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Technology Acceptance in AI-Mediated Communication: A Systematic Literature Review

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Abstract

This study investigates how AI is accepted within human communication, using the Technology Acceptance Model (TAM) as a guiding framework. While TAM has been widely applied in fields such as e-commerce and healthcare, its application in AI-mediated communication (AI-MC) remains limited. This research aims to synthesize current research, identify dominant variables, and examine conceptual and methodological gaps in TAM's use within AI communication contexts. Specifically, it seeks to explore how TAM has been applied to explain user interaction with AI as a communicative agent, rather than merely as a functional tool. Methods: A Systematic Literature Review (SLR) was conducted using the PRISMA 2020, which ensured a transparent and structured review process. A total of 158 eligible articles published between 2015 and 2024 were analyzed using narrative synthesis and bibliometric mapping. The findings show that TAM's core constructs perceived usefulness, perceived ease of use, and behavioral intention remain dominant but are often insufficient to explain the social, emotional, and ethical dimensions of AI as a communicative partner. The results highlight the growing importance of additional factors such as trust in AI, perceived agency, transparency, and emotional appropriateness. The review also reveals an over-reliance on quantitative methods, with limited integration of communication theory. Conclusion: As a result, a new conceptual framework is proposed that integrates TAM with human communication concepts, emphasizing co-constructed meaning, social presence, and ethical interaction. This study concludes that understanding AI acceptance in communication requires an interdisciplinary model that goes beyond technical functionality to consider human-AI relational dynamics.

INTRODUCTION

The advancement of artificial intelligence (AI) has become an integral part of global digital transformation (Brock & Von Wangenheim, 2019; Kumar et al., 2024). This technology influences various aspects of human life, including how people communicate and interact with one another. AI has introduced new forms of technology-mediated communication, commonly referred to as AI-mediated communication (AI-MC). In this context, intelligent systems not only assist but also generate and direct communication messages (Asif & Gouqing, 2024; Hancock et al., 2020).

AI now acts as an active agent in the communication process. This role is realized through platforms such as chatbots, virtual assistants, recommendation algorithms, and automated systems in social media and digital marketing (Hancock et al., 2020; Sarp, 2023). These changes are not only technical in nature. AI’s presence also affects the social, cognitive, and cultural dimensions of communication. This is relevant because communication itself is a symbolic and contextual process of meaning negotiation (Morreale et al., 2007; Pearson et al., 2017). For this reason, it is important to understand how AI is being accepted in everyday communication practices. AI is no longer just a tool it has become part of the symbolic systems and message exchange within society.

AI’s role in communication can generally be divided into two main categories: AI-assisted communication and AI-dominated communication. In AI-assisted contexts, AI serves as an extension of human effort, helping to improve communication effectiveness. Examples include features like auto-complete, predictive typing, and email suggestions. In these cases, humans remain the primary decision-makers in shaping the message content. In contrast, AI-dominated communication involves systems that independently design and deliver messages with minimal human input (Asif & Gouqing, 2024).

The distinction between these two forms of communication has significant implications. These include how message authenticity is perceived, the level of control over communicative intent, and the degree of trust in both the media and the message sender factors that are essential to human interaction (Morreale et al., 2007; Pearson et al., 2017). As noted by Morreale et al. (2007), communication is not simply the transfer of information. It is a process of managing messages and media to create meaning. Within AI-MC, AI is not merely a conduit; it functions as a communicator that actively constructs, modifies, and adapts messages to achieve specific goals (Hancock et al., 2020). This shift in AI’s role presents new challenges. There is a growing need for a deeper understanding of how individuals perceive and adapt to the presence of AI technologies in their communication experiences.

In this context, the concept of communication competence becomes particularly relevant. Communication competence refers to the ability to communicate both effectively and appropriately within a particular social setting (Morreale et al., 2007). When AI serves as a message sender, users’ perception of the AI's communication competence becomes a critical factor in determining their acceptance of the technology. This aligns with the Technology Acceptance Model (TAM), which suggests that perceived usefulness (PU) and perceived ease of use (PEOU) are key predictors of behavioral intention to use a technology (Davis, 1989; Kim, 2024). Users are more likely to accept AI systems if they believe the systems are helpful and easy to use, but this is also shaped by their judgment of how capable AI is as a communication partner.

Furthermore, communication is not only a process of exchanging messages but also a means of building social relationships and communities a notion described as communication as community (Morreale et al., 2007). As a communication agent, AI can either facilitate or hinder the creation of inclusive communication environments. While TAM has been applied in various domains such as e-commerce, digital advertising, online education, and AI-based healthcare services (Kim, 2024; Sarp, 2023), its application in AI-mediated communication remains limited. AI-MC presents unique characteristics, particularly because AI systems do not simply transmit information, they also shape the content and direction of communication based on predictive and adaptive algorithms (Mieczkowski et al., 2021; Towne, 2024).

The symbolic and interpretive aspects of communication play a significant role in how users perceive AI interactions. According to the theory of symbolic interactionism, meaning is constructed through continuous interaction and social experience (Pearson et al., 2017). People interpret their interactions with AI based on prior experiences, social expectations, and cultural context. For example, a study by Algouzi and Alzubi (2023) found that the acceptance of AI-generated auto-replies in email was influenced by demographic factors such as age, gender, and academic background. This suggests that interpretations of AI in communication are not universal but instead shaped by situational and socially embedded factors.

