Quantitative Economics and Management Studies (QEMS) *ISSN: 2722-6247 (online)*
Vol. 7 No. 1 (2026)
https://doi.org/10.35877/454RI.qems4590

Factors Affecting the Adoption of Artificial Intelligence: A Systematic Literature Review and Policy Perspectives in the Digital Age

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Abstract

The adoption of Artificial Intelligence (AI) has become a global strategic agenda, but its acceptance and implementation levels vary greatly between countries, sectors, and populations. This study presents a systematic literature review (SLR) of 41 empi rical studies to map the factors influencing AI adoption, with a particular focus on cognitive, emotional, socio-ethical, and technological dimensions. Using the PRISMA approach, this study identifies cognitive (AI literacy, perceived usefulness) and emotional (trust, anxiety) factors as key determinants, while socio-ethical considerations (fairness, transparency, accountability) are increasingly crucial in the context of public policy. Recent studies in Indonesia confirm this pattern by demonstrating the strong mediating role of emotions, but also reveal independent cognitive and ethical pathways that operate without emotional mediation—findings that challenge the assumptions of traditional technology acceptance models. From a policy perspective, the results of this SLR indicate the need for a multidimensional approach that focuses not only on technological infrastructure, but also on improving AI literacy, managing public emotional responses, and developing a transparent ethical framework. This article contributes to the literature by providing a comprehensive mapping of state-of-the-art AI adoption research and identifying crucial research gaps, particularly regarding affect-independent pathways mechanisms, cultural context variations, and the longitudinal dynamics of AI adoption.

Keywords: AI Adoption, cognitive factors, emotional factors, ethical considerations, public policy, systematic literature review, technology acceptance

Received: 4 December 2025 Revised: 13 February 2026 Accepted: 28 February 2026

1. Introduction

The digital transformation accelerated by Artificial Intelligence (AI) has fundamentally changed the global social, economic, and political landscape (Dwivedi et al., 2021) . From e-commerce recommendation systems to diagnostic tools in healthcare, AI has surpassed its status as an emerging technology and become an integral component of everyday life (Yin et al., 2021) . However, AI adoption is not occurring uniformly or linearly. Significant disparities are evident across countries, industries, and demographic groups, reflecting the complexity of factors influencing the acceptance of this technology (Verma & Kapoor, 2024) . In the Indonesian context, a recent empirical study by (Rinki & R, 2025) reveals the psychological dynamics of AI adoption involving 511 diverse participants. The study found that emotional factors play a central mediating role between cognitive-ethical perceptions and adoption behavior. More interestingly, the study also identified a strong direct path from cognitive and socio-ethical factors to willingness to adopt AI, which operates independently of emotional mediation—a finding that challenges the assumptions of classical technology acceptance models such as TAM (Technology Acceptance Model) and Lazarus's theory.

This phenomenon raises crucial questions: What factors consistently influence AI adoption across contexts? How do these factors interact? And most importantly from a policy perspective: How can these empirical findings be translated into effective policy interventions? To answer these questions, this study conducted a systematic literature review (SLR) of 41 empirical studies published between 2019 and 2025, covering various geographical contexts.

(Asia, Europe, America, Middle East) and application domains (health, education, business, government). This SLR aims to (1) comprehensively map the cognitive, emotional, socio-ethical, and technological factors that influence AI adoption, (2) identify consistent patterns and contextual variations in the determinants of AI adoption, (3) analyze the

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position of Indonesian studies (Sudirman et al., 2025) in the global research landscape, (4) Articulate evidence-based public policy implications to accelerate inclusive and responsible AI adoption.

The main contribution of this article lies in the integration of three elements that are rarely combined in the literature:

(1) systematic mapping of AI adoption factors based on a comprehensive SLR, (2) critical analysis of newly identified affect-independent pathways, and (3) translation of empirical findings into actionable public policy recommendations.

2. Literature Review

2.1. Theoretical Framework of Technology Adoption

Technology adoption research has long been dominated by several key theoretical models. The Technology Acceptance Model (TAM) developed by (Davis, 1989) emphasizes the role of perceived usefulness and perceived ease of use as the main determinants of behavioral intention (Choi, 2025) . The Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) expands this model by adding social influence and facilitating conditions (Norzelan et al., 2024; Sadiq et al., 2025) . In the context of AI, these classical models have been adapted and expanded. For example, Gansser and Reich (2021) integrated UTAUT2 with AI-specific factors such as health concerns, convenience comfort, and sustainability. (Stevens & Stetson, 2023) developed the TrAAIT model, which specifically measures trust and acceptance in the context of AI healthcare. Meanwhile, research in South Korea by Kim et al. (2024) applied UTAUT to understand the adoption of generative AI in organizations. However, the application of these models in the context of AI faces conceptual challenges. (Sudirman et al., 2023) notes that the traditional TAM model assumes emotions as a mandatory mediator between cognition and behavior, following the Cognitive-Motivational-Relational Theory of Emotion from (Lazarus, 1991) . This assumption has proven not to fully apply in the context of AI adoption, where cognitive and ethical factors can influence behavioral intention directly without significant emotional mediation.

2.2. Dimensions of AI adoption

2.2.1. Cognitive Factors

Cognitive factors include knowledge, understanding, and rational evaluation of AI. (Kim & Blazquez, 2024) found that cognitive evaluations such as perceived usefulness significantly influence the adoption of generative AI in Korean companies. Similarly, (Tsz et al., 2024) developed an AI Literacy Questionnaire that measures affective, behavioral, cognitive, and ethical dimensions—with the cognitive component covering the ability to distinguish between machine learning, deep learning, and AI, as well as critical appraisal skills related to the risks and benefits of AI. Indonesian research by (Sudirman et al., 2025) operationalized cognitive factors through six items that evaluated participants' understanding of fundamental AI principles. CFA results showed an acceptable model fit (TLI=0.95, GFI=0.97) with factor loadings ranging from 0.68 to 0.73, confirming construct validity. Interestingly, this study found that the 21-30 age group had the highest Cognitive Factor scores (M=21.30, SD=3.32), indicating that digital natives are more cognitively prepared to adopt AI.

