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Extending the Technology Acceptance Model (TAM) for Artificial Intelligence (AI) Adoption: A Conceptual Framework

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ABSTRACT

Artificial Intelligence (AI) can greatly improve efficiency and decision-making, but adopting it often comes with challenges. Traditional models like the Technology Acceptance Model (TAM) explain technology use but don't fully address AI-specific issues such as trust, data quality, and organizational readiness. This paper presents an extended TAM framework for AI adoption in Malaysian warehouses, adding five key factors to the original model: trust in AI, organizational readiness, leadership support, regulatory and ethical compliance, and data infrastructure quality. These factors, along with perceived usefulness and ease of use, influence both the intention to use AI and its actual application. While focused on warehouses, the framework can also apply to sectors like healthcare, education, and manufacturing. Developed from recent literature, the model is ready for future testing through surveys and interviews, offering a practical guide for both researchers and industry leaders planning AI adoption.

1. Introduction

1.1 Research Background

In recent years, the integration of Artificial Intelligence (AI) technologies into industrial operations has seen substantial growth, driven by the need for automation, efficiency, and data-driven decision-making. Warehousing, as a core function within the logistics and supply chain sector, stands at the frontier of this technological transformation [19]. However, despite AI's promising potential, its adoption within Malaysian warehouses remains slow and fragmented [26]. Among the myriad reasons are institutional, technological, and organizational barriers that hinder effective implementation. Understanding these barriers, and more importantly, the readiness and behavioural intent of warehouse stakeholders to adopt AI, is crucial for fostering a successful digital transition.

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Beyond the warehouse sector, the challenges of AI adoption and the factors addressed in this framework are highly relevant to other industries. Many of the barriers—such as trust, readiness, data quality, and governance—are universal, even if the operational context differs.

In healthcare, AI is being applied to medical imaging, predictive analytics, patient monitoring, and even personalised treatment recommendations. While these tools can significantly improve diagnostic accuracy and efficiency, adoption often depends on trust in AI's reliability, the quality of medical data, and strict compliance with patient privacy regulations [5]. A lack of transparency in AI decision-making can also create resistance among medical professionals. Here, the extended TAM framework can help by linking these trust and governance concerns directly to behavioural intention, giving hospitals and health systems a clearer roadmap for integrating AI responsibly.

In education, AI is used for personalised learning, automated grading, and administrative automation. However, effective adoption requires teacher readiness, leadership support, and clear ethical guidelines for using student data. Without these enablers, even well-designed AI tools may go unused or face resistance from educators and parents. The extended TAM framework's inclusion of organisational readiness, leadership support, and ethical compliance makes it well-suited for addressing these adoption gaps, ensuring that AI tools enhance learning rather than disrupt it.

In manufacturing, AI powers predictive maintenance, process optimisation, and supply chain forecasting. While the potential benefits are significant, many manufacturers still struggle with poor data infrastructure, limited interoperability between systems, and a shortage of skilled workers to operate AI-driven solutions [18]. The extended TAM framework's focus on data infrastructure quality and talent readiness directly addresses these barriers, providing a practical structure for manufacturers to assess and improve their AI adoption capacity.

By presenting a balanced view of individual perceptions (e.g., perceived usefulness, ease of use, trust) and organisational enablers (e.g., readiness, leadership, governance, data quality), the extended TAM framework offers a versatile model for guiding AI adoption strategies. Whether in healthcare, education, manufacturing, or warehousing, this framework helps stakeholders move beyond seeing AI as a "tech upgrade" and towards viewing it as a carefully managed organisational change process.

1.2 Literature-Supported Problem Statement

The Technology Acceptance Model (TAM), introduced by Davis [6], has been extensively used to study technology adoption by focusing on two main constructs: perceived ease of use and perceived usefulness. While the TAM model remains robust in many contexts, AI adoption—especially within industrial sectors like warehousing—demands an enriched perspective that includes technical, organizational, and external environmental factors. Recent studies [10,21,32,] argued that AI presents complexities beyond those captured by traditional TAM dimensions. Therefore, extending TAM to include additional variables relevant to AI is both timely and necessary.

