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Exploring the Future of Technology Acceptance Models in the Age of Artificial Intelligence

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Abstract
This systematic review examines how traditional Technology Acceptance Models (TAMs) can be adapted to better understand user acceptance of AI technologies. The study analyzed 80 peer-reviewed articles published between 2010 and 2025, identified through a comprehensive search of EBSCOhost, Embase, Inspec, Scopus, and Web of Science databases using keywords related to AI acceptance factors and technology acceptance models. Our analysis employed descriptive statistics, thematic analysis, and narrative synthesis to identify key factors influencing AI acceptance, including perceived usefulness, perceived ease of use, trust, transparency, explainability, and ethical considerations. We found that trust in AI systems' reliability, fairness, and privacy protection plays a crucial role in user acceptance, with low trust leading to resistance. Transparency and explainability of AI decision-making processes were identified as critical for building user trust. The review also highlights limitations of current research, including inconsistent definitions of AI technologies, inadequate exploration of cultural and contextual differences in AI acceptance, and the predominance of cross-sectional research designs. By addressing these areas, future research can provide a more comprehensive theoretical foundation for understanding user acceptance of AI technologies, guiding the development and ethical application of AI systems.

Keywords: Artificial Intelligence (AI), Trust and Explainability in AI, Technology Acceptance Models (TAM).

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استكشاف مستقبل نماذج قبول التكنولوجيا في عصر الذكاء الاصطناعي

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الملخص

يقوم هذا الاستعراض المنهجي بدراسة كيفية تكييف نماذج قبول التكنولوجيا التقليدية (TAMs) لفهم قبول المستخدمين لتقنيات الذكاء الاصطناعي بشكل أفضل. حللت الدراسة 80 مقالة تمت مراجعتها من قبل الزملاء ونُشرت بين عامي 2010 و2025، تم تحديدها من خلال بحث شامل في قواعد بيانات EBSCOhost وEmbase وInspec وScopus وWeb of Science باستخدام كلمات رئيسية متعلقة بعوامل قبول الذكاء الاصطناعي ونماذج قبول التكنولوجيا. استخدم تحليلنا الإحصاء الوصفي والتحليل الموضوعي والتجميع السردي لتحديد العوامل الرئيسية المؤثرة في قبول الذكاء الاصطناعي، بما في ذلك الفائدة المتصورة، وسهولة الاستخدام المتصورة، والثقة، والشفافية، والقابلية للتفسير، والاعتبارات الأخلاقية. وجدنا أن الثقة في موثوقية أنظمة الذكاء الاصطناعي وعدالتها وحماية خصوصيتها تلعب دورًا حاسمًا في قبول المستخدم، حيث يؤدي انخفاض الثقة إلى المقاومة. تم تحديد شفافية وقابلية تفسير عمليات صنع القرار في الذكاء الاصطناعي على أنهما أمران بالغا الأهمية لبناء ثقة المستخدم.

يسلط الاستعراض الضوء أيضًا على قيود البحث الحالي، بما في ذلك التعاريف غير المتسقة لتقنيات الذكاء الاصطناعي، والاستكشاف غير الكافي للاختلافات الثقافية والسياقية في قبول الذكاء الاصطناعي، وهيمنة التصاميم البحثية المقطعية. من خلال معالجة هذه المجالات، يمكن للبحوث المستقبلية أن توفر أساسًا نظريًا أكثر شمولاً لفهم قبول المستخدمين لتقنيات الذكاء الاصطناعي، وتوجيه تطوير وتطبيق أنظمة الذكاء الاصطناعي بشكل أخلاقي.

الكلمات المفتاحية: الذكاء الاصطناعي، نماذج قبول التكنولوجيا، الثقة وقابلية التفسير في الذكاء الاصطناعي.

1. Introduction

Technology Acceptance Models (TAMs) have been widely used to explain and predict user acceptance of information technologies

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(Davies, 1989). However, the rapid development of Artificial Intelligence (AI) has significantly altered the application scenarios and characteristics of technologies, posing new challenges to traditional TAMs (Jiang et al., 2024). AI technologies, such as machine learning algorithms and intelligent decision-making systems, often operate in a "black box" manner, making it difficult for users to understand their decision-making processes. Additionally, AI technologies raise ethical concerns like privacy protection and algorithmic bias, which may affect user acceptance (Collins et al., 2021).

In the context of AI, the application of TAMs becomes particularly complex due to the inherent characteristics of AI systems. For instance, machine learning algorithms involve complex processes that can be challenging for users to comprehend. These algorithms, including supervised learning algorithms like linear regression and logistic regression, as well as unsupervised learning algorithms like K-means clustering and principal component analysis, are designed to identify patterns and make predictions from data (Brachten et al., 2021; Venkatesh et al., 2003; Lee et al., 2004; Rahal et al., 2024; Zhang et al., 2021). However, their complexity can lead to a lack of transparency, making it difficult for users to trust and accept these systems.