2.2.2. Emotional Factors

The emotional dimension of AI adoption includes trust, anxiety, fear, and other affective responses. (Frank et al., 2024) identified that anxiety about AI use operates paradoxically: "scary to use it, scary to refuse it." (Gursoy et al., 2019) developed a measurement scale for emotional factors that includes trust and anxiety toward AI devices, which was then adapted in various contexts, including Indonesian studies. (Sudirman et al., 2025) used a unique approach by measuring emotions along bipolar dimensions: bored vs. relaxed/comfortable, melancholic/pressured vs. content, hopeless vs. optimistic, dissatisfied vs. satisfied, and annoyed vs. pleased. The results of the analysis show that the Emotional Factor has an excellent model fit (CFI=1.00, TLI=0.99, RMSEA=0.06) with factor loadings of 0.78-0.88. More importantly, emotions were found to be a strong mediator ($\beta=0.34$, $p<.001$) between cognitive-ethical factors and willingness to adopt AI, explaining 38.1% of the variance in AI adoption. These findings are consistent with the global literature. (Ho et al., 2023) found that negative perceptions of emotional AI in Japan were mainly related to concerns about losing control. Meanwhile, (Calisto et al., 2023) showed that trust and beliefs act as primary mediators between attitudes and acceptance behavior in the context of gastroenterology AI.

2.2.3. Social and Ethical Factors

The social-ethical dimension includes social influence, organizational norms, and considerations of accountability, fairness, transparency, and privacy. (Jang et al., 2022) developed the Attitudes Toward the Ethics of AI (AT-EAI) scale, which includes nine items measuring students' ethical perceptions of AI. In the Indonesian context, (Sudirman et al., 2025) adapted the AT-EAI and found that three items (SEF2, SEF3, SEF7) had poor factor loadings and should be excluded, leaving six valid items (factor loadings 0.64-0.85). The Social & Ethical Factor construct was found to have a significant direct effect on willingness to adopt AI ($\beta=0.22$, $p<.001$), independent of emotional mediation. This pattern was particularly prominent in the 31-40 and 51+ age groups, which showed high social-ethical scores and adoption willingness. Global findings support the importance of the ethical dimension. (Yu et al., 2025) in a China- South Korea study constructed an ethical perception model based on a trust-risk framework, finding that job displacement, misinformation, ethical transparency, and responsibility attribution play prominent roles in adoption intention. (Alzebda & Matar, 2024) in Palestine confirmed that government regulations can strengthen the effect of privacy/security concerns on citizen intention toward AI adoption.

2.2.4. Technological and Organizational Factors

Technological factors include the characteristics of the AI system itself—performance, reliability, compatibility, learnability—while organizational factors include top management support, organizational innovation capability, and facilitating conditions. (Yuan et al., 2025) applied the Technology-Organization-Environment (TOE) framework to China's financial industry, finding that learnability and error handling influence adoption intention, while organizational innovation capability and learning orientation also have a positive effect. Interestingly, cost- effectiveness and compatibility did not show a significant impact—a finding that indicates that psychological and organizational factors are more crucial than economic considerations alone. (Song et al., 2025) found that top management support significantly increases technology acceptance through perceived variables, and AI adoption has been shown to improve organizational decision efficiency and overall performance. This underscores that AI adoption is not only an individual psychological phenomenon, but also embedded in the organizational context.

2.3. Research Gaps and the Position of Indonesian Studies

Although the literature on AI adoption is growing rapidly, several crucial gaps remain: Geographical and Cultural Gaps

The majority of AI adoption research focuses on Western contexts (Europe, North America), with limited representation from Southeast Asia and developing countries (Guedes, 2024). The study (Sudirman et al., 2025) fills this gap by providing empirical data from Indonesia—a country with a population of over 270 million and the largest digital economy in Southeast Asia. With a sample of 511 demographically diverse participants, this study offers insights into how psychological factors operate in a collectivist cultural context and the world's largest Muslim country.

Theoretical Gap: Affect-Independent Pathways

The traditional technology acceptance model assumes that emotions mediate the relationship between cognition and behavior. However, (Sudirman et al., 2025) found that cognitive factors ($\beta=0.22$, $p<.001$) and social & ethical factors ($\beta=0.22$, $p<.001$) have a strong direct effect on willingness to adopt AI, beyond the mediation of emotional factors. These findings indicate that in the context of increasingly normalized AI, individuals can make adoption decisions based on rational evaluation or normative commitment without engaging in strong emotional experiences. This affect-independent mechanism has not been well documented in the literature and requires further investigation. This may be related to what Sousa et al. (2023) refer to as "cognitive routinization"—where AI encounters become increasingly habitual and less emotionally salient.

Methodological Gap: Longitudinal Design

Nearly all studies in this review use cross-sectional designs, which limit causal inferences and cannot capture the temporal dynamics of AI adoption (Parthasarathy et al., 2024). (Abid et al., 2024) emphasize that changes in job roles due to AI require continuous observation. Longitudinal studies can reveal how initial adoption decisions influence future engagement and re-adoption patterns.

