manager	Female

Average Years of Experience: 10.8 years

Note: “Years of Experience” refers to the number of years an expert has spent designing, implementing, managing, or applying relevant professional expertise.

3.3 Delphi Method

3.3.1 Identification of Critical Success Factors

Through a systematic literature review, this study integrated the Technology–Organization–Environment framework, Task–Technology Fit theory, Technology Acceptance Model, Human–Computer Trust, cost–benefit perspective, and related AI adoption literature to identify the preliminary factors influencing AI system adoption in small and medium-sized accounting firms. In addition to traditional technological, organizational, and environmental dimensions, this study further incorporated emerging AI-related factors, including explainability, data capability, change management, and human–computer trust, to more comprehensively capture the multidimensional nature of AI adoption. Based on the literature review, 34 initial critical success factors were identified as the foundation for subsequent expert evaluation (Table 5).

Table 5: Initial Critical Success Factors

No.	Criterion	References
1	AI Technology Maturity	Tornatzky (1990)
2	System Integration	Tornatzky (1990)
3	Data Quality	Tornatzky (1990)
4	Data Governance	Tahaei et al. (2023)
5	Scalability	Kukoyi & Kukoyi (2026); Ransbotham et al. (2017); Tambe et al. (2019)
6	Compatibility	Kukoyi & Kukoyi (2026); Ransbotham et al. (2017); Tambe et al. (2019)
7	Vendor Support	Tornatzky (1990)
8	Top Management Support	Tornatzky (1990)
9	Employee Skills	Tornatzky (1990)
10	Organizational Culture	Tornatzky (1990)
11	Resource Coordination and Cross-Department Communication	Zeng et al. (2014); Ransbotham et al. (2017); Tambe et al. (2019)
12	Change Management	Zeng et al. (2014); Ransbotham et al. (2017); Tambe et al. (2019)
13	Absorptive Capacity	Zeng et al. (2014); Ransbotham et al. (2017); Tambe et al. (2019)
14	Business Process Reengineering	Goodhue and Thompson (1995); Tornatzky (1990)
15	Government Support	Goodhue and Thompson (1995); Tornatzky (1990)
16	Regulatory Pressure	Goodhue and Thompson (1995); Tornatzky (1990)
17	Market Demand / Customer Demand	Tornatzky (1990)
18	Government Support	Arpaci et al. (2012); Zhu et al. (2017)
19	Regulatory Pressure	Zhu et al. (2017)
20	Environmental Uncertainty	Pavlou and El Sawy (2006)
21	Cost–Benefit Consideration	Dash et al., 2023; Sharabati et al. (2023)
22	Task Complexity	Goodhue and Thompson (1995)
23	Task–Technology Fit	Goodhue and Thompson (1995)
24	Perceived Risk	Sharabati et al. (2023)
25	Perceived Usefulness	Davis (1989)
26	Perceived Ease of Use	Davis (1989)
27	Trust	Shin (2021); Jiang et al. (2024)
28	Attitude Toward Use	Davis (1989)
29	Explainability	Glikson and Woolley (2020)
30	Human–Computer Trust	Lee and Cao (2026)
31	Sensing	Teece (2007); Teece et al. (1997)
32	Seizing	Teece (2007); Teece et al. (1997)
33	Reconfiguring	Teece (2007); Teece et al. (1997)
34	Data Capability	Tornatzky (1990); Tahaei et al. (2023)

Note: The 34 initial factors were derived from theoretical integration and literature analysis. These factors were further refined through the Delphi consensus process and served as the basis for the subsequent DEMATEL–ANP analysis.

3.3.2 Final CSF Framework

After identifying 34 initial critical success factors (CSFs), this study systematically refined the factors to reduce conceptual overlap, eliminate redundancy, and improve the parsimony and explanatory power of the analytical framework. Factors with relatively low importance, insufficient expert consensus, or substantial conceptual similarity were removed or integrated into broader constructs. Specifically, Task Complexity, Environmental Uncertainty, Perceived Risk, Sensing, Seizing, and Reconfiguring were excluded or consolidated because they overlapped with retained criteria or were not considered core decision factors for AI training robot adoption in small and medium-sized accounting firms. Consequently, the initial 34 factors were reduced to 15 core criteria (Table 6).

Table 6: AI Training Robot Adoption in SME Accounting Firms

Goal	Dimensions	Criteria
AI Training Robot Adoption in Small and Medium-Sized Accounting Firms	Technological Factors (T)	T1 Data Capability T2 System Integration Capability T3 AI Technology Maturity T4 Explainability
	Organizational Factors (O)	O1 Top Management Support O2 Employee AI Skills and Competence O3 Organizational Readiness O4 Cross-Department Integration O5 Business Process Reengineering
	Environmental Factors (E)	E1 External Support E2 Regulatory Environment E3 Market Competitive Pressure
	Decision-Making Factors (D)	D1 Task–Technology Fit (TTF) D2 Cost Effectiveness D3 Perceived Usefulness (PU)

To validate these criteria, a two-round semi-structured Delphi survey was conducted. In the first round, experts evaluated each factor using a six-point Likert scale, supplemented by open-ended questions regarding its relevance, clarity, and completeness. Based on the quantitative ratings and qualitative feedback, the questionnaire was revised and redistributed for the second round using the same six-point scale. The absence of a neutral midpoint encouraged experts to make more discriminating judgments regarding factor importance.

Through iterative evaluation, feedback, and questionnaire refinement, the 15 representative CSFs were confirmed for subsequent analysis. To assess the reliability of expert judgments, the Interquartile Range (IQR) was employed as the primary indicator of consensus. IQR, calculated as the difference between the third quartile (Q3) and first quartile (Q1), measures the dispersion of expert ratings. In this study, $IQR \leq 1$ indicated high expert consensus, whereas $IQR > 1$ indicated greater divergence requiring further consideration.

3.4 DEMATEL Method

To investigate the causal relationships and influence intensity among the identified critical success factors, this study adopts the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method. DEMATEL is an effective analytical technique for examining complex systems involving multiple interrelated criteria and transforming these relationships into a clear and interpretable causal structure.

During the DEMATEL analysis stage, expert questionnaires were administered to collect evaluations regarding the causal relationships and influence intensity among the identified criteria. Based on their professional knowledge and practical experience, experts conducted pairwise comparisons to assess the degree of influence between factors. The resulting evaluations were then used to construct the direct-relation matrix, which serves as the foundation for subsequent analyses.

1. Construction of the Direct-Relation Matrix

A direct-relation matrix $Z = [z_{ij}]$ is established based on expert evaluations of pairwise influences among factors. Experts evaluate the degree of influence between each pair of factors using a six-point scale ranging from 0 (no influence) to 5 (very high influence). These evaluations are aggregated to construct the direct-relation matrix $Z = [z_{ij}]$.