1.3 Research Gap and Novelty

Most prior TAM studies have focused on consumer-oriented or general enterprise IT systems, leaving a notable gap in industrial AI contexts, particularly within developing countries like Malaysia. Furthermore, few studies have developed conceptual frameworks that address warehouse-specific challenges such as talent scarcity, data governance, and operationalization barriers. This study proposes an extended TAM framework that incorporates a broader set of influencing factors—technological, organizational, and environmental—to better capture the realities of AI adoption in

Malaysian warehouses. The novelty lies in both the sector-specific focus and the enriched set of constructs.

1.4 Research Objectives

The objective of this study is to develop a conceptual framework that extends TAM to incorporate AI-specific adoption factors relevant to Malaysian warehouses, integrating organizational readiness, top management support, regulatory compliance, data quality, and trust in AI alongside core TAM constructs.

1.5 Significance of the Study

The findings of this study have implications for both academia and practice. Academically, it contributes to the evolving body of knowledge on TAM and AI by proposing a sector-specific, contextually-relevant model. Practically, it offers insights to policymakers, warehouse operators, and AI solution providers on the key determinants of AI readiness and adoption, enabling more targeted strategies for digital transformation.

2. Literature Review

2.1 The Technology Acceptance Model (TAM): Origins and Evolution

The Technology Acceptance Model (TAM) was originally introduced by Davis [6] to explain user behavior toward technology through two primary constructs: perceived usefulness (PU) and perceived ease of use (PEOU). Over time, this model has been refined and extended, including TAM2 [33] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [34]. These iterations sought to accommodate additional social, cognitive, and contextual factors.

2.2 Why TAM Remains Relevant

TAM continues to be widely adopted because of its simplicity, empirical robustness, and adaptability across domains [8,9,15]. In the AI context, constructs like PEOU and PU still serve as foundational determinants of user behavior. However, scholars have argued that AI technologies—being more complex, dynamic, and data-intensive—demand expanded models that account for organizational and environmental influences [20,22,30].

In the context of Artificial Intelligence (AI), however, technology complexity, autonomy, and reliance on dynamic data ecosystems introduce new layers of uncertainty and user concern that are not fully captured by the original TAM. AI systems often involve opaque decision-making (black-box algorithms), personalization, and self-learning capabilities, which require users not only to find the system useful and easy to use but also trustworthy, ethical, and aligned with organizational goals [27,30].

As such, while TAM offers a strong starting point, researchers have increasingly called for its extension or integration with other models to capture the multifaceted nature of AI adoption. For example, Maroufkhani et al. [20,22] argued that in the age of AI and Industry 4.0, organizational and environmental factors play as significant a role as individual perceptions. This has led to frameworks like the Unified Theory of Acceptance and Use of Technology (UTAUT), which adds constructs like social influence and facilitating conditions [34], and the Technology–Organization–Environment (TOE) framework, which emphasizes organizational readiness and external pressure [31].

Nevertheless, TAM's adaptability has enabled researchers to tailor the model to fit evolving technological paradigms. For instance, recent studies on AI adoption in logistics and healthcare have successfully extended TAM by incorporating constructs such as trust in AI, algorithm transparency, and ethical perception [2,14]. These extensions validate the core of TAM while recognizing its limitations in addressing AI-specific challenges.

Thus, while models like UTAUT or TOE offer broader lenses, TAM remains highly relevant due to its flexibility, foundational clarity, and ability to integrate new variables. Its continued evolution ensures it can remain applicable even in the face of disruptive technologies like AI, provided it is contextually enriched with constructs that capture the socio-technical nuances of emerging systems.

2.3 Limitations of Traditional TAM in AI Contexts

While TAM provides a valuable starting point, it does not sufficiently address the nuances of AI systems. AI introduces ethical concerns, data quality issues, governance challenges, and a need for advanced talent—factors absent in earlier models [7,11]. Additionally, TAM assumes a rational decision-making process that may not align with the real-world complexities of AI integration, especially in industrial sectors [16].