Integration Gap: Psychology and Technology

Existing theoretical frameworks such as TAM and UTAUT often overlook the deep psychological dimensions that influence user behavior (Braganza et al., 2020; Horvath et al., 2023). (Chang et al., 2024) show that technostress resulting from AI adoption can hinder user acceptance, indicating the need to comprehensively understand emotional and psychological responses. (Sudirman et al., 2025) attempt to integrate psychological perspectives with technology through detailed measurements of bipolar emotional states and cognitive competencies.

3. Research Method and Materials

3.1. Research Design

This study uses a systematic literature review (SLR) following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol to ensure transparency, replicability, and comprehensiveness. SLR was chosen as the method because of its ability to synthesize empirical evidence from various studies, identify consistent patterns, and reveal research gaps (Verma & Kapoor, 2024).

3.2. Inclusion and Exclusion Criteria Inclusion Criteria

The inclusion criteria in this study included empirical studies, using quantitative, qualitative, or mixed-methods approaches, that specifically examined factors influencing the adoption of artificial intelligence (AI). The included studies must be published in English between 2019 and 2025 to ensure the relevance and novelty of the findings. In addition, the research must use a clear and proven theoretical framework, such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Theory of Planned Behavior (TPB), or other derivative models. Selected studies must also cover at least one of four main dimensions, namely cognitive, emotional, socio-ethical, or technological dimensions, which are relevant in explaining AI adoption behavior.

Conversely, exclusion criteria were applied to maintain the focus and quality of the review. Conceptual studies not supported by empirical data were excluded from the analysis. Research that only focuses on the performance or technical aspects of AI without discussing acceptance or adoption from the user’s perspective is also not included. In addition, publications in the form of book chapters, conference abstracts without full manuscripts, and dissertations or theses that have not been published in scientific journals are also excluded from the scope of this study.

3.3. Search and Selection Strategy

Databases used: Scopus, Web of Science, IEEE Xplore, and Google Scholar. Search keywords: (“artificial intelligence” OR “AI” OR “machine learning”) AND (“adoption” OR “acceptance” OR “intention to use”) AND (“factors” OR “determinants” OR “predictors”). The selection process followed the PRISMA flow:

a. Identification: 247 articles were identified from the databases
b. Screening: 156 articles remained after duplicates were removed
c. Eligibility assessment: 89 full-text articles were reviewed for eligibility
d. Final inclusion: 41 studies met all criteria and were included in the analysis

3.4. Data extraction and analysis

For each included study, the following data were extracted:

a. Basic information (authors, year, country, context)
b. Research design and analysis methods
c. Theoretical framework used
d. Factors of adoption studied (categorization: cognitive, emotional, social-ethical, technological)
e. Key findings (significance, effect sizes, relationships)
f. Limitations and recommendations for future research

Data extracted into an Excel matrix and analyzed using:

a. Content analysis to identify the frequency of the factors studied
b. Thematic analysis to identify patterns in the findings
c. Cross-case comparison to compare results across geographical contexts and application domains
d. Bibliometric analysis using VOSviewer to map co-occurrence keywords and collaboration networks

3.5. Quality Assessment

The methodological quality of each study was assessed using the following criteria:

a. Sample size adequacy (power analysis)
b. Validity and reliability measures (Cronbach’s α, CFA results)
c. Model fit indices for SEM studies (CFI, TLI, RMSEA, SRMR)
d. Transparency in reporting (data availability, ethical approval)

The 41 studies, 36 (87.8%) had a high quality score, 4 (9.8%) had a moderate score, and 1 (2.4%) had a low score. The prisma flowchart shown on Figure 1.