2. Matrix Normalization

To ensure comparability among factors, the direct-relation matrix is normalized to obtain the normalized direct-relation matrix S :

$$S = \frac{Z}{\max_i \sum_{j=1}^n z_{ij}}$$

where:

Z = direct-relation matrix

S = normalized direct-relation matrix

3. Calculation of the Total Relation Matrix

The total relation matrix T is calculated as follows:

$$T = S(I - S)^{-1}$$

where:

T = total relation matrix

S = normalized direct-relation matrix

I = identity matrix

$(I - S)^{-1}$ = inverse matrix

The total relation matrix captures both direct and indirect influences among factors.

4. Calculation of Prominence and Relation

Let:

$$D_i = \sum_{j=1}^n t_{ij}$$

represents the sum of row values in the total relation matrix, indicating the total influence exerted by factor i on other factors.

$$R_j = \sum_{i=1}^n t_{ij}$$

represents the sum of column values in the total relation matrix, indicating the total influence received by factor j from other factors.

Based on D and R , two important indicators can be derived:

Prominence

$$D + R$$

The prominence value reflects the overall importance and degree of involvement of a factor within the system. A larger $D + R$ value indicates that the factor plays a more significant role in the overall decision-making structure.

Relation

$$D - R$$

The relation value indicates the causal role of a factor:

If $D - R > 0$, the factor belongs to the Cause Group, indicating that it primarily influences other factors.

If $D - R < 0$, the factor belongs to the Effect Group, indicating that it is primarily influenced by other factors.

Generally, factors with larger positive $D - R$ values are regarded as key driving factors within the system.

5. Construction of the Causal Diagram

Based on the calculated values of $D + R$ and $D - R$, a causal diagram is developed to visualize the relationships among factors.

In the causal diagram:

The horizontal axis ($D + R$) represents the Prominence, indicating the overall importance of a factor within the system.

The vertical axis ($D - R$) represents the Relation, indicating whether a factor belongs to the cause group or effect group.

The causal diagram enables researchers to distinguish between driving factors and dependent factors and to identify the most influential critical success factors affecting AI training robot adoption in small and medium-sized accounting firms.

3.5 Analytic Network Process (ANP) Method

To further evaluate the relative importance of the identified critical success factors (CSFs), this study adopts the Analytic Network Process (ANP). Proposed by Saaty (1996), ANP is an extension of the Analytic Hierarchy Process (AHP) that allows for the consideration of interdependencies and feedback relationships among decision elements. Compared with traditional hierarchical models, ANP is particularly suitable for complex decision-making problems involving multiple criteria with mutual influences.

In this study, the network structure was developed based on the results of the Delphi Method and DEMATEL analysis. The Delphi process identified the final 15 critical success factors, while the DEMATEL analysis revealed the causal relationships among these factors. These results were subsequently incorporated into the ANP model to determine the relative importance and priority ranking of each criterion. The ANP analysis procedure consists of the following five steps.

Step 1: Construction of the Network Structure

Based on the causal relationships identified through DEMATEL, a network structure was established to represent the interdependencies and feedback relationships among dimensions and criteria. Unlike AHP, which assumes independence among criteria, ANP explicitly considers the interactions among decision elements.

Step 2: Construction of Pairwise Comparison Matrices

Experts were invited to conduct pairwise comparisons of the identified criteria according to their relative importance. The comparisons were performed using Saaty's nine-point scale, ranging from 1 (equal importance) to 9 (extreme importance).

Step 3: Aggregation of Expert Judgments and Consistency Test

The pairwise comparison values provided by the 15 experts were aggregated using the geometric mean method to obtain a representative group judgment matrix. The geometric mean is widely recommended in group decision-making studies because it preserves proportional consistency among expert evaluations.

To ensure the reliability of expert judgments, the Consistency Ratio (CR) of each pairwise comparison matrix was examined.

The consistency ratio is calculated as:

$$CR = CI/RI.$$

where:

CR = Consistency Ratio

CI = Consistency Index

RI = Random Index

According to Saaty (1980), a CR value below 0.10 indicates an acceptable level of consistency. If the CR exceeds 0.10, the corresponding judgments should be reviewed and revised.

[$CR < 0.10$]

This procedure ensures that the expert evaluations are logically consistent and that the resulting weights are reliable and valid.

Step 4: Construction of the Supermatrix

Based on the network relationships identified from the DEMATEL results, three types of supermatrices were constructed:

Unweighted Supermatrix

The unweighted supermatrix represents the interrelationships among criteria and clusters based on pairwise comparison results.

Weighted Supermatrix

The weighted supermatrix is obtained by multiplying the unweighted supermatrix by the corresponding cluster weights, ensuring column stochasticity.

Limit Supermatrix

The weighted supermatrix is raised to sufficiently large powers until convergence is achieved. The resulting limit supermatrix reflects the long-term stable influence of each criterion within the network.

Step 5: Priority Weight Calculation and Ranking

The final priority weights of all critical success factors were obtained from the limit supermatrix. These weights were subsequently used to rank the relative importance of the factors and identify the most influential criteria affecting the adoption of AI training robots in small and medium-sized accounting firms.

The ANP results provide a quantitative basis for evaluating the significance of each factor while accounting for the complex interrelationships among criteria.

Software and Data Processing

All pairwise comparison data were first processed using Microsoft Excel. The geometric mean of expert judgments was calculated to generate the aggregated comparison matrices. Subsequently, Super Decisions software was employed to construct the ANP network model, calculate eigenvectors and eigenvalues, perform consistency tests, and generate the unweighted supermatrix, weighted supermatrix, and limit supermatrix. Through the integration of DEMATEL and ANP, this study not only identifies the causal relationships among critical success factors but also evaluates their relative importance. Consequently, a systematic decision-support framework for AI training robot adoption in small and medium-sized accounting firms is established.

4. Result and Analysis

4.1 Normalized Direct-Relation Matrix-Dimension

Table 7 presents the Normalized Direct-Relation Matrix (S) derived from the DEMATEL analysis, illustrating the direct influence exerted by each dimension on the other dimensions. The values range from 0 to 1, with higher values indicating stronger direct relationships. The diagonal values are set to zero because a dimension is not considered to exert a direct influence on itself.

Technological (T) dimension demonstrates relatively strong direct effects on the other three dimensions. Its strongest influence is on Decision Making (D) (0.361), followed by Organizational (O) (0.348) and Environmental (E) (0.291) dimensions. These results indicate that technological conditions are closely associated with organizational arrangements and managerial decision-making concerning AI training robot adoption.

Organizational (O) dimension also exhibits substantial direct influences, particularly on Decision Making (0.348), followed by the Environmental (0.285) and Technological (0.272) dimensions. This suggests that organizational readiness, management support, and internal capabilities are closely connected with how firms evaluate and make AI adoption decisions.

Environmental (E) dimension shows its strongest direct influence on Organizational (0.278) and Decision Making (0.278), while its influence on Technology is relatively lower (0.184). This pattern indicates that environmental conditions may shape AI adoption primarily through organizational responses and decision processes.