As the use of AI in communication continues to grow, there is an urgent need to examine how users accept this technology within increasingly complex communication contexts. Although many studies have applied the TAM across various domains, a significant academic gap remains in understanding the dynamics of AI acceptance, particularly in interpersonal, social, and organizational communication settings. For instance, previous research has often focused on AI as a purely functional tool, without fully considering the psychological and social elements that are inherent in human communication mediated by AI (Asif & Gouqing, 2024; Hancock et al., 2020).

Another limitation lies in the lack of integrated studies that combine human communication frameworks with technology-oriented models like TAM. Much of the literature remains fragmented, often focusing on utilitarian aspects while overlooking affective, sociocultural, and ethical dimensions of communication (Guzman & Lewis, 2020; Ozili, 2024). Recent literature has also pointed out that TAM tends to emphasize initial adoption decisions and is less capable of capturing long-term relational and emotional dynamics involved in ongoing AI usage (Ozili, 2024; Baroni et al., 2022). For instance, feelings of awkwardness, distrust, or unmet social expectations around AI systems are frequently excluded from the model, even though these factors are critical to communication outcomes (Hancock et al., 2020; Mieczkowski et al., 2021).

As a result, newer frameworks such as the Technology Impact Model (TIM) have been proposed to broaden the scope of TAM by incorporating social expectations, relational influence, and the long-term impact of technology use on values and social norms (Ozili, 2024). This aligns with the idea of communication as a form of social construction, where the success of any communicative act is not solely about message efficiency, but also about a system's ability to foster connection, trust, and collaboration among individuals (Morreale et al., 2007; Pearson et al., 2017). In this regard, perceptions of AI are not limited to usefulness and ease of use but also involve trust, perceived risk, and emotional closeness factors that may not be fully captured by traditional TAM variables.

Based on these considerations, the main research question in this study is: "How can the TAM be applied and extended to explain user acceptance of AI in communication, particularly in AI-mediated communication contexts?" This question is highly relevant because perceptions of AI as a communication agent affect not only interaction effectiveness but also have broader implications for how individuals shape their digital identities, assess trust, and build social connections in virtual environments. The study will address the following questions: (1) What are the main factors influencing AI acceptance in communication, according to existing studies? (2) How has TAM evolved in its application to communication settings involving AI? (3) What are the conceptual and methodological gaps that still exist in current research?

This problem formulation has broad social implications, especially in the development of ethical, inclusive, and socially responsive AI communication systems. If negative perceptions of AI are not adequately addressed, this could lead to resistance that slows innovation, widens the digital divide, and reduces the effectiveness of communication in areas like public services, education, or business (Boucher, 2020; Ozili, 2024). Hence, it is essential to systematically explore how TAM can enrich our understanding of AI acceptance within the framework of human communication.

This study aims to conduct a systematic literature review (SLR) of research that applies TAM to examine AI acceptance in communication contexts. Specifically, it seeks to (1) identify and synthesize key findings from prior TAM-based studies in AI communication; (2) assess how core TAM variables such as perceived usefulness, perceived ease of use, and behavioral intention are applied or modified in AI communication; (3) propose a conceptual framework that integrates technology and communication approaches for a more comprehensive understanding of AI acceptance; and (4) outline new directions for theoretical and methodological development in this research domain.

Using the systematic literature review approach offers substantial benefits for answering complex questions about how TAM is applied in the context of AI acceptance in communication. This method involves compiling and objectively analyzing a broad set of relevant academic articles to produce a conceptual map and evaluative framework. It is particularly effective when dealing with diverse sociocultural contexts, varied AI applications, and methodological differences in how TAM has been used. The SLR follows explicit steps: formulating research questions, applying strict inclusion and exclusion criteria in literature search, assessing study quality, and conducting thematic and conceptual analysis.

To guide the review process, this study applies the PRISMA 2020 protocol. PRISMA 2020 ensures transparency, consistency, and replicability throughout the review (Page et al., 2021). This structured procedure allows for evidence-based decisions and minimizes bias in literature selection. Through these procedures, the SLR does not simply summarize existing knowledge but also identifies theoretical gaps and opportunities for expanding models that better reflect the realities of AI-mediated communication. The outcomes of this research are expected to provide not only theoretical contributions to the intersection of communication and technology studies but also practical guidance for policymakers, technology developers, and communication professionals in designing AI systems that are more inclusive, trustworthy, and socially acceptable in todays and tomorrow’s digital society.

RESEARCH METHOD

This research employed the framework of a Systematic Literature Review (SLR). This framework is utilized to comprehend the application of the TAM in communication research based on AI. This approach is deemed relevant as it facilitates the process of identification, quality assessment, and synthesis of findings from various studies in a systematic manner (Petticrew & Roberts, 2006). Through this framework, selection bias that often emerges in literature search and screening procedures can be avoided by adhering to clear guidelines. Furthermore, the SLR approach provides a clear structure for distinguishing between studies that are genuinely relevant and those that merely mention specific keywords in passing. Such clarity allows for traceability in each stage of decision-making, from the formulation of research questions to the determination of the final articles to be synthesized.