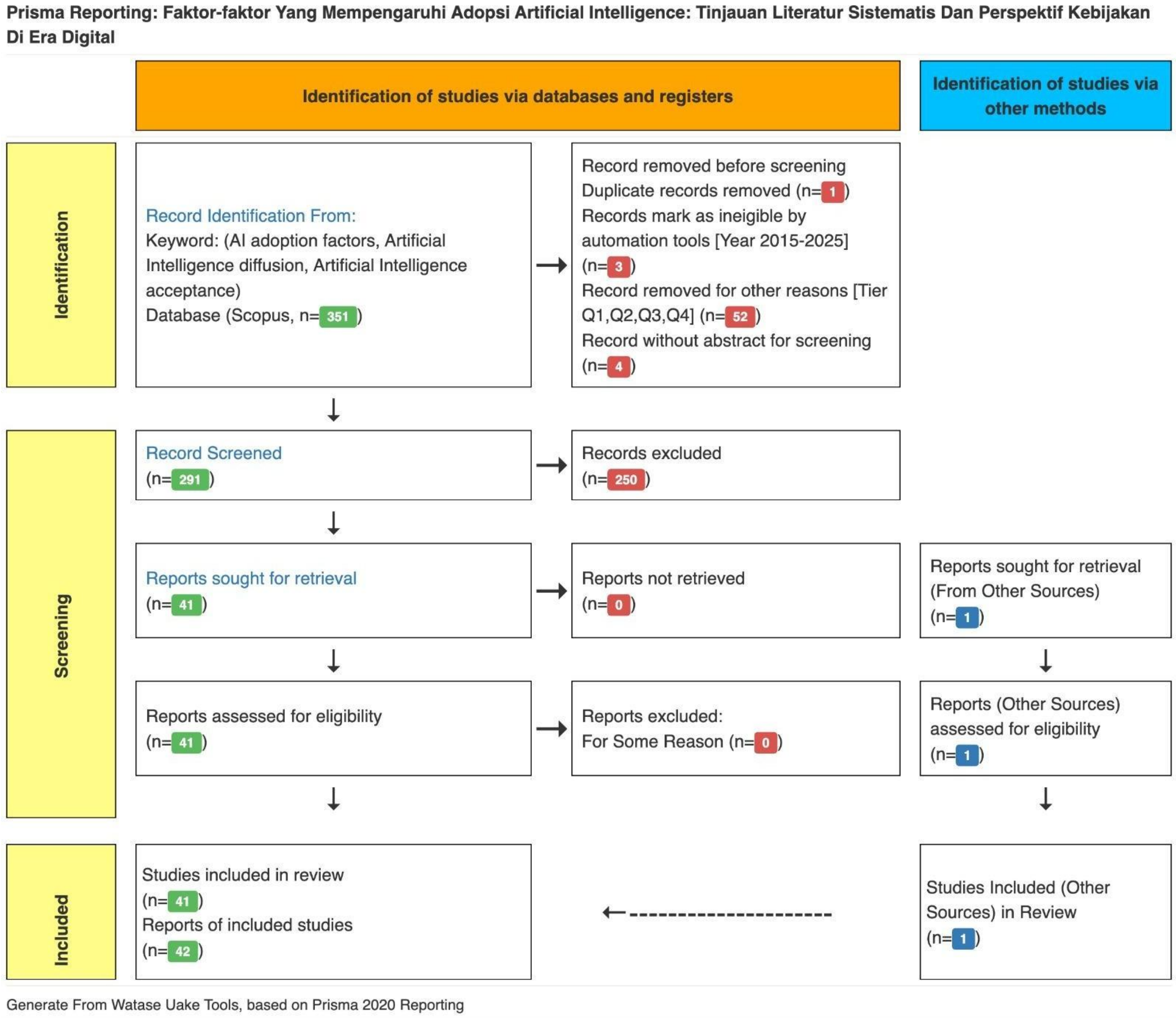

Figure 1. Prisma flowchart

4. Results and Discussions

4.1. Characteristics of Included Studies

The 41 studies analyzed, the geographical distribution shows a concentration in Asia (n=17, 41.5%), followed by Europe (n=12, 29.3%), America (n=8, 19.5%), and the Middle East (n=4, 9.7%). This distribution confirms the trend of AI research globalization, but also highlights the under-representation of Africa and Latin America.

Application Context:

a. Organizations/businesses: 14 studies (34.1%)
b. Health: 9 studies (22.0%)
c. Education: 8 studies (19.5%)
d. Public services/government: 6 studies (14.6%)
e. Consumer applications: 4 studies (9.8%)

Dominant Theoretical Framework:

a. TAM and its extensions: 18 studies (43.9%)
b. UTAUT/UTAUT2: 11 studies (26.8%)
c. Combination of TAM-UTAUT: 6 studies (14.6%)
d. Theory of Planned Behavior: 3 studies (7.3%)
e. Other frameworks (Trust-Risk, TOE): 3 studies (7.3%

Analysis Methods:

a. Structural Equation Modeling (SEM): 28 studies (68.3%)
b. Regression analysis: 7 studies (17.1%)
c. Qualitative/thematic analysis: 4 studies (9.8%)
d. Machine learning algorithms: 2 studies (4.9%)

4.2. Mapping Factors of AI Adoption

4.2.1. Cognitive Factors

The analysis shows that cognitive factors appear in 35 of 41 studies (85.4%), making it the most consistently researched dimension. The main constructs include: **Perceived Usefulness (PU):** Researched in 29 studies (70.7%). Almost all studies found PU to be a significant predictor of adoption intention. Lu (2024) in the context of AI- resurrection technologies found PU → attitude (β=0.45, p<.001). (Topsakal, 2024) in Gen-AI travel planning found PU → intention (β=0.52, p<.001). This pattern is consistent across contexts. **Perceived Ease of Use (PEOU**): Examined in 26 studies (63.4%). The effect of PEOU is more varied. Choi et al. (2022) found PEOU to be the most influential factor in teachers' acceptance of EAITs (β=0.61). However, " found that effort expectancy (analogous to PEOU) did not significantly influence AI acceptance in Malaysia's shared service industry. **AI Literacy/Knowledge:** Examined in 15 studies (36.6%). (found AI literacy to be the most influential factor in teachers' acceptance of GenAI (β=0.58, p<.001). Schiavo et al. (2024) confirmed that AI literacy positively influences AI acceptance (β=0.42) and AI anxiety mediates this relationship. **Position of Indonesian Studies:** (Sudirman et al., 2025) operationalized the cognitive factor through a comprehensive AI literacy measure that included: (1) the ability to distinguish between ML, deep learning, and AI; (2) recognition of real-world AI applications; (3) critical appraisal skills related to risks and benefits; (4) ethical awareness of algorithmic bias; and (5) the ability to communicate AI concepts. This study found cognitive factor → emotional factor (β=0.37, p<.001) and cognitive factor → WAAI (β=0.22, p<.001), confirming the dual-pathway mechanism.

What is unique about the Indonesian study is the finding that the 21-30 age group—digital natives—had the highest cognitive factor score (M=21.30, SD=3.32), while the willingness to adopt AI was highest among the 51+ age group (M=27.32, SD=4.15). This discrepancy indicates that cognitive readiness does not automatically result in adoption willingness; other factors such as life experience and normative commitment play an important role.

4.2.2. Emotional Factors

Emotional factors appeared in 32 of 41 studies (78.0%), with the following constructs:

Trust: The most dominant construct, studied in 28 studies (68.3%). " developed a specific TrAAIT model for clinician trust in AI healthcare, finding that trust explains 56% of the variance in acceptance and 36% in post-adoption trusting stance. Rathnayake et al. (2025) in the context of Sri Lanka's government AI chatbot found social influence → trust (β=0.54, p<.001) and trust → perceived ease of use (β=0.48, p<.001).