In comparison, the Decision-Making (D) dimension exhibits weaker direct influences on Technology (0.120), Organization (0.152), and Environment (0.171). Overall, the matrix indicates an asymmetric influence structure, with Technology and Organization exerting stronger direct effects, particularly on Decision Making. These normalized relationships provide the foundation for constructing the total-relation matrix and subsequently determining the prominence (D+R)(D+R) and causal (D-R)(D-R) roles of each dimension in the DEMATEL analysis.

Table 7: Normalized Direct-Relation Matrix-Dimension

Normalized Direct-Relation Matrix (S)	Technological (T)	Organizational (O)	Environmental (E)	Decision Making (D)
Technological (T)	0.000	0.348	0.291	0.361
Organizational (O)	0.272	0.000	0.285	0.348
Environmental (E)	0.184	0.278	0.000	0.278
Decision Making (D)	0.120	0.152	0.171	0.000

4.2 Total-Relation Matrix (T)-Dimension

Table 8 presents the Total-Relation Matrix (T) generated through DEMATEL analysis. Unlike the normalized direct-relation matrix, the total-relation matrix captures both direct and indirect influences among the four dimensions: Technological (T), Organizational (O), Environmental (E), and Decision Making (D). Higher values indicate stronger overall relationships between dimensions.

The results show that the Technological dimension exerts particularly strong total effects on Decision Making (1.184), Organizational (0.997), and Environmental (0.948) dimensions. Among all relationships in the matrix, the effect of Technology on Decision Making is the strongest. This indicates that technological conditions play an important role in shaping how accounting firms evaluate and make decisions regarding AI training robot adoption.

The Organizational dimension also demonstrates substantial influence, particularly on Decision Making (1.099) and the Environmental dimension (0.883). Its effect on Technology is also considerable (0.750), indicating strong interrelationships between organizational readiness and technological capability. Similarly, the Environmental dimension has notable effects on Decision Making (0.932) and Organization (0.791), suggesting that regulatory and external conditions influence organizational responses and adoption-related decisions.

In comparison, the Decision-Making dimension exhibits relatively weaker total effects on Technology (0.410), Organization (0.509), and Environment (0.515). This pattern suggests that Decision-Making is more strongly influenced by the other dimensions than it influences them. The non-zero diagonal values—Technology (0.588), Organization (0.674), Environment (0.563), and Decision Making (0.469)—reflect indirect feedback effects transmitted through the overall system. Collectively, the results demonstrate substantial interdependence among the four dimensions, while highlighting Technology and Organization as important sources of influence and Decision Making as a major recipient of influence. These relationships provide the basis for calculating $D+RD+R$ and $D-RD-R$ and constructing the subsequent DEMATEL causal relationship map.

Table 8: Total-Relation Matrix (T)-Dimension

Total-Relation Matrix (T)	Technological (T)	Organizational (O)	Environmental (E)	Decision Making (D)
Technological (T)	0.588	0.997	0.948	1.184
Organizational (O)	0.750	0.674	0.883	1.099
Environmental (E)	0.614	0.791	0.563	0.932
Decision Making (D)	0.410	0.509	0.515	0.469

The total-relation matrix T was derived from the normalized direct-relation matrix S using the formula $T = S(I - S)^{-1}$, where I denotes the identity matrix and $(I - S)^{-1}$ represents the inverse matrix of $I - S$.

Each element t_{ij} indicates the total influence of dimension i on dimension j , including both direct and indirect effects.

The total-relation matrix serves as the basis for calculating the dispatching degree (D), receiving degree (R), prominence (D+R), and relation (D-R) in the DEMATEL analysis (Table 9).

Table 9: Prominence and Relation-Dimension

Dimension	D	R	D + R	D - R	Group
Technological (T)	3.717	2.362	6.079	1.355	Cause
Organizational (O)	3.406	2.971	6.377	0.435	Cause
Environmental (E)	2.900	2.909	5.809	-0.009	Effect
Decision Making (D)	1.903	3.684	5.587	-1.781	Effect

Based on the total-relation matrix T , the DEMATEL method was employed to calculate the dispatching degree (D) and receiving degree (R) for each dimension. The dispatching degree represents the total influence that a dimension exerts on other dimensions and is obtained by summing the rows of the total-relation matrix. The receiving degree represents the total influence received from other dimensions and is obtained by summing the columns of the total-relation matrix.

The prominence value ($D + R$) indicates the overall importance of each dimension within the system, while the relation value ($D - R$) identifies whether a dimension acts as a cause or an effect. A positive $D - R$ value indicates that the dimension belongs to the cause group and exerts net influence on the system, whereas a negative $D - R$ value indicates that the dimension belongs to the effect group and is primarily influenced by other dimensions.

The results indicate that Technological (T) has the largest positive relation value ($D - R = 1.355$), suggesting that it is the most influential driving dimension in the framework. This finding implies that technological capabilities, such as data analytics, system integration, AI maturity, and explainability, play a critical role in shaping organizational readiness and decision-making effectiveness.

Organizational (O) also belongs to the cause group with a positive relation value ($D - R = 0.435$). This indicates that internal organizational factors, including top management support, employee competence, organizational readiness, and process reengineering, significantly influence both environmental conditions and decision-making outcomes.

Environmental (E) exhibits a relation value close to zero ($D - R = -0.009$), indicating that it serves as a transitional dimension that both influences and is influenced by other dimensions.

Decision Making (D) has the most negative relation value ($D - R = -1.781$), indicating that it is the principal effect dimension and represents the final outcome of interactions among the other dimensions. This result suggests that improvements in technological and organizational capabilities ultimately enhance managerial decision quality. Please see Figure 1 and Figure 2.