Moreover, the integration of AI into various sectors such as healthcare, finance, and customer service introduces new dimensions to the technology acceptance landscape. In healthcare, AI diagnostic systems can enhance treatment outcomes, but their acceptance depends on factors like perceived usefulness and trust in the technology's reliability (Verma & Singh, 2022). Similarly, in finance, AI-based investment advisory services must overcome user concerns regarding privacy and security to gain acceptance (Khalifa & Rahal, 2024).

This paper makes several important contributions to the field:

- It provides a comprehensive review of the current state of research on TAMs in the AI era.
- It examines how traditional TAMs can be adapted to address the challenges posed by AI technologies.
- It explores the factors that influence AI acceptance and discusses the limitations of current research.
- It offers a detailed analysis of these aspects to contribute to the ongoing discourse on technology acceptance in the age of AI.

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- It provides valuable insights for future research and practice in this field.

2. Literature Review

2.1. Overview of Technology Acceptance Models

The Technology Acceptance Model (TAM), introduced by Davis in 1989, posits that a user's decision to adopt a technology is primarily driven by two factors: perceived usefulness and perceived ease of use. While TAM has been widely applied, its simplicity may not fully capture the complexity of AI technologies.

Venkatesh et al (Venkatesh et al., 2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) in 2003, which integrates insights from eight existing acceptance theories. UTAUT identifies four key determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions. Despite its comprehensiveness, UTAUT's application to AI contexts has revealed limitations in addressing AI-specific concerns.

Factors Influencing AI Acceptance

Perceived Usefulness and Performance Expectancy: Studies confirm that perceived usefulness remains a significant predictor of AI acceptance (Lee et al., 2004; Rahal et al., 2024; Zhang et al., 2021). For example, in healthcare, patients are more likely to accept AI diagnostic systems if they believe these systems improve treatment outcomes.

Perceived Ease of Use and Effort Expectancy: The complexity of AI interfaces impacts user acceptance. Research indicates that as AI interfaces improve, perceived ease of use increases, enhancing acceptance (Rahal & Khalifa, 2024).

Trust: Trust in AI systems' reliability, fairness, and privacy protection plays a crucial role in AI acceptance. A study by (Zhang et al, 2021) found that low trust can lead to resistance toward AI technologies.

Transparency and Explainability: Transparency in AI decision-making processes is critical for building user trust. Research by (Verma & Singh, 2022) shows that explainable AI systems are more likely to be accepted by users.

Ethical and Social Factors: Algorithmic bias, fairness, and accountability concerns can lead to rejection of AI technologies. A study by (Khalifa & Rahal, 2024) found that AI recruitment systems exhibiting gender bias faced significant resistance.

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2.2. Application of TAMs in AI Research

The Extended Technology Acceptance Model (ETAM) incorporates additional constructs such as trust. Studies have shown that trust mediates the relationship between perceived usefulness, perceived ease of use, and AI acceptance (Jussupow et al., 2021).

The Intelligent Systems Technology Acceptance Model (ISTAM) integrates transparency and accountability into the TAM framework. Research using ISTAM has demonstrated that these factors positively influence trust and acceptance of AI technologies (Rahal & Elloumi, 2024).

2.3. Critique of Existing Models in AI Contexts

While existing models like TAM and UTAUT have provided valuable insights, they have several limitations when applied to AI technologies (Hradecky et al., 2022):

Insufficient Incorporation of AI-Specific Factors: Traditional models do not adequately address factors such as transparency, explainability, and ethical considerations that are critical in AI contexts.

Lack of Dynamic Adaptation: AI technologies evolve rapidly, but existing models are often static and fail to account for the dynamic nature of AI acceptance.

Inadequate Consideration of Contextual Factors: Existing research has not sufficiently explored how cultural backgrounds, organizational cultures, and industry characteristics influence AI acceptance.

Methodological Limitations: Most studies adopt cross-sectional designs, capturing user acceptance at a single point in time. Longitudinal studies are needed to track changes in AI acceptance over time.

2.4. Research Gaps

Need for AI-Specific Model Extensions: Future research should develop TAM extensions that incorporate AI-specific constructs such as transparency, explainability, and ethical considerations (Yu et al., 2021).

Insufficient Attention to Contextual Factors: More research is needed to explore how cultural and contextual differences influence AI acceptance.

Longitudinal and Experimental Studies: There is a need for longitudinal studies to track how AI acceptance changes over time and experimental studies to validate theoretical models.

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Addressing Self-Reported Data Limitations: Future research should employ diverse methods such as naturalistic observation and case studies to gain deeper insights into AI acceptance in real-world settings.