The adoption of the SLR framework enables the identification of various factors influencing AI acceptance within the domain of communication. This framework offers a comprehensive overview of a given research topic (Booth et al., 2016). AI-based communication studies are multidisciplinary in nature, encompassing fields such as information technology, psychology, sociology, and marketing. This framework facilitates the systematic inclusion of diverse cross-disciplinary literature by applying eligibility assessments based on predetermined criteria. The process also underscores the importance of documenting each decision to include or exclude a study, in order to ensure the accountability of this research. Moreover, this framework reinforces the reliability of the conclusions, as selected publications have undergone rigorous and integrated review procedures.

This study follows the review protocol in accordance with PRISMA 2020 recommendations. This protocol is adopted to ensure that each phase is reported transparently, particularly during the identification, screening, and eligibility assessment of articles (Page et al., 2021). Additionally, the construction of the PRISMA 2020 flow diagram is intended to illustrate the number of articles at each stage, including the reasons for exclusion of ineligible articles. This is crucial to guide study replication and enable verification of the exclusion points. The protocol also requires each study to provide a detailed account of the search method, including keywords, time span, and databases. With such detailed descriptions, the entire selection process can be subject to open auditing.

The inclusion criteria are determined by considering the range of publication years as well as the presence of TAM and AI elements within the field of communication. These criteria ensure that the selected studies explicitly employ the intended constructs, in accordance with the recommended formulation of inclusion standards prior to the search process (Petticrew & Roberts, 2006). This study utilizes TAM constructs, such as perceived usefulness and perceived ease of use, within the context of AI applications related to communication studies. The selection of the last ten years is aimed at capturing the evolution of modern AI. In contrast, studies that do not emphasize communication aspects in the application of AI are excluded, as they do not address the formulated research question. Articles must also be available in full-text format to enable an in-depth analysis of methodological design and research findings.

In addition to defining inclusion criteria, the PRISMA 2020 protocol mandates the specification of exclusion criteria. These criteria are focused on eliminating studies that fall outside the scope or lack the required depth of analysis (Booth et al., 2016). Studies that merely mention the keyword “technology acceptance” without employing the TAM framework are considered irrelevant, especially if they do not provide an elaboration of user perceptions regarding AI within the communication context. Articles that only address AI algorithm development without measuring human responses are also deemed unsuitable. Accordingly, boundaries are established to ensure that all articles in this study address both dimensions simultaneously namely, technology acceptance within AI-based communication contexts.

The article search technique employs the Scopus database. This database is selected as it serves as a reference for cross-sector research addressing both technological and social topics (Petticrew & Roberts, 2006; Booth et al., 2016). The keywords used in this study include “technology acceptance model,” “TAM,” “artificial intelligence,” “AI,” and “communication.” All keywords are combined using Boolean operators to optimize search sensitivity. The snowballing method is applied by tracing reference lists from key studies. This method is necessary, given that certain publications may not be optimally indexed. Detailed documentation is carried out to facilitate the presentation of the PRISMA 2020 diagram, which requires the reporting of article counts at each stage (Page et al., 2021). Document duplication must be removed early in the process to ensure a more efficient screening stage.

The screening process entails an evaluation of titles and abstracts to assess their relevance to the research topic. Candidate articles that fail to meet the criteria are excluded at this stage, while uncertain articles are retained to minimize the risk of discarding potentially significant studies (Petticrew & Roberts, 2006). AI-based communication must constitute the core of the discussion, rather than a peripheral topic. Additionally, articles that fall outside the specified publication period are excluded during this stage, so that the final corpus comprises only relevant studies. The reasons for exclusion must be documented to enhance transparency. In doing so, future researchers can evaluate the logical soundness of these exclusion decisions.

Following screening, each full-text article undergoes a thorough review during the eligibility stage. This step enables a more detailed verification of the research design, analytical methods, and findings (Booth et al., 2016). Articles that only briefly mention TAM or incorporate AI without a communication-related explanation are excluded at this stage. This approach ensures thematic coherence, as the study aims to synthesize literature that is specifically focused on TAM constructs in AI applications for communication. The number of excluded articles should be recorded, along with the rationale for their methodological irrelevance due to insufficient alignment with the selected constructs (Page et al., 2021).

Data analysis integrates narrative synthesis and visualization using the VOSviewer software. Narrative synthesis serves to categorize research findings based on themes, methodologies, and additional constructs beyond the selected framework (Petticrew & Roberts, 2006). Narrative analysis also highlights contextual backgrounds, such as industry sectors or user environments. The VOSviewer software facilitates keyword co-occurrence mapping to aid in the identification of specific research clusters, wherein particular terms frequently appear together. The integration of quantitative bibliometric techniques with narrative synthesis is deemed sufficient to explain how constructs are utilized in academic research (Booth et al., 2016).

The study must disclose the primary limitations of the SLR, particularly concerning data availability and search coverage. Descriptions of study boundaries and bias risk assessments that may influence findings are required by the PRISMA 2020 protocol (Page et al., 2021). Although the Scopus database is extensive, it may not encompass all relevant AI publications. Additionally, the selection of publication years may shift the focus toward more recent research, potentially overlooking foundational ideas from earlier periods. Nevertheless, such measures are consistent with SLR recommendations to define clear inclusion criteria from the outset, thereby ensuring consistency in the selection process (Petticrew & Roberts, 2006).