First, traditional TAM primarily centers on two cognitive beliefs—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—which presuppose rational and conscious decision-making. However, AI systems, especially those leveraging machine learning and autonomous decision-making, introduce ambiguity, unpredictability, and opaqueness (black-box behavior) that complicate user assessments of usefulness or ease of use [27]. Users may find it difficult to judge the performance or reliability of AI tools due to their opaque logic, making trust, perceived risk, and ethical alignment equally—if not more—important than ease of use.

Second, AI integration demands significant organizational transformation, including governance frameworks, talent reskilling, ethical policies, and changes in workflows. These factors are external to the traditional TAM, which does not account for the socio-organizational and environmental contexts of technology deployment [20,22,30]. For example, concerns over algorithmic bias, data quality, accountability, and regulatory compliance are paramount in AI adoption but lie outside the scope of TAM's original constructs.

Third, the assumption that users evaluate technologies based purely on instrumental reasoning underplays the role of emotions, cognitive overload, and cultural dimensions, particularly relevant in the AI context [14]. For instance, employee resistance to AI might stem from fear of job loss or loss of control—factors unrelated to whether the system is deemed "useful" or "easy to use."

Moreover, TAM was initially designed for voluntary adoption scenarios, whereas AI systems are often implemented at an organizational level, where end-users may have limited influence or control over adoption decisions. This raises issues of forced usage and institutional pressure, which are better addressed through frameworks like the Technology–Organization–Environment (TOE) framework or Unified Theory of Acceptance and Use of Technology (UTAUT), both of which include organizational and environmental variables [31,34].

Therefore, the relevance of traditional TAM in AI contexts is limited unless it is extended or integrated with additional constructs such as trust, transparency, ethical alignment, organizational readiness, and external influences. Several scholars have responded to this limitation by proposing extended TAM models that incorporate these dimensions, especially in high-stakes fields like healthcare, logistics, and finance [2,7,11].

In summary, while TAM offers a strong theoretical baseline, its traditional form lacks the depth to fully capture the socio-technical, ethical, and cognitive complexities involved in AI adoption. Future models must evolve beyond perceived usefulness and ease of use to remain relevant in the era of intelligent technologies.

2.4 Comparative Evaluation of Other Adoption Models

Other models like the Diffusion of Innovation Theory [28] and UTAUT offer broader constructs but often lack the focus and parsimony of TAM. Moreover, these models are less frequently applied in industrial contexts and may overemphasize social influence at the expense of technical feasibility. Therefore, a tailored extension of TAM that captures AI-specific and sector-specific elements appears to offer the best of both worlds.

3. The Proposed Conceptual Framework
3.1 Framework Overview

The proposed framework extends TAM by integrating constructs relevant to the AI adoption landscape in Malaysian warehouses. As shown in Figure 1, the model introduces additional dimensions such as the nature of AI, talent barriers, data governance, and geopolitical influences, all of which feed into the perception of usefulness and ease of use.