3. Methods

3.1. Search Strategy

To identify relevant studies on Technology Acceptance Models (TAMs) in the context of Artificial Intelligence (AI), a comprehensive search was conducted across multiple academic databases. The following databases were searched: EBSCOhost, Embase, Inspec (Engineering Village), Scopus, and Web of Science. The search keywords included "AI acceptance factors", "AI technology acceptance models", and "AI digital innovations". The search was limited to peer-reviewed journals and conference proceedings published between 2010 and 2025.

3.2. Inclusion and Exclusion Criteria

Studies were included if they:

- Focused on user acceptance of AI technologies.
- Utilized TAMs or extended TAMs to evaluate AI acceptance.
- Provided empirical data on factors influencing AI acceptance.
- Were published in English.

Studies were excluded if they:

- Did not focus on AI technologies.
- Did not address user acceptance.
- Were theoretical or conceptual without empirical validation.
- We're not published in peer-reviewed journals or conference proceedings.

3.3. Study Selection Process

To ensure the study selection process was systematic and transparent, the researchers adhered to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Initially, 515 articles were found. The search was limited to peer-reviewed journals and conference proceedings published between 2010 and 2025. This time frame was chosen to capture the most recent developments in AI technologies and their impact on user acceptance, as AI has evolved rapidly over the past decade.

3.4. Data Extraction and Synthesis

From each included study, the following data were extracted:

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- Study demographics (e.g., sample size, participant characteristics).
- AI technology type and application context.
- TAM constructs used and any additional constructs.
- Key findings related to AI acceptance factors.
- Methodological approaches (e.g., quantitative, qualitative, mixed-methods).

The extracted data were synthesized to identify common themes, gaps, and trends in the literature. This synthesis provided a comprehensive overview of how TAMs have been applied to AI technologies and the factors influencing AI acceptance.

3.5. Analysis Methods

Descriptive statistics were employed to provide a summary of the main characteristics of the studies that were included in the analysis. Thematic analysis was employed to identify recurring themes and patterns in the findings. Additionally, a narrative synthesis was conducted to integrate the results and provide a cohesive overview of the current state of research on TAMs in the AI era (Figure 1).

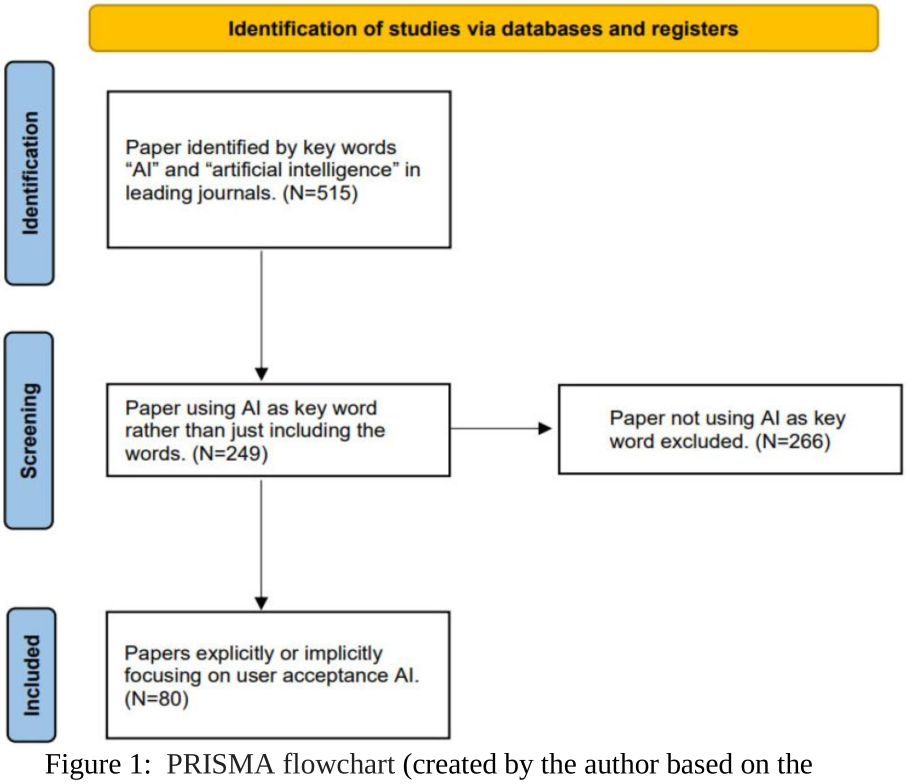

Figure 1: PRISMA flowchart (created by the author based on the PRISMA guidelines

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4. Results

4.1. Factors Influencing AI Acceptance

Based on the reviewed literature, the factors were found to significantly influence AI acceptance are shown in Table 1.