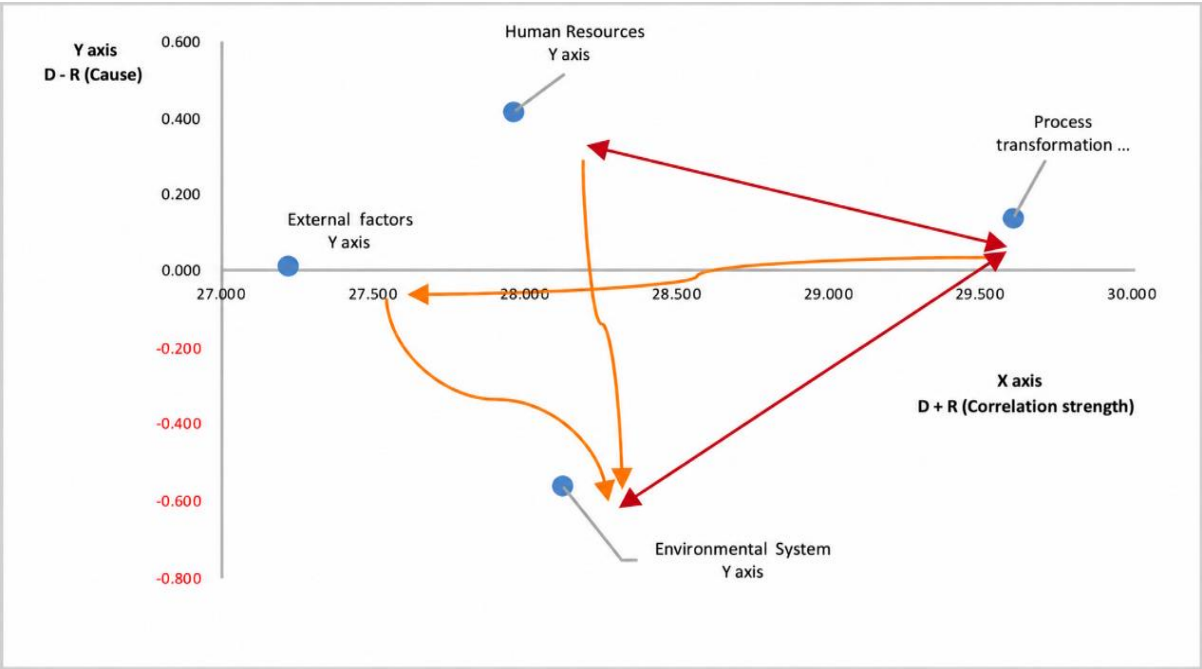


Figure 1: Cause and Effect Diagram

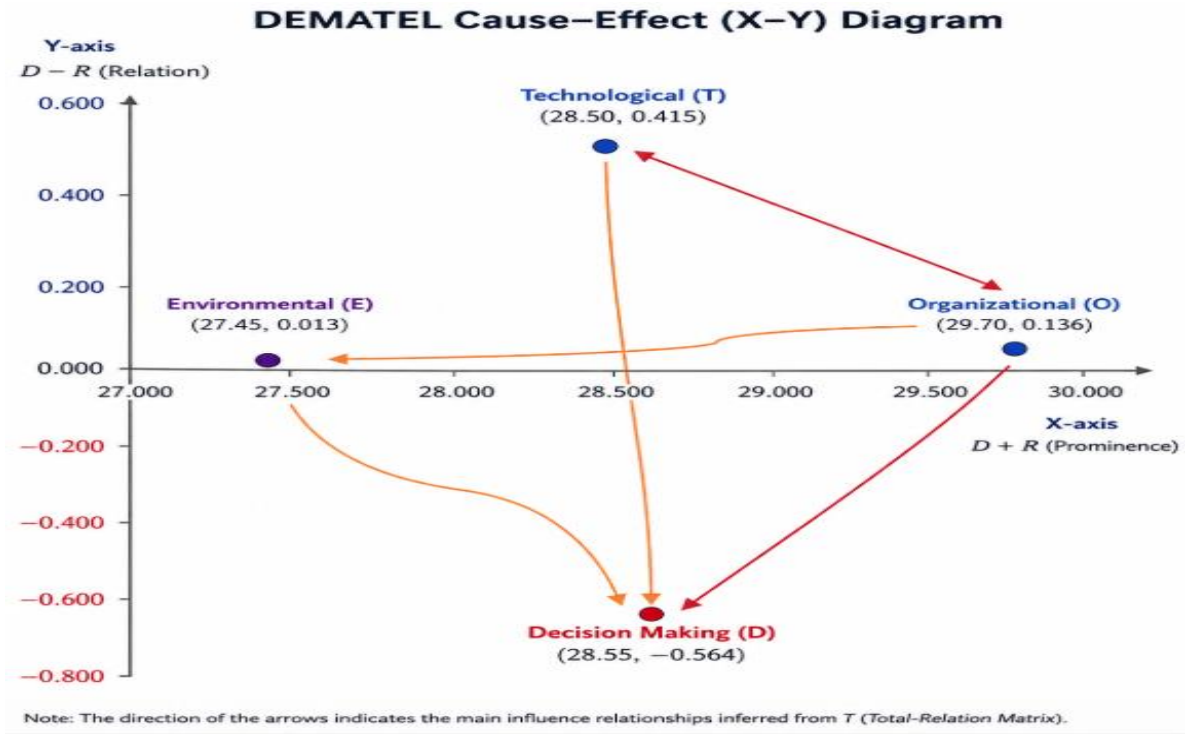


Figure 2: DEMATEL Cause-Effect(X-Y) Diagram

4.3 Direct-Relation Matrix Z- Criteria

The average direct-relation matrix at the criterion level presents the pairwise influences among the 15 criteria, based on evaluations by 15 experts. Each matrix element represents the average degree to which one criterion directly influences another, ranging from 0 (no influence) to 4 (very high influence). Diagonal elements are set to zero because self-influence is excluded. The matrix provides the basis for normalization, total-relation matrix calculation, and subsequent DEMATEL cause–effect analysis.

Preliminary results reveal several important patterns. As shown in Table 10, first, the technological criteria (T1–T4) exert strong influences on organizational and decision-making criteria. Notably, AI Maturity (T3) shows the strongest direct effects on Perceived Usefulness (D3) and Perceived Ease of Use (D4), both reaching 4.00, highlighting technological maturity as an important driver of users' evaluations of AI systems.

Second, the organizational criteria (O1–O5) demonstrate substantial influences on decision-making criteria. In particular, Top Management Support (O1) strongly affects D1–D4, emphasizing the importance of managerial commitment in AI adoption.

Third, the environmental criteria (E1–E3) exert moderate but consistent influences, reflecting the importance of external and regulatory conditions. In contrast, decision-making criteria (D1–D4) generally exert weaker influences, suggesting that they primarily function as effect factors, while technological and organizational criteria represent the principal causal drivers.

Table 10: The Direct-Relation Matrix Z- Criteria

Direct-Relation Matrix (Z)	T1	T2	T3	T4	O1	O2	O3	O4	O5	E1	E2	E3	D1	D2	D3	Column Sum
T1	0.000	2.600	2.600	2.467	3.400	3.467	3.667	3.600	3.600	2.867	2.867	2.467	3.733	3.667	3.867	44.87
T2	2.400	0.000	2.533	2.533	3.400	3.400	3.267	3.667	3.267	2.733	2.800	2.467	3.933	3.867	3.733	44.00
T3	2.533	2.533	0.000	2.667	3.667	3.800	3.667	3.933	3.400	3.067	2.733	2.667	3.867	3.733	4.000	46.27
T4	2.200	2.000	2.267	0.000	3.333	3.267	3.333	3.067	3.133	2.533	2.800	2.600	3.667	3.600	3.800	41.60
O1	3.133	3.133	3.133	2.800	0.000	2.867	3.400	3.200	2.933	2.933	2.733	2.733	3.800	3.867	3.800	44.47
O2	2.800	2.600	2.800	2.800	2.400	0.000	2.400	2.533	2.267	2.333	2.467	2.533	3.467	3.467	3.667	38.53
O3	2.800	2.667	3.000	3.133	2.533	2.867	0.000	2.867	2.867	2.467	2.333	2.133	3.933	3.467	3.600	40.67
O4	2.800	2.600	2.933	2.867	2.267	2.600	2.600	0.000	2.600	2.267	2.200	2.267	3.200	3.667	3.333	38.20
O5	2.800	2.600	2.800	2.600	2.533	2.000	2.533	2.600	0.000	2.400	2.333	2.400	3.467	3.267	3.333	37.67
E1	2.067	2.200	1.933	1.933	2.600	2.533	2.933	2.867	2.467	0.000	2.200	1.933	3.000	2.933	2.933	34.53
E2	2.267	2.067	2.067	2.467	2.800	2.733	3.200	3.267	2.800	2.200	0.000	2.333	3.533	2.867	3.267	37.87
E3	1.867	2.000	1.800	2.200	2.733	2.533	2.733	2.867	2.933	1.667	2.067	0.000	3.133	2.733	3.067	34.33
D1	2.067	2.067	1.600	1.867	2.467	2.400	2.400	2.667	2.133	1.867	2.133	1.867	0.000	2.600	2.733	30.87
D2	1.800	1.133	1.333	1.867	1.867	1.933	2.133	2.467	2.200	1.600	1.600	1.933	2.067	0.000	2.200	26.13
D3	1.333	1.733	1.400	2.067	2.333	2.400	2.333	2.267	2.000	1.800	1.600	1.667	2.667	2.200	0.000	27.80
Row Sum	15.87	15.53	16.33	16.40	18.73	19.67	19.73	22.87	21.47	18.93	18.73	17.60	26.40	25.67	26.47	