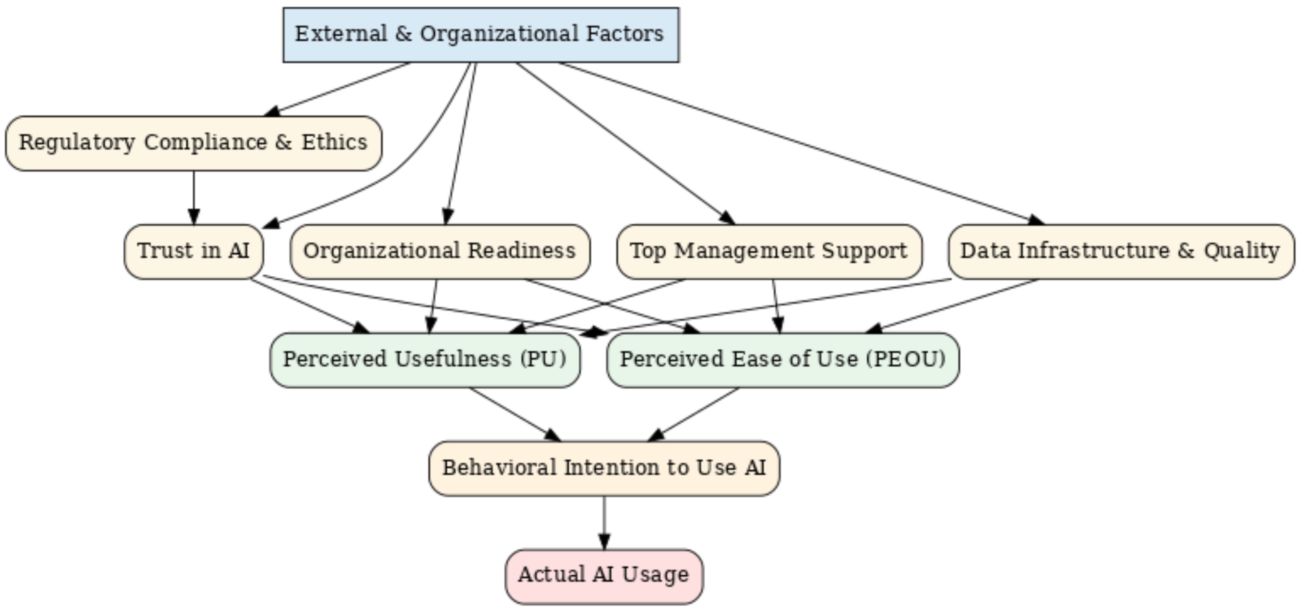

Fig. 1. *Source: Adapted from TAM with AI-specific extensions (Author's own)*

3.2 Key Variables in the Extended TAM Framework
3.2.1 Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)

These remain central to the framework. PU refers to the belief that using AI will enhance job performance, while PEOU reflects the degree to which one believes that using AI is free of effort. In the warehouse context, AI tools such as predictive analytics, smart inventory systems, and robotics can enhance efficiency, reduce errors, and improve safety [18].

3.2.2 Trust in AI

In the context of Artificial Intelligence (AI), especially within industrial environments such as warehousing, trust has emerged as a foundational component for successful adoption. While traditional TAM focuses on cognitive evaluations such as perceived usefulness (PU) and perceived ease of use (PEOU), it falls short of capturing the emotional and relational dimensions that are central to human-AI interaction [14]. The inclusion of trust is therefore not only timely but essential.

Trust in AI can be defined as the belief that the AI system will perform as expected, act in the user's best interest, and function reliably within the operational environment. In warehousing operations—where AI may be used for demand forecasting, inventory optimization, autonomous vehicles, and predictive maintenance—the consequences of system failures can be severe. Hence, users must have high confidence in both the competence and integrity of the AI systems to accept and integrate them into daily workflows [3,4, 27].

AI systems are often perceived as opaque or "black box" technologies. Unlike traditional IT systems, the decision-making process of AI, especially those based on machine learning, may not always be interpretable or explainable to the end user. This lack of transparency can generate scepticism and resistance, particularly among warehouse staff who may not have technical backgrounds. Trust, therefore, acts as a psychological bridge that helps users cope with uncertainty and delegate control to AI-based systems.

Moreover, trust is especially important when AI operates autonomously or makes decisions with direct operational implications, such as route planning for autonomous forklifts or safety compliance monitoring. In such scenarios, users are more likely to accept AI-generated recommendations if they trust the system's competence, reliability, and ethical alignment.

Another critical factor affecting trust in AI is job security. Warehouse personnel may perceive AI as a threat to their employment, which can hinder adoption unless proactive efforts are made to foster trust [20,22]. Organizations must frame AI not as a replacement, but as a collaborator—augmenting human capabilities rather than eliminating them. Training programs, participatory design processes, and clear communication about the role of AI can enhance perceived fairness and trustworthiness [12].