(Gerlich, 2024) in a multi-country study (US, UK, Germany, Switzerland) found trust to be the most significant factor for AI acceptance, with cultural factors having minimal impact—indicating that trust is a universal concern. Anxiety/Fear: Examined in 18 studies (43.9%). (identified a paradox: "scary to use it, scary to refuse it." Schiavo et al. (2024) found that AI anxiety mediates the relationship between AI literacy and AI acceptance (indirect effect=0.18, p<.01). (found that in high-stakes decisions (medical services), consumers are more reluctant to rely on AI than human advice agents due to self-threats.

Positive and Negative Emotions: Lu (2024) in the AI-RTs study found that positive emotions (β=0.31, p<.001) and negative emotions (β=-0.24, p<.001) simultaneously influence attitude, with the relationship varying across VR, chatbot, and deepfake contexts. Position of Indonesian Studies: (Sudirman et al., 2025) uses a novel approach by measuring emotions along bipolar dimensions: bored↔relaxed/comfortable, melancholic/pressured↔content, hopeless↔optimistic, dissatisfied↔satisfied, annoyed↔pleased. Emotional factors are proven to have:

- Excellent model fit (CFI=1.00, TLI=0.99, RMSEA=0.06)

- Strong factor loadings (0.78–0.88)
- Significant mediating role: CF → EF (β=0.37, p<.001); SEF → EF (β=0.28, p<.001); EF → WAAI (β=0.34,
- p<.001)
- Explains 28.4% variance in emotional responses and contributes to 38.1% variance explained in WAAI

Most crucially, the Indonesian study found that although emotional factors are strong mediators, cognitive and social-ethical factors still have significant direct effects on WAAI. This indicates affect-independent pathways—a finding that distinguishes this study from the majority of other studies that assume emotions as mandatory mediators.

4.2.3. Social and Ethical Factors

Social-ethical factors appeared in 33 of 41 studies (80.5%), with a significant increase in recent years: Social Influence: Examined in 22 studies (53.7%). Sadiq et al. (2025) in Asian social commerce found that social influence positively impacts behavioral intentions (β=0.38, p<.001). (using the UTAUT model found that social influence is a critical determinant of AI adoption in Korean companies. Ethical Concerns: Examined in 25 studies (61.0%), with a sharp increase from 2023 to 2025. (constructed an ethical perception model based on a trust-risk framework, finding job displacement, misinformation, ethical transparency, and responsibility attribution as prominent roles. (Kinney et al., 2024) developed a comprehensive framework that integrates the 7 requirements of Trustworthy AI (EU HLEG) with UTAUT constructs.

Fairness, Transparency, Accountability: (Alzebda & Matar, 2024) found that privacy/security concerns significantly influence citizen intention toward AI adoption, and government regulations reinforce these effects. (in an AI medicine study identified 19 key factors influencing trust, with 16 considered highly relevant (performance, transparency, accountability) and 3 low relevance (patient demographics).

Position of Indonesian Studies: (Sudirman et al., 2025) adapted the Attitudes Toward the Ethics of AI (AT-EAI) scale from (Jang et al., 2022) , with operationalization covering: Endorsement of strict AI regulations to avoid ethical violations, Demands for fairness in AI's use of information sources, Transparency regarding information sources, Beliefs that AI should be applied for positive social purposes, Imperative that users maintain control over AI utilization, Ability to correct AI errors

The study found social & ethical factors → emotional factors (β=0.28, p<.001) and social & ethical factors → WAAI (β=0.22, p<.001). This pattern was particularly prominent in:

- The 31-40 age group with the highest SEF score (M=27.66, SD=2.79)
- Professionals and civil servants with high SEF scores
- Individuals with a Master's degree (M=27.70, SD=1.85)

These findings indicate that socio-ethical orientations can become deeply internalized and translate directly into behavioral intentions, particularly in age groups that are more attuned to social responsibility or have greater life experience.

4.2.4. Technological and Organizational Factors

Organizational technology factors appeared in 27 of 41 studies (65.9%): Performance/Reliability: (Yuan et al., 2025) found that learnability and error handling positively affect GenAI adoption intention in financial services. Dahlke et al. (2024) found that direct linkages to sources of deep AI knowledge and cognitive proximity significantly influence adoption rates. Organizational Factors: (Song et al., 2025) found that top management support significantly enhances technology acceptance (β=0.52, p<.001), and AI adoption significantly improved organizational decision efficiency and overall performance. Patnaik and Bakkar (2024) found that transformational leadership positively influences AI adoption intention, with vision and intellectual stimulation being crucial. Facilitating Conditions: (Norzelan et al., 2024) found that facilitating conditions have no link with AI technology acceptance—contrary to UTAUT predictions. This indicates that in the context of AI, psychological and skill factors are more crucial than infrastructure conditions.

Position of Indonesian Studies: (Sudirman et al., 2025) does not explicitly measure organizational factors because it focuses on individual-level adoption. However, subgroup analysis shows an interesting pattern: Civil servants/military/police: high SEF (M=27.11) and WAAI (M=26.21), Private sector/state-owned: high SEF (M=27.30) and WAAI (M=26.04), Entrepreneurs: lowest WAAI (M=23.98, SD=3.90)

This pattern indicates that structured work environments with strong organizational norms facilitate AI adoption, while entrepreneurs may be concerned about AI disrupting existing business models.