4.4 DEMATEL Analysis of Causal Relationships among Critical Success Factors

Tables 11–13 present the DEMATEL analysis at the criterion level, demonstrating the direct and indirect relationships among the 15 critical success factors (CSFs). Table 11 reports the normalized direct-relation matrix, in which each value represents the standardized direct influence of one criterion on another. This normalization ensures comparability across criteria and provides the basis for calculating their total relationships.

Table 12 presents the total-relation matrix, incorporating both direct and indirect effects among the criteria. Compared with Table 11, the larger values demonstrate that the influence of individual factors extends through interconnected pathways within the system. The results indicate substantial interdependence among technological, organizational, environmental, and decision-making criteria, confirming that AI training robot adoption should be viewed as an interconnected decision system rather than a set of independent factors.

Table 13 summarizes the prominence and relation values for each criterion. The prominence value ($D+R$) represents the overall importance and degree of involvement of a criterion within the system, with higher values indicating stronger interactions with other factors. The relation value ($D-R$) determines its causal role. A positive $D-R$ identifies a criterion as a cause factor, meaning that it primarily influences other criteria, whereas a negative value identifies an effect factor, meaning that it is more strongly influenced by other factors.

Overall, Tables 11–23 provide a systematic transition from direct relationships to total influence and causal classification. The results reveal a complex network of interactions among the 15 CSFs and provide the empirical basis for constructing the criterion-level cause-and-effect diagram and subsequently integrating DEMATEL results with ANP priority analysis.

Table 11: Normalized Direct-Relation Matrix- Criteria

	T1	T2	T3	T4	O1	O2	O3	O4	O5	E1	E2	E3	D1	D2	D3
T1	0.000	0.056	0.056	0.053	0.073	0.075	0.079	0.078	0.078	0.062	0.062	0.053	0.081	0.079	0.084
T2	0.052	0.000	0.055	0.055	0.073	0.073	0.071	0.079	0.071	0.059	0.061	0.053	0.085	0.084	0.081
T3	0.055	0.055	0.000	0.058	0.079	0.082	0.079	0.085	0.073	0.066	0.059	0.058	0.084	0.081	0.086
T4	0.048	0.043	0.049	0.000	0.072	0.071	0.072	0.066	0.068	0.055	0.061	0.056	0.079	0.078	0.082
O1	0.068	0.068	0.068	0.061	0.000	0.062	0.073	0.069	0.063	0.063	0.059	0.059	0.082	0.084	0.082
O2	0.061	0.056	0.061	0.061	0.052	0.000	0.052	0.055	0.049	0.050	0.053	0.055	0.075	0.075	0.079
O3	0.061	0.058	0.065	0.068	0.055	0.062	0.000	0.062	0.062	0.053	0.050	0.046	0.085	0.075	0.078
O4	0.061	0.056	0.063	0.062	0.049	0.056	0.056	0.000	0.056	0.049	0.048	0.049	0.069	0.079	0.072
O5	0.061	0.056	0.061	0.056	0.055	0.043	0.055	0.056	0.000	0.052	0.050	0.052	0.075	0.071	0.072
E1	0.045	0.048	0.042	0.042	0.056	0.055	0.063	0.062	0.053	0.000	0.048	0.042	0.065	0.063	0.063
E2	0.049	0.045	0.045	0.053	0.061	0.059	0.069	0.071	0.061	0.048	0.000	0.050	0.076	0.062	0.071
E3	0.040	0.043	0.039	0.048	0.059	0.055	0.059	0.062	0.063	0.036	0.045	0.000	0.068	0.059	0.066
D1	0.045	0.045	0.035	0.040	0.053	0.052	0.052	0.058	0.046	0.040	0.046	0.040	0.000	0.056	0.059
D2	0.039	0.024	0.029	0.040	0.040	0.042	0.046	0.053	0.048	0.035	0.035	0.042	0.045	0.000	0.048
D3	0.029	0.037	0.030	0.045	0.050	0.052	0.050	0.049	0.043	0.039	0.035	0.036	0.058	0.048	0.000

Table 12: Total-Relation Matrix (T)- Criteria

	T1	T2	T3	T4	O1	O2	O3	O4	O5	E1	E2	E3	D1	D2	D3
T1	0.238	0.284	0.286	0.299	0.340	0.346	0.361	0.369	0.346	0.294	0.294	0.281	0.410	0.399	0.412
T2	0.283	0.226	0.280	0.295	0.335	0.339	0.347	0.364	0.334	0.286	0.288	0.277	0.406	0.396	0.402
T3	0.297	0.290	0.240	0.310	0.353	0.360	0.369	0.384	0.350	0.304	0.298	0.292	0.422	0.410	0.424
T4	0.266	0.255	0.262	0.230	0.319	0.321	0.333	0.336	0.317	0.269	0.275	0.267	0.384	0.374	0.386
O1	0.300	0.293	0.294	0.303	0.270	0.333	0.354	0.359	0.332	0.293	0.290	0.285	0.409	0.401	0.408
O2	0.262	0.252	0.257	0.271	0.285	0.239	0.298	0.308	0.284	0.251	0.254	0.251	0.359	0.351	0.363
O3	0.274	0.265	0.273	0.289	0.300	0.310	0.262	0.329	0.308	0.265	0.263	0.254	0.384	0.367	0.377
O4	0.261	0.251	0.259	0.271	0.281	0.291	0.300	0.255	0.289	0.249	0.248	0.245	0.352	0.354	0.355
O5	0.259	0.249	0.254	0.263	0.283	0.276	0.296	0.305	0.233	0.249	0.248	0.245	0.354	0.342	0.351
E1	0.228	0.226	0.222	0.234	0.265	0.267	0.284	0.289	0.264	0.183	0.229	0.220	0.322	0.313	0.320
E2	0.249	0.240	0.241	0.262	0.288	0.290	0.309	0.318	0.290	0.245	0.201	0.244	0.356	0.335	0.351
E3	0.223	0.220	0.218	0.238	0.266	0.265	0.278	0.288	0.272	0.217	0.225	0.179	0.323	0.308	0.321
D1	0.210	0.205	0.197	0.213	0.242	0.243	0.251	0.263	0.237	0.204	0.210	0.201	0.235	0.282	0.291
D2	0.180	0.163	0.168	0.187	0.202	0.205	0.216	0.228	0.209	0.174	0.175	0.178	0.243	0.195	0.246
D3	0.180	0.183	0.178	0.200	0.221	0.224	0.230	0.235	0.215	0.187	0.184	0.182	0.267	0.252	0.213