Traceability constitutes an essential component of the SLR method. This is particularly relevant to AI studies that may overlap with other areas such as machine learning or data analytics. The SLR method enhances the validity of conclusions, as each stage from keyword formulation to bibliometric analysis is conducted in a structured manner (Booth et al., 2016). Consequently, articles that address unrelated topics but fail to include an analysis of technology acceptance behavior are legitimately excluded. The PRISMA 2020 approach ensures that readers may consult the flow diagram to review the justification for the exclusion of specific studies (Page et al., 2021). Accordingly, the findings are expected to more comprehensively reflect field conditions, especially in relation to the factors shaping user attitudes toward AI systems in communication.

The implications of this synthesis include providing a foundation for scholars to develop theoretical variations (Petticrew & Roberts, 2006). For instance, TAM adaptations may be developed to accommodate the unique characteristics of AI technology not present in conventional systems. Furthermore, this study must consider the addition of new constructs within the theory and explain their respective implications. Narrative analysis may assist in identifying the extent to which moral concerns and user privacy influence technology acceptance. Meanwhile, bibliometric mapping reveals whether such findings are repeated across disciplines or limited to a specific domain (Booth et al., 2016).

The research findings are organized into a detailed report. The structure includes the search method, selection criteria, a summary of the final articles, and an explanation of the main findings (Page et al., 2021). With this structure, the study can identify references that support TAM's effectiveness in predicting AI usage intention, as well as instances of failure due to technological complexity. This study also outlines the design of the SLR to ensure that diverse data, ranging from quantitative surveys to qualitative explorations, can be synthesized into a unified conclusion. Furthermore, the study serves as a foundational reference for the future development of AI technology acceptance models, while emphasizing the significance of user behavior analysis in optimizing AI-based communication.

The study must transparently disclose its limitations. SLR depends on the completeness of the available literature, while databases may present imbalances in authorship or language (Petticrew & Roberts, 2006). Limitations also include the use of applications that emphasize keyword relationships, yet fail to capture the nuances of terminology in other disciplines (Booth et al., 2016). Nevertheless, the PRISMA 2020 protocol is expected to minimize inconsistencies in study selection by requiring all decisions to be accompanied by supporting rationale and evidence (Page et al., 2021). By considering all aspects, this study aims to provide a robust methodological foundation for interpreting results while facilitating future replication.

RESULTS AND DISCUSSION

The core findings of this study are presented with reference to the PRISMA 2020 protocol, which served as the primary methodological guideline. This protocol ensured a transparent and structured process of identifying, selecting, and analyzing relevant articles. It also established that the findings derived from this review result from a rigorous selection of literature and empirical evidence concerning the application of the TAM in the context of AI-mediated communication. The discussion that follows not only outlines the content of the identified studies but also interprets thematic patterns, methodological approaches, and conceptual limitations found within the literature corpus. The emphasis lies not merely on descriptive reporting but rather on critical analysis of the intellectual developments reflected in prior research.

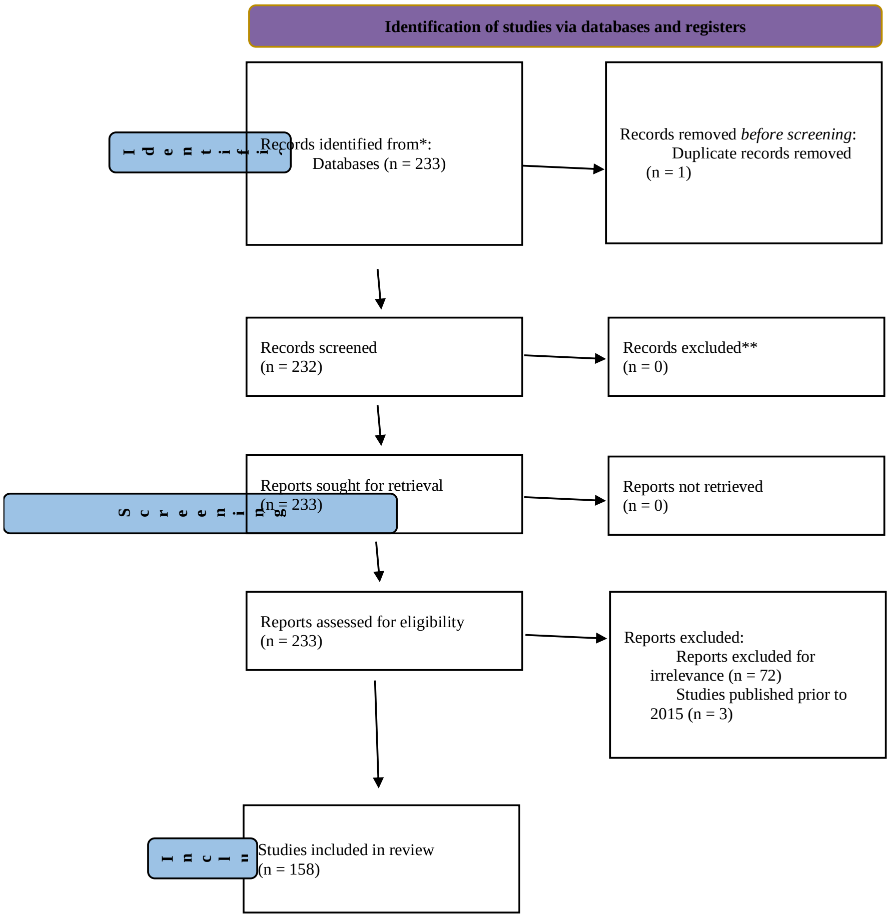

Figure 1. PRISMA Flow Diagram of Study Selection Process
Source: Research Results, 2025

Out of 233 articles initially identified through the Scopus database, one article was excluded at the preliminary stage due to duplication. The remaining 232 articles were screened based on their titles and abstracts to assess initial relevance to the focus of the review, namely the application of TAM in AI-based communication. At this stage, no articles were eliminated, and all were retained for further examination. This inclusive approach aligns with the principle that initial screening should account for potentially relevant information that may not be explicitly presented in the title or abstract.