4.3. Affect-Independent Pathways Mechanism

One of the most significant findings of this SLR is the identification of affect-independent pathways in AI adoption—pathways where cognitive and socio-ethical factors influence adoption intention without substantial emotional mediation. Evidence from Indonesian Studies: (Sudirman et al., 2025) found Cognitive factor → WAAI: $\beta=0.22$, $p<.001$ (direct effect), Social & ethical factor → WAAI: $\beta=0.22$, $p<.001$ (direct effect), Emotional factor → WAAI: $\beta=0.34$, $p<.001$ (mediating effect)

Total effect of cognitive factor: 0.22 (direct) + 0.37×0.34 (indirect via emotion) = 0.348 Total effect of social-ethical factor: 0.22 (direct) + 0.28×0.34 (indirect via emotion) = 0.315 Proportion of direct effect: Cognitive = 63.2% of total; Social-ethical = 69.8% of total

This shows that the majority of the effects of cognitive and social-ethical factors are direct, not through emotional mediation—contrary to Lazarus's Cognitive-Motivational-Relational Theory, which states that emotions are essential intermediaries.

Converging Evidence from Other Studies:

Horvath et al. (2023) found that in UK AI permit processing systems, system-level factors such as accuracy and cost are more influential than human involvement—indicating that rational evaluations override emotional preferences.

(Song et al., 2025) found that perceived usefulness is the core factor driving technology adoption ($\beta=0.58$), with perceived ease of use having a weaker effect ($\beta=0.23$)—suggesting rational utility calculations dominate.

Čubrić (2020) in a comprehensive tertiary study found that ethical convictions can serve as independent drivers of AI adoption, particularly in institutional environments with strong normative expectations. Theoretical Explanation:

Several mechanisms can explain affect-independent pathways:

- Cognitive Routinization: Sousa et al. (2023) and Li et al. (2024) argue that with the increasing normalization of AI in everyday life, individuals encounter and evaluate AI tools in more habitual and cognitively routinized ways, limiting emotional salience.
- Normative Compliance: In structured environments (government, professional settings), individuals may adopt AI out of obligation or social conformity rather than emotional engagement (Papagiannidis et al., 2023; Williamson & Prybutok, 2024).
- Strength of Convictions: When cognitive understanding or ethical convictions are very strong and clear, they can directly drive behavior without requiring emotional validation (Ferrer et al., 2021; Buhmann & Fieseler, 2021).
- Life Experience Moderator: Indonesian studies found that older adults (51+) and individuals with higher education showed the strongest alignment across socio-ethical and adoption variables—suggesting accumulated life experience strengthens normative pathways.

Theoretical Implications: These findings challenge the dominance of TAM and Lazarus' theory in the technology acceptance literature. We need integrative theoretical models that account for both rational-normative motivations alongside emotional dynamics. A comprehensive AI acceptance model must accommodate: Dual-processing pathways (affective and cognitive), Context sensitivity (habitual vs. novel AI encounters), Individual differences (age, education, experience), Cultural factors (collectivist vs. individualist orientations)

4.4. Contextual Variations

Geographical Differences: Cross-regional analysis reveals several patterns: Asia: Trust and social influence tend to be more dominant. (Kim & Blazquez, 2024) Korea found social influence to be a critical determinant. Zhang et al. (2021) China found trust to mediate the relationship between functionality and acceptance. This is consistent with the collectivist cultural orientation in Asia.

Europe: Ethical concerns are more prominent. (Kinney et al., 2024) Portugal developed a framework comprehensively integrating trustworthy AI requirements. Brauner et al. (2025) Germany found that participants viewed AI scenarios as risky with limited benefits, with value judgments strongly influenced by perceived benefits over risks.

America: Performance and usefulness are more emphasized. (Frank et al., 2024) The USA found that consumers are reluctant to rely on AI in high-stakes decisions primarily due to performance doubts. (Topsakal, 2024) The USA found that perceived usefulness directly affects intention ($\beta=0.52$).

Middle East: Government regulations and privacy concerns are very salient. (Alzebda & Matar, 2024) Palestine found that government regulations strengthen the effects of privacy/security concerns.

Application Domain Differences Healthcare: Trust and accountability are most crucial. Stevens and Stetson (2023) found that trust explains 56% of the variance in acceptance. Schulz et al. (2023) found trust and beliefs to be primary mediators. Education: Pedagogical beliefs and perceived ease of use are dominant. Choi et al. (2022) found PEOU to be most influential (β=0.61). Celik et al. (2025) found trust and subjective norms crucial.

Business/Organization: Performance expectancy and organizational support are key. (Song et al., 2025) found top management support crucial (β=0.52). Patnaik and Bakkar (2024) found transformational leadership positively influences adoption. Public Services: Fairness, transparency, and human oversight are vital. (Horvath et al., 2023) found that system accuracy and cost are more influential than human involvement in permit processing.

4.5. Implications for Policy

The findings of this SLR have significant public policy implications:

4.5.1. Improving AI Literacy

Recommendation: Governments need to invest in comprehensive AI literacy programs that not only teach technical knowledge but also critical appraisal skills to evaluate AI risks and benefits, ethical awareness about algorithmic bias, and communication skills to discuss AI with others.

Evidence: Al-Abdullatif (2024) found AI literacy to be the most influential factor (β=0.58). (Sudirman et al., 2025) found that the 21-30 age group with the highest cognitive scores was more ready to adopt AI. Schiavo et al. (2024) confirmed that AI literacy positively influences acceptance.

Implementation of AI literacy integration in formal education curricula (K-12 to higher education), AI training programs for the workforce, specifically targeted at age groups 40+ who show lower cognitive scores, and public awareness campaigns using accessible language and real-world examples.

4.5.2. Emotional Response Management

Recommendation: Policies should address emotional dimensions, particularly trust-building and anxiety reduction. Evidence: (Sudirman et al., 2025) found that emotional factors explain 28.4% of variance and play a strong mediating role (β=0.34). (Gerlich, 2024) found trust to be the most significant factor across countries. (Hartyándi, 2025) identified the anxiety paradox.