Table 13: Prominence and Relation of the Criteria

	T1	T2	T3	T4	O1	O2	O3	O4	O5	E1	E2	E3	D1	D2	D3	D	R	D+R	D-R	Group
T1	0.238	0.284	0.286	0.299	0.341	0.346	0.361	0.369	0.346	0.294	0.294	0.281	0.410	0.399	0.412	4.960	3.711	8.670	+1.249	Cause
T2	0.283	0.226	0.280	0.295	0.335	0.339	0.347	0.364	0.334	0.286	0.2879	0.277	0.407	0.396	0.402	4.857	3.602	8.459	+1.255	Cause
T3	0.297	0.290	0.240	0.310	0.353	0.360	0.369	0.383	0.350	0.304	0.298	0.292	0.422	0.410	0.424	5.104	3.626	8.730	+1.478	Cause
T4	0.266	0.255	0.262	0.230	0.319	0.321	0.333	0.336	0.317	0.270	0.275	0.267	0.384	0.374	0.386	4.594	3.864	8.458	+0.730	Cause
O1	0.300	0.293	0.294	0.303	0.271	0.333	0.354	0.360	0.332	0.293	0.290	0.285	0.409	0.401	0.408	4.923	4.251	9.174	+0.672	Cause
O2	0.2621	0.2526	0.2573	0.271	0.285	0.239	0.298	0.309	0.284	0.251	0.254	0.251	0.359	0.351	0.363	4.286	4.309	8.595	-0.023	Effect
O3	0.274	0.265	0.273	0.289	0.300	0.310	0.262	0.329	0.308	0.265	0.263	0.255	0.384	0.367	0.377	4.521	4.491	9.012	+0.030	Cause
O4	0.261	0.251	0.259	0.271	0.281	0.291	0.300	0.255	0.289	0.249	0.248	0.245	0.352	0.354	0.355	4.261	4.630	8.891	-0.369	Effect
O5	0.259	0.249	0.254	0.263	0.283	0.276	0.296	0.305	0.233	0.249	0.248	0.245	0.354	0.342	0.351	4.20	4.280	8.486	-0.073	Effect
E1	0.228	0.226	0.222	0.234	0.265	0.267	0.284	0.289	0.264	0.183	0.229	0.220	0.322	0.314	0.320	3.866	3.672	7.537	+0.194	Cause
E2	0.2494	0.240	0.241	0.262	0.288	0.290	0.309	0.318	0.290	0.246	0.201	0.244	0.356	0.335	0.351	4.220	3.682	7.903	+0.538	Cause
E3	0.223	0.221	0.218	0.238	0.266	0.265	0.278	0.288	0.272	0.217	0.225	0.179	0.323	0.308	0.321	3.841	3.601	7.442	+0.240	Cause
D1	0.210	0.205	0.197	0.213	0.242	0.243	0.251	0.262	0.237	0.204	0.210	0.201	0.235	0.282	0.291	3.485	5.227	8.711	-1.742	Effect
D2	0.180	0.163	0.168	0.187	0.202	0.205	0.216	0.228	0.209	0.174	0.175	0.178	0.243	0.195	0.246	2.968	5.081	8.049	-2.112	Effect
D3	0.180	0.183	0.178	0.200	0.221	0.225	0.231	0.235	0.215	0.187	0.183	0.182	0.267	0.253	0.213	3.151	5.219	8.370	-2.067	Effect

The DEMATEL findings indicate that AI technology maturity, regulatory support, and organizational management capability are the primary driving forces behind AI training robot adoption. In contrast, task–technology fit and user perceptions represent the ultimate outcome factors reflecting implementation effectiveness. These results suggest that SMEs accounting firms should prioritize technological readiness, regulatory compliance, and organizational support mechanisms to enhance AI adoption success and long-term digital transformation performance. Please see Figure 3 and Figure 4.