All 233 articles were then subjected to full-text eligibility assessment based on predefined inclusion and exclusion criteria. At this stage, 72 articles were excluded for lacking relevance to the study focus for instance, studies that did not engage with communication aspects or those mentioning TAM without fully applying the theoretical framework in an AI context. An additional three articles published before 2015 were also excluded for falling outside the designated publication window. The time range was set to capture the emergence of generative AI technologies and automated communication systems, which began to see significant development after 2015, making recent literature more representative of the current state of the phenomenon.

Following the full screening process, 158 articles were deemed eligible for further analysis. This selection process is visualized through a PRISMA 2020 diagram, which transparently details the number of articles at each stage and the rationale for exclusion. The use of the PRISMA protocol not only enhances reproducibility but also ensures that the article selection process is systematic, well-documented, and free from subjective bias. This approach safeguards the methodological integrity of the review and ensures that the synthesis of findings is academically accountable.

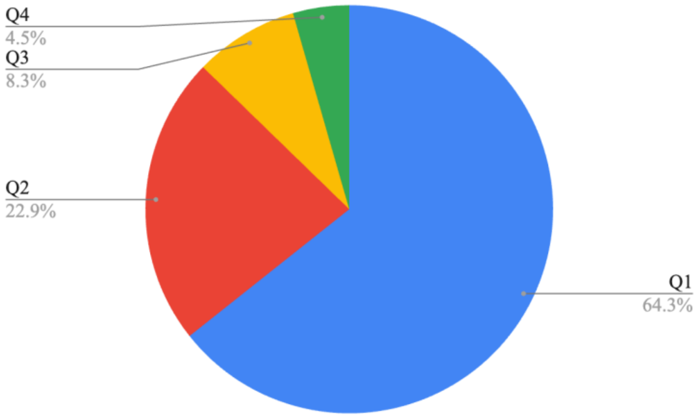

Figure 2. Journal Quartile Distribution of Included Studies
Source: Research Results, 2025

Based on journal quartile distribution data, 101 articles (64.3%) were published in Q1 journals, indicating a predominance of studies featured in top-tier scholarly outlets. This was followed by 36 articles (22.9%) in Q2 journals, 13 articles (8.4%) in Q3, and 7 articles (4.5%) in Q4. The dominance of Q1 and Q2 publications highlights the growing academic interest and rigorous scrutiny surrounding AI technology acceptance within the TAM framework.

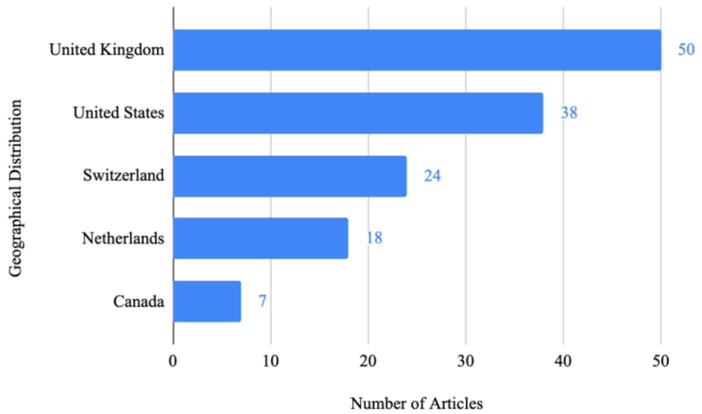

Figure 3. Top 5 Geographical Distribution of Included Studies
Source: Research Results, 2025

Geographical distribution of the journals further reflects a concentration of scholarly publishing in countries with well-established academic ecosystems. Journals based in the United Kingdom accounted for 50 articles (31.6%), followed by the United States with 38 articles (24.1%), and Switzerland with 24 articles (15.2%). Other contributing countries included the Netherlands (11 articles, 7.0%), and Canada (7 articles, 4.4%).