By integrating trust as a variable in an enhanced TAM model, researchers and practitioners acknowledge the emotional and social dimensions of technology adoption, which are particularly relevant in high-risk, operationally critical domains like warehousing. Trust not only facilitates initial acceptance but is also crucial for long-term engagement, continuous use, and the eventual realization of AI’s full potential in industrial settings.

3.2.3 Organizational Readiness

Organizational readiness refers to the degree to which a company's infrastructure, culture, leadership, and human capital are prepared to embrace and effectively implement technological innovations like AI. In the context of warehouse operations, where AI integration often entails major shifts in workflows, decision-making processes, and even organizational structure, readiness becomes a critical determinant of success [36].

While traditional TAM focuses largely on individual perceptions (i.e., PU and PEOU), it does not fully account for organizational-level enablers and barriers that can influence adoption outcomes. Particularly for AI—an inherently complex, dynamic, and resource-intensive technology—the organizational environment plays an equally important, if not greater, role in shaping adoption behavior.

Unlike simpler digital tools, AI demands high interconnectivity between systems, departments, and roles. For example, predictive maintenance solutions require seamless data flows from sensors to analytics engines to frontline technicians. Any weakness—whether technical (poor data quality), human (lack of skills), or managerial (lack of vision)—can lead to project failure [16].

In warehousing, operational efficiency and real-time decision-making are paramount. If staff cannot use AI applications confidently, if systems fail to deliver real-time insights, or if leaders are skeptical about investing further, then the AI system's potential impact is fundamentally compromised. Organizational readiness thus serves as a "gatekeeper variable"—without it, even the most useful and easy-to-use AI technology will likely be rejected or underutilized.

Organizational readiness also indirectly influences Perceived Usefulness and Perceived Ease of Use. Well-prepared organizations provide smoother onboarding experiences, better support structures, and clearer communication about AI's role—all of which enhance users' positive perceptions and reduce technology-related anxiety [7,11].

Thus, by integrating organizational readiness into an extended TAM framework, researchers can provide a more holistic and realistic understanding of AI adoption dynamics, particularly in the highly operational, risk-sensitive environment of warehouse management.

3.2.4 Top Management Support

Top management support is a critical enabler in the successful adoption of any organizational technology, including Artificial Intelligence (AI). In the context of the enhanced Technology Acceptance Model (TAM) for AI adoption in Malaysian warehouses, leadership commitment functions as both a catalyst and a stabilizer throughout the digital transformation process.

Research consistently underscores that top-level leadership plays a central role in innovation success by aligning AI initiatives with strategic goals, ensuring adequate resources, and fostering a culture that embraces change [17]. When leaders visibly support AI integration—whether through public endorsements, budget allocation, or strategic planning—they legitimize the technology within the organization. This legitimization increases employee confidence in the change process and mitigates resistance [8].

Moreover, top management can influence perceived usefulness (PU) and perceived ease of use (PEOU)—the core constructs of TAM—by mandating training programs, setting performance benchmarks, and integrating AI into long-term operational visions. In warehouse settings, where many employees may have concerns about job displacement, strong leadership can reshape the narrative from "replacement" to "augmentation." This reframing helps reduce fear and increases trust, which is another key variable discussed earlier.

Particularly in Malaysia, where organizational hierarchies are often respected and top-down communication is prevalent, leadership plays a disproportionately influential role. Warehouse managers and staff are more likely to adopt AI tools if they see that these tools are championed at the top levels of management.

Therefore, embedding "Top Management Support" as a core external factor in the extended TAM framework is not just theoretical—it's practical and necessary. It bridges the gap between technology introduction and successful implementation by reinforcing commitment across organizational layers.

3.2.5 Regulatory Compliance and Ethical Concerns

In the context of AI adoption, especially within operational domains like warehousing, regulatory compliance and ethical concerns form a foundational pillar that influences user acceptance and organizational readiness. Unlike traditional IT systems, AI technologies often operate with vast datasets and algorithmic decision-making that can be opaque, dynamic, and occasionally unpredictable. As such, their implementation raises critical concerns related to data privacy, labor ethics, and algorithmic fairness—issues that cannot be overlooked if adoption is to be successful and sustainable.