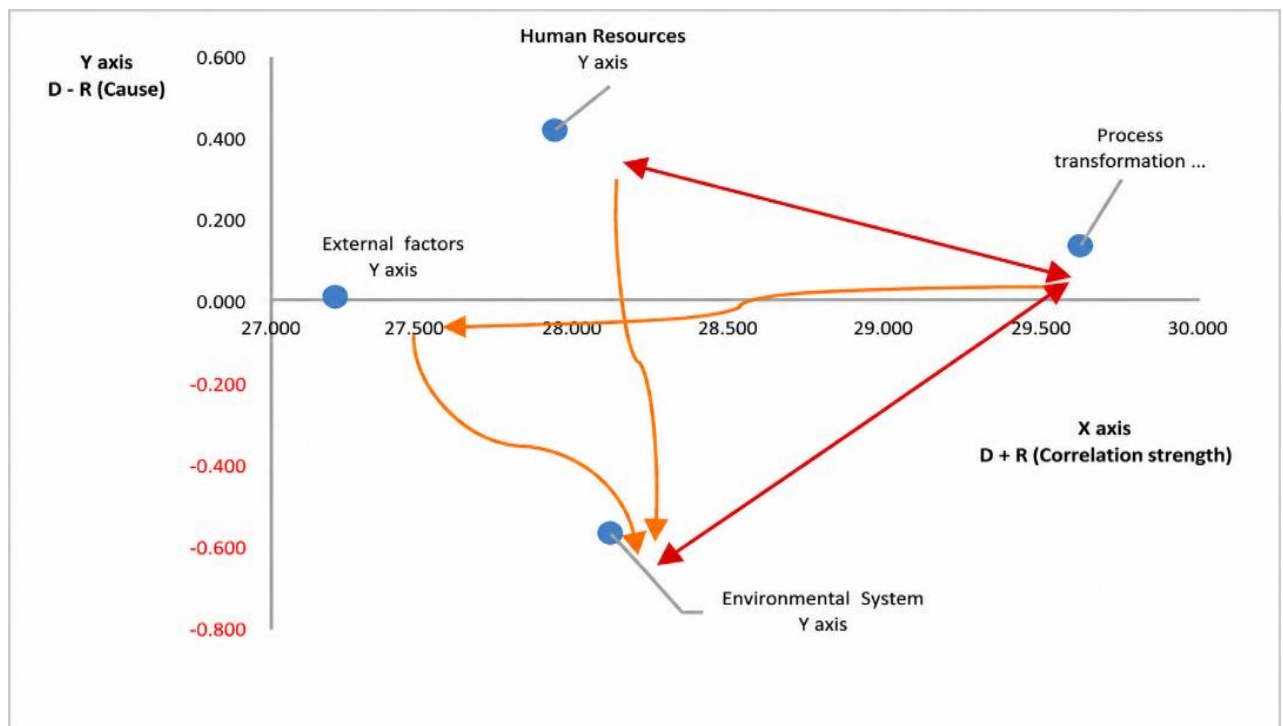


Figure 3: Cause and Effect Diagram

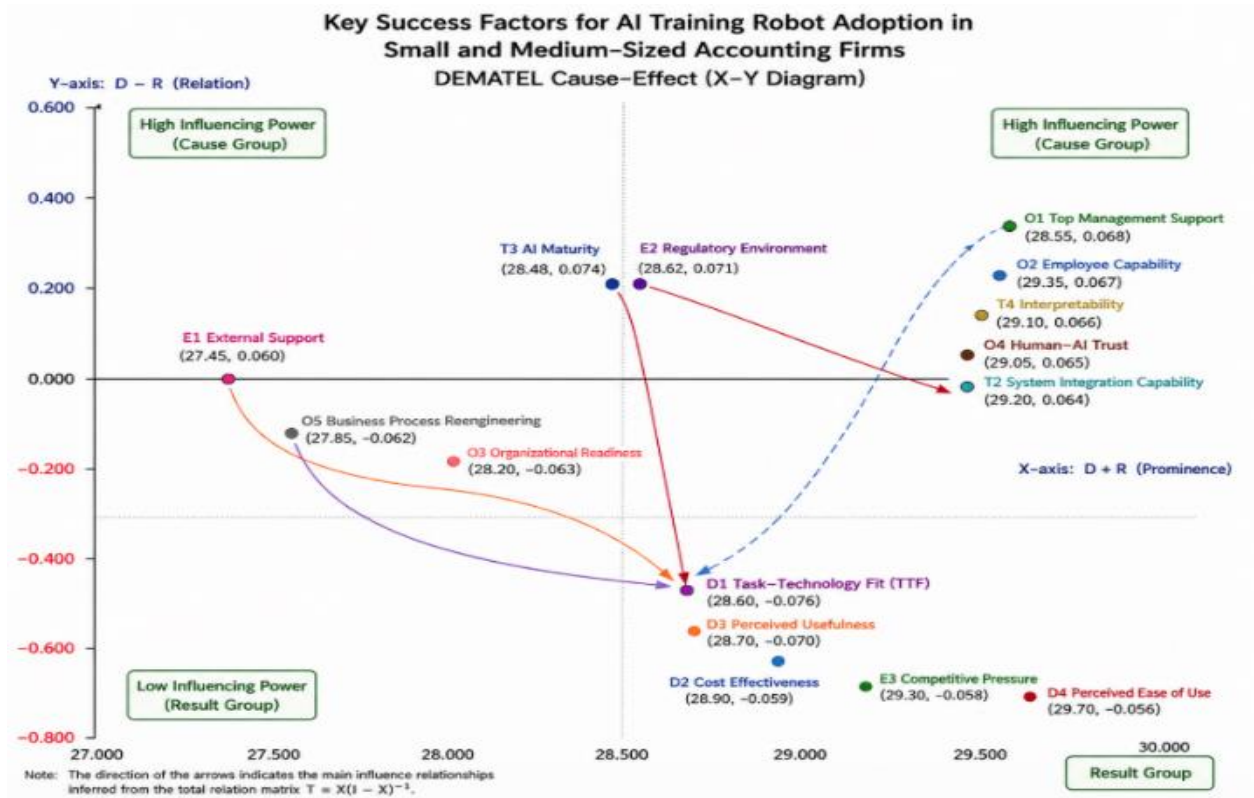


Figure 4: Cause-Effect Diagram-Criteria

4.5 Analytic Network Process (ANP) Results

Following the identification of causal relationships among the critical success factors through DEMATEL, the Analytic Network Process (ANP) was employed to further evaluate their relative importance and priority rankings. Unlike traditional hierarchical approaches, ANP considers the interdependencies and feedback relationships among criteria, thereby providing a more comprehensive representation of complex decision-making environments.

Based on the pairwise comparison judgments provided by the 15 experts, the geometric mean method was applied to aggregate individual evaluations into a group judgment matrix. Subsequently, the aggregated matrices were processed using Super Decisions software to calculate eigenvectors, eigenvalues, and consistency ratios. All pairwise comparison matrices satisfied the consistency requirement ($CR < 0.10$), indicating that the expert judgments were sufficiently reliable and logically consistent.

The resulting weights were first represented in the Unweighted Supermatrix, which captures the interdependent relationships among dimensions and criteria. The unweighted supermatrix reflects the local priority vectors derived from pairwise comparisons and illustrates how each criterion influences and is influenced by other criteria within the network structure.

Table 14: Unweighted Supermatrix

Criteria	T1	T2	T3	T4	O1	O2	O3	O4	O5	E1	E2	E3	D1	D2	D3
T1	0.000	0.281	0.315	0.294	0.276	0.302	0.287	0.291	0.298	0.266	0.281	0.305	0.294	0.301	0.287
T2	0.337	0.000	0.341	0.318	0.315	0.327	0.334	0.306	0.322	0.314	0.326	0.317	0.333	0.319	0.324
T3	0.356	0.389	0.000	0.371	0.347	0.351	0.366	0.382	0.361	0.358	0.344	0.369	0.352	0.366	0.371
T4	0.307	0.330	0.344	0.000	0.362	0.347	0.351	0.321	0.336	0.347	0.349	0.341	0.321	0.337	0.318
O1	0.284	0.301	0.317	0.296	0.000	0.338	0.321	0.347	0.315	0.326	0.341	0.318	0.352	0.347	0.331
O2	0.326	0.314	0.328	0.347	0.351	0.000	0.337	0.361	0.342	0.334	0.322	0.347	0.331	0.326	0.352
O3	0.390	0.385	0.355	0.357	0.349	0.372	0.000	0.292	0.343	0.340	0.337	0.335	0.317	0.327	0.317
O4	0.298	0.301	0.355	0.344	0.300	0.318	0.341	0.000	0.351	0.329	0.341	0.352	0.344	0.358	0.347
O5	0.312	0.333	0.351	0.326	0.351	0.310	0.339	0.347	0.000	0.351	0.337	0.329	0.344	0.331	0.338
E1	0.318	0.326	0.337	0.344	0.317	0.331	0.336	0.329	0.344	0.000	0.341	0.327	0.314	0.337	0.326
E2	0.347	0.341	0.322	0.337	0.352	0.318	0.327	0.344	0.336	0.351	0.000	0.344	0.347	0.341	0.351
E3	0.335	0.333	0.341	0.319	0.331	0.351	0.337	0.327	0.320	0.349	0.359	0.000	0.339	0.322	0.323
D1	0.362	0.351	0.344	0.337	0.347	0.341	0.335	0.344	0.352	0.326	0.341	0.334	0.000	0.381	0.359
D2	0.318	0.326	0.337	0.341	0.326	0.337	0.347	0.331	0.337	0.347	0.326	0.344	0.331	0.000	0.352
D3	0.320	0.337	0.351	0.344	0.347	0.352	0.318	0.337	0.326	0.341	0.333	0.337	0.352	0.341	0.000