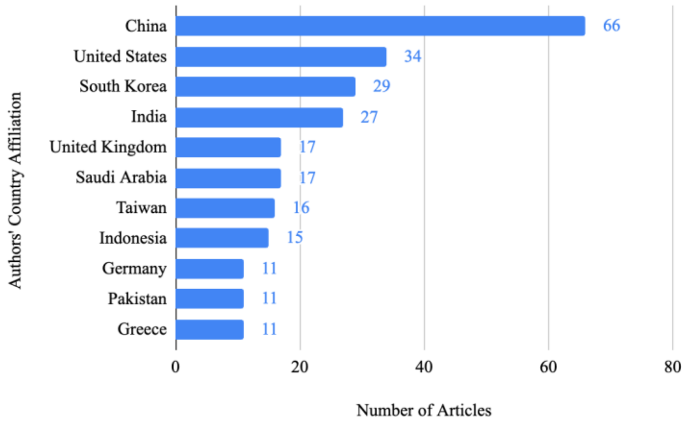

Figure 4. Authors' Country Affiliations of Included Studies
Source: Research Results, 2025

In contrast, the distribution of authors' country affiliations reveals considerable geographical diversity. China contributed the most with 66 articles (17.6%), followed by the United States with 34 articles (9.1%) and South Korea with 29 articles (7.7%). India produced 27 articles (7.2%), while both the United Kingdom and Saudi Arabia contributed 17 articles each (4.5%). Taiwan followed with 16 articles (4.3%), Indonesia with 15 articles (4.0%), and Pakistan, Greece, and Germany each with 11 articles (2.9%).

Although authors from China represent the largest group of contributors to publications on AI-based technology adoption and communication, most of their articles are published in international journals based outside of China, particularly in the United Kingdom, the United States, and Switzerland. This reflects a tendency among Chinese academics to publish their research in globally recognized journals in order to reach a broader audience and gain international recognition. Moreover, journals from these Western countries generally have higher indexation and quartile rankings (such as Q1 or Q2), which serves as a key incentive for authors seeking to enhance the visibility and impact of their research.

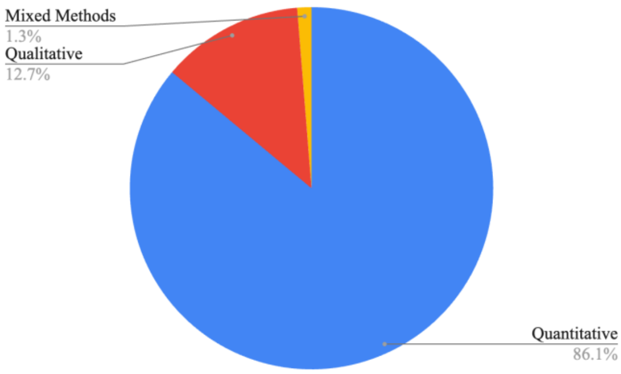

Figure 5. Methodology of Included Studies
Source: Research Results, 2025

Methodologically, the majority of articles employed a quantitative survey approach, with 136 articles (86.1%) using structured questionnaires to measure core TAM variables such as perceived usefulness, perceived ease of use, and behavioral intention. This approach is consistent with the predictive and quantitative orientation of TAM. Meanwhile, 20 articles (12.7%) employed qualitative methods such as in-depth interviews or contextual case studies, and only 2 articles (1.3%) adopted mixed methods.

The dominant application contexts in these studies involved AI-based communication systems such as chatbots, virtual assistants, or conversational applications. The primary focus was on how users respond to digital communication agents that replace human roles in providing information, services, or two-way interactions. These studies assessed user perceptions regarding both the utility and comfort of interacting with AI, commonly within sectors such as education, customer service, e-commerce, and digital media.

Three selected studies from the dataset demonstrate thematic diversity in applying TAM to AI-based communication. One study examined ChatGPT adoption by general users and found that trust in the AI system served as a crucial mediating mechanism between perceived usefulness and behavioral intention. These finding highlights that, in the absence of human interlocutors, trust becomes foundational before functional aspects are considered (Ma et al., 2025). Another study emphasized the importance of institutional context, particularly in higher education, where perceived ease of use is only effective when supported by organizational legitimacy and systemic readiness (Alshurideh et al., 2024). A bibliometric study in the tourism sector reported a growing exploration of chatbots as a response to customer interaction needs in the post-pandemic era, signaling an expansion of TAM’s function from adoption prediction to human-machine relational dynamics (Gökçe et al., 2024).

Complementary to these findings, two conceptually relevant studies from Indonesia though not included in the PRISMA dataset underscore the importance of local dimensions. One study on public service chatbots found that adapting the interface to local communication norms enhanced perceived ease of use and behavioral intention (Puspitasari et al., 2022). Another study analyzing a hotel chatbot (Bershca) revealed that informal language, personalized naming, and symbolic affinity with Indonesian youth improved perceptions of usefulness and engagement (Gunawan et al., 2020). These studies reinforce the idea that AI adoption in domestic contexts cannot be separated from sensitivity to local communication cultures, thereby extending the analytical reach of TAM toward more contextual and participatory orientations.

The bibliometric analysis of the reviewed articles generated a visual map of thematic structures and collaborative networks in TAM-related research on AI-mediated communication. Keyword co-occurrence analysis revealed dominant terms such as technology acceptance model, artificial intelligence, ChatGPT, along with classic TAM variables like perceived usefulness, perceived ease of use, and behavioural intention indicating their foundational role in explaining technology adoption across diverse settings (Ma et al., 2025; Alshurideh et al., 2024).