Table 1: Factors that influence AI acceptance

Factor	Description	Significance
Perceived Usefulness	Users' belief that AI technology can enhance their job performance or provide benefits	A key predictor of AI acceptance
Perceived Ease of Use	Users' belief that using AI technology will be effortless	Influences AI acceptance, with improvements in AI interfaces enhancing this perception
Trust	Users' confidence in AI systems' reliability, fairness, and privacy protection	Plays a crucial role in AI acceptance, with low trust leading to resistance
Transparency and Explainability	The degree to which AI decision-making processes are understandable to users	Critical for building user trust and acceptance
Ethical and Social Factors	Concerns such as algorithmic bias, fairness, and accountability	Can lead to rejection if users perceive AI as unethical or socially harmful

4.2. Application of TAMs in AI Research

The following table summarizes the application of different TAMs in AI research are shown in Table 2.

Table 2: Application of different TAMs in AI research

Model	Description	Examples
Extended Technology Acceptance Model (ETAM)	Adds new constructs such as trust to TAM	Some studies have added trust as a mediator between perceived usefulness/ease of use and AI acceptance
Intelligent Systems Technology Acceptance Model (ISTAM)	Integrates transparency and accountability into TAM	Proposes that transparency and accountability positively influence trust and AI acceptance

4.3. Hypotheses Test Results

Table 3 presents the hypotheses test results from a study on the acceptance of AI applications.

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Table 3: Hypotheses test results

Hypotheses	Results
Without the effect of moderators, trust towards the application explains 38% of the variation in acceptance attitude ($R^2 = .38$, $p < .001$) and 31% of the variation in general trusting stance ($R^2 = .31$, $p < .001$)	Trust significantly influences AI acceptance
When additional influencing factors (moderators) were incorporated into the model, the ability to explain the variability in clinicians' acceptance beliefs significantly improved, accounting for 56% of the variation (R^2=.56). This result was highly statistically significant (p<.001), with a substantial effect size (f^2=.439). Similarly, the model's capacity to explain the variation in clinicians' general trusting stance towards AI after adopting it also increased significantly, explaining 36% of this variation (R^2=.36). This finding was also highly statistically significant (p<.001) and represented a moderate to large effect size (f^2=.382).	Moderators such as organizational support, user experience, and age enhance the predictive power of the model

5. Discussions

5.1. Future Directions for TAMs in the AI Era

Future TAMs should include new constructs such as transparency, explainability, and ethical considerations to comprehensively reflect the factors influencing AI acceptance. For example, researchers could develop a new AI TAM by integrating constructs like trust, transparency, and perceived fairness.

More attention should be paid to contextual factors, such as cultural background, organizational culture, and industry characteristics, and their moderating effects on AI acceptance. For instance, studies could explore how cultural differences influence the relative importance of different acceptance factors.

To address the limitations of self-reported data, future research should employ diverse methods, such as experimental studies and longitudinal surveys, to validate theoretical models. Additionally, naturalistic observation and case studies could be used to gain deeper insights into AI acceptance in real-world settings.

As AI technologies continue to evolve, their characteristics and application scenarios will change. TAMs need to adapt to these changes to better predict and explain user acceptance of emerging AI technologies. For example, with the development of generative

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AI, research could focus on user acceptance of AI-generated content.

5.2. Practical Implications

Understanding the factors influencing AI acceptance can help developers design more user-friendly and trustworthy AI products (Aoki, 2020). By enhancing transparency, improving explainability, and addressing ethical concerns, developers can increase user acceptance of AI technologies.

Organizations should consider the factors affecting AI acceptance and develop corresponding strategies to promote AI adoption. For example, they can provide training to employees to enhance their understanding and trust in AI technologies and establish robust ethical guidelines and accountability mechanisms to ensure the ethical use of AI.

6. Conclusion

The rapid advancement of AI technologies has posed new challenges to traditional Technology Acceptance Models. Research on AI acceptance within the TAM framework has made significant progress, but several limitations remain. To enhance the understanding of user acceptance of AI technologies, future research should focus on developing new TAM extensions that include constructs such as transparency, explainability, and ethical considerations. For example, future models could integrate variables like perceived fairness and privacy protection. Additionally, research could investigate the moderating effects of cultural backgrounds, organizational cultures, and industry characteristics on AI acceptance. Moving beyond cross-sectional studies to employ longitudinal research that tracks changes in AI acceptance over time, as well as experimental studies to validate theoretical models and explore causal relationships, would also be beneficial. Combining quantitative surveys with qualitative methods such as interviews and case studies can provide deeper insights into users' perceptions and experiences with AI technologies.

Finally, adapting TAMs to address the unique acceptance challenges posed by emerging AI technologies such as generative AI, autonomous systems, and AI in the Internet of Things (IoT) is crucial.

By implementing these recommendations, future research can provide a more comprehensive theoretical foundation for

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understanding user acceptance of AI technologies, guiding the development and application of AI technologies and promoting their widespread adoption and ethical use in various contexts.

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