In Malaysia, regulatory frameworks such as the Personal Data Protection Act 2010 (PDPA) mandate clear guidelines on how personal data is collected, processed, stored, and shared. Organizations that fail to adhere to these guidelines risk not only legal penalties but also reputational damage, which in turn can significantly erode user trust [25]. For instance, AI systems used in warehouse logistics may require employee tracking data, biometric inputs, or productivity analytics—all of which must comply with local privacy laws to avoid ethical violations.

Moreover, AI introduces ethical complexities such as potential job displacement due to automation, and biases embedded in machine learning algorithms that may unfairly penalize certain workers or decision scenarios. These concerns can influence Perceived Usefulness (PU) and Trust in AI, two critical constructs in the extended TAM model. If warehouse personnel perceive AI as threatening their livelihood or functioning unfairly, even the most technically advanced systems may be met with resistance.

To address this, companies must ensure ethical AI governance, which includes transparent algorithms, human oversight, regular audits for bias, and inclusive stakeholder communication. This not only facilitates smoother AI adoption but also enhances the legitimacy and social acceptance of technological interventions.

Therefore, regulatory compliance and ethical sensitivity are not peripheral concerns—they are central to AI acceptance, particularly in sectors like warehousing where human-machine interaction is operationally intensive. Including this dimension in your extended TAM model acknowledges the socio-legal realities of AI deployment and strengthens the framework's applicability in real-world settings.

3.2.6 Data Infrastructure and Quality

Data is the lifeblood of artificial intelligence. The efficacy of AI systems in warehouse environments—be it for inventory prediction, demand forecasting, or route optimization—relies heavily on the availability, quality, and integration of data across systems. However, one of the most common roadblocks in Malaysian warehouses is the prevalence of legacy systems, data silos, and unstandardized formats, all of which compromise the effectiveness of AI deployment [7].

For AI algorithms to produce accurate and actionable insights, they require structured, clean, and timely data inputs. Poor data quality—such as missing values, inconsistent records, or outdated inventory logs—not only reduces AI performance but also erodes user trust in system outputs. Furthermore, fragmented databases or incompatible systems limit real-time data sharing, which is essential for dynamic decision-making in high-volume warehouse environments.

In the context of the extended TAM model, this variable significantly impacts Perceived Usefulness (PU) and Ease of Use (PEOU). Users are more likely to accept and adopt AI systems when the output is consistent, the interface is intuitive, and the system responds with precision—all of which are direct consequences of underlying data quality. If the AI produces incorrect recommendations or operational bottlenecks due to poor data, users will quickly lose confidence in its utility.

Additionally, data governance and interoperability play a crucial role in enabling AI integration across warehouse operations. Warehouses must invest in upgrading their digital infrastructure by implementing cloud-based platforms, real-time data pipelines, and automated data cleansing mechanisms. Training staff in data handling and analytics can further reinforce this foundation.

Abdullah et al. [7] highlighted that in Malaysian logistics and warehousing sectors, data infrastructure is often overlooked in digital transformation initiatives. This oversight not only delays AI adoption but also reduces its strategic impact. Therefore, data readiness must be treated as a precondition—not an afterthought—when designing AI implementation roadmaps.

In summary, by embedding data infrastructure and quality into the extended TAM framework, we acknowledge that user acceptance is not solely a psychological or attitudinal matter—it is deeply intertwined with technical feasibility. Addressing this variable ensures that AI systems are not only adopted but are also operationally effective in the long term.

3.3 Theoretical Justification

By combining TAM's internal user-focused constructs with external organizational and environmental variables, the framework aligns with recent calls in literature for more context-sensitive models of AI adoption [7,11,16]. It balances simplicity and comprehensiveness, providing a practical yet theoretically grounded tool for future empirical validation.