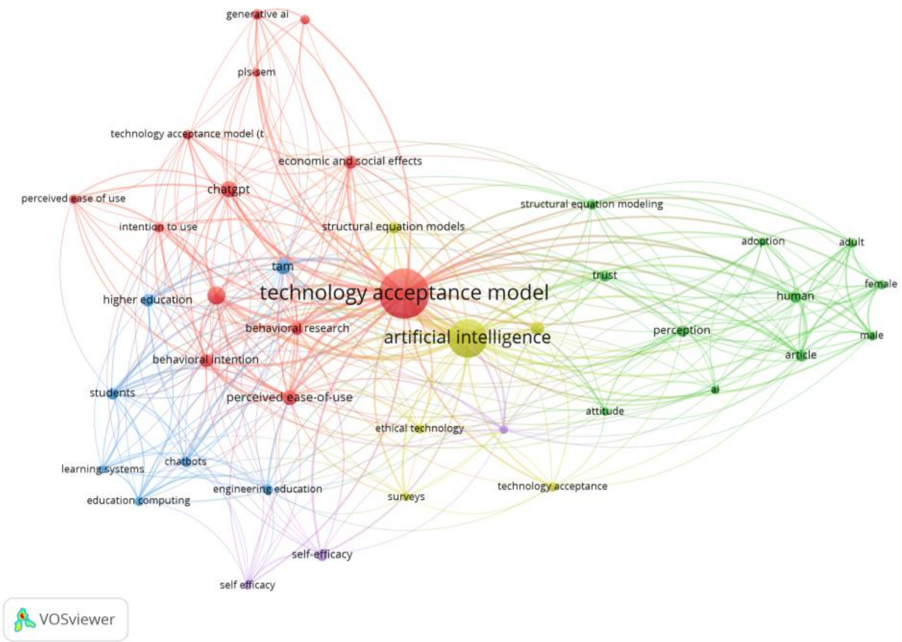

Figure 6. Major Thematic Cluster
Source: VOSviewer, 2025

At least three major thematic clusters emerged. The first cluster focused on education, strongly associated with keywords such as students, learning systems, and engineering education. Studies in this cluster emphasised that the integration of AI into learning environments is influenced by ease of use and institutional support perceived by educators and students alike (Alshurideh et al., 2024; Thüs et al., 2024). The second cluster centered on the use of chatbots in public services and industry sectors. Gökçe et al. (2024) noted that, in the post-pandemic context, AI-powered chatbots have become common interfaces for customer interaction, signaling a shift toward new digital norms. The third cluster reflected a more technicist approach to communication, focusing on methods such as structural equation modelling and variables like trust and attitude, illustrating the dominance of survey-based and PLS-SEM approaches in modelling technology adoption (Ma et al., 2025).

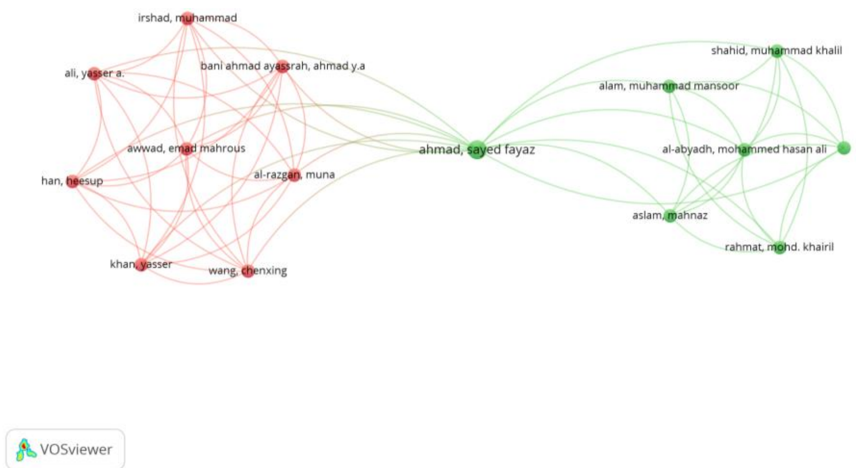

Figure 7. Co-authorship Network
Source: VOSviewer, 2025

In terms of author collaboration, the co-authorship network indicated a concentration of academic cooperation in West and South Asia, with key contributors such as Ahmad Sayed Fayaz and Emad Mahrous Awwad. This suggests a shifting research gravity from Western regions toward the Global South in TAM-related AI studies.

The application of the Technology Acceptance Model (TAM) in AI-mediated communication contexts reveals theoretical boundaries when addressing technologies that are interactive, autonomous, and communicative. Classical TAM assumes technology as a passive object adopted based on functional considerations, namely perceived usefulness and perceived ease of use (Davis, 1989; Venkatesh & Davis, 2000). However, AI-mediated communication (AI-MC) not only mediates but also modifies and generates messages, positioning AI as a communication agent that challenges the user's exclusive control over interactions (Hancock et al., 2020).

Many TAM-based studies on AI systems such as ChatGPT continue to rely on classical constructs without adapting to the dynamics of agency and AI participation in communication. These studies, including those addressing the use of ChatGPT in higher education, public administration, and online platforms, assess adoption primarily through perceived usefulness and ease of use, often overlooking the AI's role in meaning-making rather than serving merely as a functional tool (Ma et al., 2025; Alshurideh et al., 2024; Thüs et al., 2024).

AI communication technologies introduce theoretical challenges not accounted for by TAM's classical structure. In AI-driven systems like Gmail smart replies, AI not only influences message content but also alters users' linguistic style, affecting perceptions of warmth and competence in interpersonal exchanges (Mieczkowski et al., 2021). AI-MC thus actively co-constructs linguistic expression and mediates social identity, shaping how individuals perceive one another (Guzman & Lewis, 2020).