Implementation of Transparency initiatives: Government and organizations must openly communicate about how AI systems work, what data they collect, and how decisions are made. Demonstrative pilots: Small-scale, successful AI implementations can build trust through observable results. Human-AI collaboration frameworks: (found that appropriate levels of human involvement increase acceptance. Grievance mechanisms: Ability to correct AI errors and contest decisions (Sudirman et al., 2025)

4.5.3. Ethical and Regulatory Framework

Recommendation: Establish comprehensive ethical frameworks and regulatory infrastructure for AI adoption. Evidence: (Yu et al., 2025) found ethical transparency and responsibility attribution prominent. (Alzebda & Matar, 2024) found government regulations strengthen effects. (Kinney et al., 2024) identified 16 highly relevant factors including transparency, accountability, fairness.

Implementation of national AI ethics guidelines based on international best practices (EU HLEG 7 requirements), sector-specific regulations (healthcare, finance, education) that address unique ethical challenges, independent AI oversight bodies with a mandate to audit systems and investigate complaints, mandatory AI impact assessments for high-risk applications, data protection frameworks that ensure privacy and consent.

4.5.4. Organizational and Infrastructure Support

Recommendation: Strengthen organizational capabilities and infrastructure for AI adoption.

Evidence: (Song et al., 2025) found top management support crucial (β=0.52). (Yuan et al., 2025) found organizational innovation capability positively influences adoption. (Norzelan et al., 2024) found skill and technical capability major impacts.

Implementation of organizational change management programs that prepare employees for AI integration, technical infrastructure investments (cloud computing, data storage, computing power), skill development programs: reskilling and upskilling the workforce for AI-era jobs, public-private partnerships to share knowledge and resources

4.5.5. Targeted Interventions for Diverse Populations

Recommendation: Recognize and address heterogeneity in AI readiness across demographic groups. Evidence: (Sudirman et al., 2025) found significant variations by age, gender, education, and occupation. (Ho et al., 2023) found senior patients perceive emotional AI more negatively. (found that age and socio-economic status moderate innovation attitudes.

Implementation:

- Age-specific programs: Younger groups benefit from advanced technical training; older groups need basic literacy and trust-building
- Gender-sensitive approaches: Address marginal gender differences with inclusive design
- Education-based targeting: Individuals with lower education need more foundational support
- Occupation-specific strategies: Entrepreneurs may need reassurance that AI complements rather than disrupts business models; civil servants need integration with existing workflows

4.5.6. Longitudinal Monitoring and Adaptive Policy

Recommendation: Establish systems to monitor AI adoption trends and adapt policies accordingly. Evidence: Research gap analysis shows a scarcity of longitudinal studies. (Abid et al., 2024) highlight the need for sustained observation. (Chang et al., 2024) note that technostress effects evolve over time.

The implementation of AI adoption policies needs to be carried out systematically and sustainably through several key mechanisms. First, conducting annual national AI adoption surveys is an important tool for mapping adoption levels, public perceptions, and changes in public attitudes and behaviors toward AI over time. Second, longitudinal tracking of early adopter groups is necessary to understand the long-term impacts of AI use, including changes in productivity, work behaviors, and possible social and ethical implications. Third, the application of policy evaluation frameworks equipped with clear, measurable, and relevant performance indicators enables objective evaluation of policy effectiveness, while providing feedback loops that support evidence-based policy improvement. Finally, the implementation of adaptive governance models is crucial for AI governance to be flexible and responsive, enabling it to respond quickly to new challenges, unanticipated risks, and the rapid dynamics of AI technology development.

5. Discussion and Research Contributions

5.1. Theoretical Contributions

This SLR research contributes to technology acceptance theory in several ways:

- Multi-Dimensional Integration: This study comprehensively maps the four dimensions of AI adoption—cognitive, emotional, socio-ethical, and technological—which were previously often studied in isolation. This integration shows that AI adoption is a complex and multi-determined phenomenon, requiring a holistic understanding.
- Affect-Independent Pathways: The identification and documentation of cognitive-normative pathways that operate independently of emotional mediation challenges fundamental assumptions of TAM and Lazarus's theory. This opens new avenues for theoretical development that accommodates dual-processing mechanisms.
- Context Sensitivity: Cross-regional and cross-domain analysis reveals that the determinants of AI adoption vary substantially based on cultural context and application domain. Universal theories of technology acceptance need to be modified to account for cultural and contextual factors.
- Positioning of Indonesia Study: (Sudirman et al., 2025) study contributes by: Providing empirical evidence from an under-researched region (Southeast Asia, Muslim-majority country), Using innovative bipolar emotional measurement, Identifying affect-independent pathways through rigorous SEM analysis, Demonstrating that age, education, and occupation significantly moderate adoption patterns

5.2. Methodological Contributions

Comprehensive SLR Framework: The use of the PRISMA protocol with systematic extraction and quality assessment ensures rigor and transparency. Multi-Method Synthesis: The integration of various analytical techniques (SEM, regression, qualitative) in a single review provides a richer understanding than meta-analysis, which only focuses on quantitative studies. Bibliometric Analysis: Complementing content analysis with bibliometric mapping (VOSviewer) visualizes the knowledge structure and collaboration networks in AI adoption research.

5.3. Practical Contributions

Actionable Policy Recommendations: Translating empirical findings into specific policy interventions with clear implementation pathways. Evidence-Based Decision Making: Policymakers can use findings to prioritize interventions based on the relative importance of factors.