3.4 Implications and Future Work

The decision to extend the original Technology Acceptance Model (TAM) by integrating both internal user-focused constructs and external organizational and environmental factors is not arbitrary; it responds directly to evolving scholarly critiques and practical realities of AI adoption. While TAM's core constructs Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) remain highly predictive of technology acceptance across various settings [33], researchers have increasingly emphasized that emerging technologies like AI require more context-sensitive frameworks [7,11, 16]. This study adopts a conceptual design approach, developing an extended Technology Acceptance Model (TAM) framework for AI adoption in Malaysian warehouses based on an extensive review of recent literature. The framework integrates both internal user-focused constructs (e.g., perceived usefulness, perceived ease of use) and external organizational and environmental variables. While the present paper does not include empirical data, the framework is intentionally structured to support future validation through mixed-method research:

Quantitative Surveys

A structured questionnaire could be developed to measure relationships between the proposed constructs. Items would be adapted from validated TAM and AI adoption literature, using a Likert-scale format. Data could be collected from warehouse managers, operations supervisors, IT staff, and other stakeholders across diverse warehouse types in Malaysia. A sample size of at least 200 responses is recommended for robust statistical analysis using Structural Equation Modelling (SEM).

Qualitative Interviews

Semi-structured interviews could be conducted with AI solution providers, industry policymakers, and operational managers to gather in-depth insights. Thematic analysis would be used to refine construct definitions, explore sector-specific adoption challenges, and capture contextual nuances not easily measured in surveys.

A mixed-method approach would allow triangulation of findings, improving both reliability and validity. Quantitative results could confirm the hypothesised relationships within the extended TAM framework, while qualitative insights would provide explanatory depth. This dual strategy would enhance the academic rigor of the model and strengthen its practical applicability across industries.

AI technologies differ substantially from traditional IT systems: they are autonomous, probabilistic rather than deterministic, and require ongoing learning from vast datasets. As a result, user acceptance is influenced not only by perceptions of ease and usefulness but also by trust in the system, organizational readiness, ethical considerations, and top management support—elements largely external to the user's direct experience but crucial for successful implementation [20,22,25].

By incorporating these broader variables, the enhanced model achieves an important theoretical balance between parsimony and completeness. As noted by Benbasat and Barki, one of the enduring criticisms of TAM is that while it offers simplicity, it often overlooks contextual richness, thereby limiting its explanatory power for complex technological innovations. Extending TAM in this way directly addresses these limitations without sacrificing its core strength: empirical robustness and ease of application.

Furthermore, this framework echoes calls from models like the Unified Theory of Acceptance and Use of Technology (UTAUT) [34], which advocate for including organizational and social influences. However, instead of fully replacing TAM, the proposed extension selectively integrates only the most critical external factors relevant to AI in Malaysian warehouse contexts. This approach avoids the excessive complexity sometimes associated with larger models, maintaining practicality for empirical testing.

Finally, the proposed framework aligns with modern innovation adoption theories, such as the Technology-Organization-Environment (TOE) Framework [31]], which emphasizes that successful adoption depends not just on individual users, but on organizational capacity and environmental pressure. By acknowledging these multi-layered influences, the extended TAM model becomes a more holistic and theoretically grounded tool for guiding future research and managerial strategies in AI deployment, particularly in sectors like logistics and warehousing where operational intricacies are high.

In conclusion, the theoretical justification for enhancing TAM lies in its ability to bridge the gap between user psychology and systemic realities, ensuring that AI acceptance studies are both empirically grounded and contextually relevant.

4. Conclusions

This paper proposes an extended Technology Acceptance Model (TAM) designed specifically to understand and facilitate AI adoption in Malaysian warehouses. By integrating variables such as trust in AI, data readiness, organizational support, and regulatory concerns, the model reflects the multidimensional nature of AI technology and its implementation environment. The proposed framework not only addresses theoretical gaps in TAM literature but also provides practical insights for stakeholders aiming to implement AI in logistics and warehousing. As Malaysia continues its journey toward digital transformation, understanding these factors becomes essential in ensuring sustainable and effective AI integration.

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