Criticism of TAM within the context of AI-MC has intensified, particularly concerning trust and ethical concerns. When AI is unrecognized as a communication agent, it may create perceptions of manipulation, especially when users are unaware they are interacting with automated systems. In such cases, models like TAM fall short in accounting for factors such as perceived deception, trust in automation, and machine agency, all of which significantly affect user acceptance (Hancock et al., 2020; Hohenstein & Jung, 2020).

AI's ability to actively shape communication by tailoring speech styles, suggesting socially contextualized responses, and engineering interactions aligned with user culture further necessitates a more complex model for technology evaluation. Emerging constructs such as perceived agency, transparency, empathic AI response, and ethics of mediation are essential for advancing user-centric evaluation (Asif & Gouqing, 2024).

Some studies have addressed this gap by extending TAM's structure. Recent research has introduced variables such as AI familiarity, privacy concern, and perceived moral alignment as additional predictors of behavioural intention (Lavidas et al., 2024; Kleine et al., 2023). In education, user perceptions of AI autonomy and potential takeover of instructional roles are more influential than ease-of-use perceptions alone (Zhang & Hou, 2024). In health communication, concerns over transparency and technological anxiety outweigh basic system functionality in shaping user responses (Ye et al., 2019).

TAM applications in healthcare contexts also demonstrate the importance of trust, security, and technological literacy especially among elderly populations where resistance to change, cognitive limitations, and perceived dependency cannot be explained by PU and PEOU alone (Kim, 2024). These findings underscore the need for models that account for affective and social dimensions of technology used in decision-making and communication.

Furthermore, the collaborative nature of human-AI communication calls for a shift from linear to relational models. In interactions where both user and system contribute to message construction, the relationship evolves from user-tool to agent-agent. Conceptual frameworks that account for co-created meaning and shared control are therefore crucial for building acceptance models suited to the AI-MC era (Towne, 2024; Asif & Gouqing, 2024).

This review contributes conceptually to the development of the Technology Acceptance Model (TAM) within AI-mediated communication by demonstrating the need to integrate contextual variables such as trust, social presence, and emotional appropriateness. The systematic review highlights that classical approaches focusing on utility and ease of use are insufficient to explain the interactive and affective dimensions of human-AI relations (Guzman & Lewis, 2020; Hancock et al., 2020).

The proposed conceptual framework offers a foundation for building more holistic adoption models that reflect the social and ethical dynamics of intelligent communication systems. These findings open avenues for future research to employ qualitative approaches that explore the linguistic, relational, and cultural aspects embedded in AI-mediated communication, while also testing the model’s applicability across diverse contexts and populations (Asif & Gouqing, 2024; Lavidas et al., 2024).

CONCLUSION

This systematic review addresses three central research questions: the key factors influencing AI acceptance in communication, the evolution of TAM's application in this domain, and the conceptual and methodological gaps found in previous studies. Through an in-depth synthesis of 158 selected articles, this study affirms that the Technology Acceptance Model (TAM) remains a widely adopted and analytically powerful framework for examining how individuals engage with AI-based communication technologies. Core constructs such as perceived usefulness, perceived ease of use, and behavioral intention continue to dominate the explanatory landscape, particularly in studies employing quantitative survey methods. However, the review also reveals a significant shift in how these constructs are being adapted or at times insufficiently modified to account for the unique attributes of AI-mediated communication. Unlike traditional technologies, AI in communication contexts does not function solely as a tool but often as an autonomous, interactive agent that participates in meaning-making processes. This evolution demands a theoretical reconfiguration of TAM to better capture relational, affective, and ethical dimensions of user experience. The review identifies critical factors such as trust in AI, perceived agency, social presence, emotional appropriateness, and transparency as increasingly relevant variables that mediate or moderate AI acceptance in communication. In light of these findings, this study proposes a new conceptual framework that bridges TAM with communication theories, incorporating variables that reflect the socio-relational and interactive nature of AI systems. The framework highlights the need to move beyond functionalist paradigms and to adopt interdisciplinary approaches that integrate insights from media studies, human–machine communication, and socio-technical systems. From a methodological standpoint, the dominance of quantitative research points to an underexplored space for qualitative and mixed-methods inquiry, which could uncover deeper layers of meaning related to user perceptions, cultural contexts, and linguistic adaptation. Practically, the review underscores the importance for developers, designers, and communication practitioners to consider how AI systems are perceived not just in terms of efficiency but also in terms of interpersonal engagement, emotional sensitivity, and ethical responsibility, particularly in high-stakes sectors such as education, healthcare, and public service where the quality of human–AI interaction can significantly impact outcomes. Ultimately, this study contributes to the development of a more comprehensive, communicatively grounded model of technology acceptance. For future research, it is suggested that scholars adopt more diverse methodological approaches including ethnographic, conversational, or critical discourse methods to enrich current understandings of AI acceptance. Additionally, future studies should explore cross-cultural comparisons of AI acceptance, investigate long-term user engagement rather than one-time perceptions, and examine how different levels of AI transparency and disclosure affect user trust and relational legitimacy across various communication contexts. Developers and policymakers are also encouraged to establish ethical guidelines for AI communication systems that prioritize user agency, emotional appropriateness, and accountability, ensuring that technological advancement aligns with human-centered values.

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