Stakeholder Guidance: This framework is applicable to various stakeholders—government agencies, educational institutions, healthcare organizations, businesses—planning AI adoption initiatives.

5.4. Limitations

Several limitations should be acknowledged:

- Publication Bias: Studies with null results or negative findings tend to be under-published, potentially biasing synthesis toward positive relationships.
- Language Limitation: Restricting to English-language publications may miss important insights from non- English literature, particularly from China, which is extremely active in AI research.
- Cross-Sectional Dominance: 95% of studies use cross-sectional designs, limiting causal inferences. True causal relationships require experimental or longitudinal approaches.
- Measurement Heterogeneity: Different studies operationalize the same constructs differently (e.g., trust measured with 3-7 items across studies), complicating direct comparisons.
- Self-Report Bias: The majority of studies rely on self-reported intentions rather than actual behavior, introducing social desirability bias.
- Geographic Imbalance: Despite improvement, Africa and Latin America remain under-represented, limiting global generalizability.

5.5. Future Research Directions

Based on the analysis, several research directions are crucial:

- Longitudinal Studies: Tracking AI adoption trajectories over time to understand how factors evolve, how initial adoption decisions affect future engagement, and the dynamics of re-adoption or abandonment.
- Cross-Cultural Comparisons: Systematic comparative studies across cultures to disentangle universal versus culturally-specific determinants. Particularly valuable would be comparisons between collectivist (Asian) and individualist (Western) societies.
- Mechanism Studies: Deep-dive investigations into affect-independent pathways using experimental designs, physiological measures (EEG, fMRI), and experience sampling methods to capture real-time cognitive- emotional processes.
- Intervention Experiments: RCTs testing the effectiveness of various interventions—literacy programs, transparency initiatives, ethical frameworks—in enhancing AI adoption.
- Vulnerable Populations: Focused studies on how AI adoption factors differ for vulnerable groups—elderly, low-income, rural populations, people with disabilities—to ensure inclusive digital transformation.
- Negative Cases: Investigations of AI rejection or abandonment post-adoption to understand what goes wrong and how to prevent it.
- Ethical Implementation: Research on how ethical principles translate into actual practice, and the impact of ethical AI design on trust and adoption.
- AI Evolution Effects: As AI capabilities advance (particularly generative AI), how do perceptions and adoption factors change? Comparative studies across AI generations are needed.

For Results, provide sufficient detail to allow the results to be meaningful and informative. For Discussion, this should explore the significance of the results of the work, not repeat them. A combined Results and Discussion section is often appropriate. Avoid extensive citations and discussion of published literature.

6. Conclusion

This systematic literature review of 41 empirical studies provides a comprehensive mapping of factors influencing the adoption of Artificial Intelligence, with significant insights for theory, research, and policy.

6.1. Key Findings

- Multi-Dimensional Nature: AI adoption is influenced by a complex interplay of cognitive factors (AI literacy, perceived usefulness), emotional factors (trust, anxiety), social-ethical factors (fairness, transparency, accountability), and technological-organizational factors (performance, organizational support).
- Emotional Mediation: Emotional factors, particularly trust, consistently play a central mediating role across contexts, explaining why individuals with similar cognitive understanding can have vastly different adoption intentions.
- Affect-Independent Pathways: A novel finding is that cognitive and socio-ethical factors can directly influence adoption intentions without substantial emotional mediation, challenging traditional technology acceptance theories. This mechanism is particularly prominent in structured environments and among individuals with strong normative commitments or extensive life experience.
- Contextual Variations: Geographic and domain-specific variations indicate that universal theories of technology acceptance need substantial modification to account for cultural orientations (collectivist vs. individualist) and application contexts (healthcare vs. education vs. business).
- Indonesia Study Positioning: The study (Sudirman et al., 2025) contributes significantly by providing evidence from the under-researched Southeast Asian context, using innovative bipolar emotional measurement, and demonstrating affect-independent pathways through rigorous SEM analysis with 511 diverse participants.

6.2. Policy Implications

From a public policy perspective, the findings of this SLR underscore the need for a multi-pronged approach that includes investment in comprehensive AI literacy programs, not just technical training but also critical thinking and ethical awareness, trust-building initiatives through transparency, demonstrative pilots, and appropriate human-AI collaboration frameworks, robust ethical frameworks with clear regulations, oversight mechanisms, and accountability structures, organizational support systems including change management, infrastructure investments, and skill development, targeted interventions that recognize heterogeneity across age groups, education levels, occupations, and demographic segments, and longitudinal monitoring systems to track adoption trends and enable adaptive policy responses.

6.3. Theoretical Advancement

This research shows that AI adoption cannot be understood through single-lens theoretical frameworks.

Integrative models are needed that accommodate dual-processing pathways (cognitive-normative and emotional-affective), contextual embeddedness (cultural, organizational, institutional), individual differences (age, education, experience, personality), and temporal dynamics (evolution of perceptions and behaviors over time).

6.4. Final Remarks

The digital era marked by the proliferation of AI technologies demands evidence-based, contextually-sensitive, and ethically-grounded policy responses. This systematic literature review provides a foundation for such responses by mapping state-of-the-art knowledge, identifying critical gaps, and articulating actionable recommendations. Studies such as (Sudirman et al., 2025) that explore the psychological dynamics of AI adoption in diverse cultural contexts are crucial for building a truly global and inclusive understanding. As society navigates the complexities of AI transformation, collaboration between researchers, policymakers, practitioners, and civil society becomes imperative. Only through such collaborative efforts can we ensure that AI adoption proceeds in a manner that maximizes benefits, minimizes risks, and remains grounded in the fundamental human values of fairness, transparency, accountability, and dignity.

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