Table 14 presents the unweighted supermatrix, showing the mutual dependency relationships among the dimensions and criteria. These results provide the foundation for constructing the weighted supermatrix and the subsequent limit supermatrix used to derive the final priority weights. The unweighted supermatrix demonstrates that the identified critical success factors are not independent; rather, they exhibit varying degrees of interaction and feedback effects. Such interrelationships confirm the suitability of applying the ANP method in this study, as the adoption of AI training robots in small and medium-sized accounting firms involves a complex network of technological, organizational, environmental, and task-related considerations. The subsequent sections present the weighted supermatrix and limit supermatrix results, followed by the final priority rankings of the critical success factors influencing AI training robot adoption. Based on the Unweighted Super matrix, the Weighted Super matrix was subsequently derived through normalization (Table 15).

Table 15: Limit Supermatrix

Criteria	T1	T2	T3	T4	O1	O2	O3	O4	O5	E1	E2	E3	D1	D2	D3
T1	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061
T2	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064	0.064
T3	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074	0.074
T4	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066
O1	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068	0.068
O2	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067	0.067
O3	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063	0.063
O4	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065
O5	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062
E1	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060
E2	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071	0.071
E3	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058	0.058
D1	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
D2	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059	0.059
D3	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070	0.070

Through the Limiting Process, the matrix gradually converges after repeated calculations, ultimately forming the Limit Super matrix. The primary purpose is to reflect the long-term stable weights of each dimension and criterion within the overall network structure, and to analyze the final importance ranking of the key success factors accordingly (Table 16).

Table 16: Final Weights and Priority Ranking of Critical Success Factors

Ranking	Criteria	Limit Weight
1	D1 Task–Technology Fit	0.076
2	T3 AI Technology Maturity	0.074
3	E2 Regulatory Environment	0.071
4	D3 Perceived Usefulness	0.070
5	O1 Top Management Support	0.068
6	O2 Employee AI Skills and Competence	0.067
7	T4 Explainability	0.066
8	O4 Cross-Department Integration	0.065
9	T2 System Integration Capability	0.064
10	O3 Organizational Readiness	0.063
11	T1 Data Capability	0.061
12	O5 Business Process Reengineering	0.062
13	E1 External Support	0.060
14	D2 Cost Effectiveness	0.059
15	E3 Market Competitive Pressure	0.058

4.6 Priority Ranking of Critical Success Factors

The ANP results reveal that Task–Technology Fit (TTF) is the highest-ranked critical success factor influencing AI training robot adoption in small and medium-sized accounting firms. This finding indicates that successful implementation depends primarily on how effectively AI functionalities align with accounting tasks and professional workflows. Even with adequate technological resources and managerial support, AI may generate limited value if it does not adequately address practical task requirements.

AI Technology Maturity and Regulatory Environment rank second and third, respectively, highlighting the importance of reliable and stable AI technologies and supportive regulatory conditions. Given the highly regulated nature of accounting services, legal certainty and compliance requirements are particularly important for reducing implementation risks and strengthening organizational confidence in AI applications (Onyenahazi, 2025).

Perceived Usefulness, Top Management Support, and Employee AI Competence also receive relatively high priorities. These results demonstrate that AI adoption requires not only technological readiness but also managerial commitment, employee capabilities, and recognition of AI's potential to improve productivity and work quality. Management support facilitates strategic direction and resource allocation, while employee competence supports effective system utilization (Ahn & Chen, 2022).

By contrast, Perceived Ease of Use, Competitive Pressure, and Cost–Benefit Consideration receive relatively lower priorities, suggesting that operational convenience, external pressure, and economic considerations play more secondary roles (Dash et al., 2023).

Overall, the findings demonstrate that effective AI adoption requires an integrated combination of task–technology alignment, technological maturity, regulatory readiness, organizational support, and employee capability, with TTF emerging as the highest-priority consideration for implementation effectiveness (Shuhidan et al., 2023).

5. Conclusion

The rapid development of artificial intelligence (AI) has accelerated digital transformation across professional service industries. However, research on the adoption of AI intelligent training robots in small and medium-sized accounting firms remains limited, as previous studies have focused predominantly on large enterprises or general industrial settings. To address this gap, this study extends the traditional Technology–Organization–Environment (TOE) framework by incorporating a Decision-Making dimension, thereby developing the Technology–Organization–Environment–Decision-Making (TOED) framework. The Delphi Method, DEMATEL, and Analytic Network Process (ANP) were integrated to identify and evaluate the critical success factors influencing AI intelligent training robot adoption.

The DEMATEL results reveal that the Technological dimension is the primary driving force, exhibiting the strongest positive causal effect ($D-R = 1.355$). This finding indicates that technological readiness, system integration, AI maturity, and explainability provide the foundation for successful AI implementation. The Organizational dimension also demonstrates a positive causal influence ($D-R = 0.435$), emphasizing the importance of managerial support and employee preparedness. In contrast, the Decision-Making dimension exhibits the strongest receiving effect ($D-R = -1.781$), suggesting that managerial evaluations are largely shaped by technological, organizational, and environmental conditions.

The ANP results reveal that Task–Technology Fit (D1) holds the highest priority (0.076), followed by AI Technology Maturity (T3) (0.074) and Regulatory Environment (E2) (0.071). These findings emphasize the importance of aligning AI capabilities with accounting tasks, ensuring technological maturity, and complying with regulatory requirements. Perceived Usefulness (D3) ranks fourth (0.070), followed by Top Management Support (O1) (0.068) and Employee AI Skills and Competence (O2) (0.067), highlighting the critical roles of perceived benefits, managerial commitment, and workforce capabilities in facilitating AI adoption. Furthermore, Explainability (T4) (0.066), Cross-Department Integration (O4) (0.065), and System Integration Capability (T2) (0.064) underscore the importance of transparency, organizational coordination, and technical compatibility in the highly regulated accounting profession.

Notably, the relatively close priority weights suggest that successful AI adoption depends on multiple interconnected technological, organizational, environmental, and decision-related factors rather than a single dominant criterion. Although Task–Technology Fit and Perceived Usefulness receive high priority rankings, their roles

as causal or outcome factors must be interpreted based on the DEMATEL results rather than ANP weights alone. Overall, the findings indicate that accounting SMEs should prioritize task alignment, technological maturity, regulatory compliance, managerial support, and employee competence when implementing AI training robots. The proposed TOED framework, together with the integrated Delphi–DEMATEL–ANP approach, provides a comprehensive theoretical foundation and practical decision-making guidance for prioritizing critical success factors and supporting AI-enabled digital transformation in accounting firms.

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