Science, Engineering and Technology Vol. 6, No. 1, pp. 138-149
www.setjournal.com https://doi.org/10.54327/set2026/v6.i1.321

AI-Driven Conversational Interfaces in IoT Ecosystems: Systematic Review of User Acceptance Models for Chatbots

Veit Schlaus

Universidad Católica San Antonio de Murcia, Murcia, Spain.

Abstract

Digital communication based on artificial intelligence and chatbots is rapidly expanding in Internet-of-Things (IoT) environments. User interaction with chatbots is being integrated into various systems, such as smart homes and connected devices. Adoption is determined by acceptance, influenced by psychological and technical factors that vary across different IoT use cases. While the Technology Acceptance Model (TAM) has been applied to diverse technologies and contexts, limited research addresses its application specifically to chatbots in IoT ecosystems. This study aims to systematically identify key acceptance factors and propose an integrated framework extending traditional TAM with IoT-specific variables. A systematic literature review (SLR) of peer-reviewed articles was conducted across six academic databases (October 2024 to December 2025), covering the last five years and yielding 11 studies meeting all inclusion criteria. Results reveal five critical acceptance factor categories: cognitive and affective factors, empathy and personalization, reliability and privacy, transparency and data management and social influence. The study's novel contribution is the integration of IoT-specific considerations including device interconnectivity, context-awareness, and data sensitivity with traditional TAM constructs, thereby addressing a significant gap in chatbot acceptance within connected device environments. Further research should validate this framework and explore long-term intentions.

Keywords: *Artificial Intelligence, Chatbots, IoT Ecosystem, User Acceptance, Data Privacy and Trust.*

1. Introduction

Digital communication based on artificial intelligence (AI) and chatbots is rapidly expanding in Internet of Things (IoT) environments [1]. User interaction with chatbots is expanding and becoming integrated into various industries. Adoption is determined by acceptance, influenced by psychological and technical factors [2]. Prominent scientific models for explaining user acceptance are based on the Technology Acceptance Model (TAM), which focuses on two core constructs: perceived usefulness and perceived ease of use [3]. Beyond the core TAM constructs, recent scientific surveys indicate that factors such as reliability, data security and transparency significantly influence users [4]. Additionally, trust in chatbots is becoming an increasingly decisive factor [5]. Furthermore, communication that is affective, contextual and demonstrates empathic, human-like behavior is crucial [6]. For this research, AI refers to machine learning systems capable of processing natural language. Chatbots are conversational agents that enable human-machine interaction through dialogue. IoT ecosystems represent networks of interconnected devices that collect and exchange data.

While the TAM has been applied to a wide variety of technologies, user contexts and industries, which is why they are considered scientifically generalizable and valid. Yet its application to chatbots specifically within IoT ecosystems remains limited [7]. Previous research has addressed TAM in isolation and chatbots in isolation, but

Corresponding author: *Veit Schlaus (vschlaus@alu.ucam.com)*
Received: 16 November 2025; Revised: 21 February 2026; Accepted: 25 February 2026; Published: 2 March 2026

lacks cross-analysis of TAM constructs applied specifically to conversational interfaces within IoT environments. This scope is particularly significant because IoT environments introduce unique technical considerations including device interconnectivity, context awareness and data sensitivity that extend beyond traditional technology acceptance research [8]. This study aims to address this gap. This study contributes to the existing body of knowledge by systematically identifying acceptance factors for chatbots in IoT contexts and proposing a conceptual framework that integrates traditional TAM constructs with IoT-specific variables. The research question is: “What key factors derived from theoretical acceptance models influence the use of chatbots and could these findings be applied to AI-driven conversational interfaces within IoT ecosystems?”

The article is structured as follows: After the introduction, section 2 provides a theoretical overview of TAM and establishes their connection to chatbots and IoT ecosystem. Section 3 presents the methodology, covering the design of the data collection process, criteria and analysis. Section 4 summarises the results and relates them to the IoT ecosystem. Section 5 presents a discussion of the results. Finally, Section 6 ends with a conclusion and potential future work.

2. Theoretical background

This section establishes the theoretical foundation for understanding chatbot acceptance. Section 2.1 presents the evolution of Technology Acceptance Models, establishing the theoretical constructs that underpin chatbot acceptance research. Section 2.2 then contextualizes these theories within IoT environments, demonstrating how traditional acceptance models apply to conversational interfaces in connected device ecosystems.

AI is widely regarded as the key development that will enhance human performance and minimise costs in the years ahead. Against this backdrop, AI is set to transform every sector of the economy [9]. Today, this technology is used in a variety of context-related IoT applications, such as search web-engines, image recognition, and the understanding and processing of human speech [10]. In this context, AI is defined as follows: “unnatural object or entity that possesses the ability and capacity to meet or exceed the requirements of the task it is assigned when considering cultural and demographic circumstances“ [9]. For decades, the research community has been working to influence the use of information and communication technologies (ICT), particularly with regard to acceptance [11].

2.1. Technology acceptance models overview

Since 1980, the acceptance of technology has been a key area of research, investigating people's willingness to use new systems in an increasingly digitalised working world [12]. The TAM, developed by Davis [13], is therefore considered to be the foundation and expansion of the Theory of Reasoned Action [14] and the Theory of Planned Behavior [15]. TAM focuses on acceptance research and determining the intention to use technology [12].

According to the TAM, intention to use is determined by two factors: perceived usefulness (PU) and perceived ease of use (PEOU). Davis describes the former as “the degree to which a person believes that using a particular system would enhance his or her job performance” [16]. Secondly, PEOU is defined as “the degree to which a person believes that using a particular system would be free of effort” [16]. The TAM has undergone extensive scientific testing on a variety of technologies, contexts and users, establishing it as the most widely used model for predicting user acceptance [17].

Following the TAM, Venkatesh et al. published the UTAUT model, which integrates key constructs that predict behavioural intention and use [18]. The model states that the intention to use technology is determined by behavioural intention, and that the likelihood of using technology depends on four key constructs: performance expectancy, effort expectancy, social influence and facilitating conditions. The effect depends on age, gender, experience, and whether use is voluntary [19].

Central TAM have undergone continuous expansion. Social influences, emotional factors, and aspects of AI have been incorporated. The following overview in Table 1 provides insight into central TAM developments over 40 years, from Davis's original constructs (PU, PEOU) to recent AI-specific models like Scheuer's AIAM (2020). This historical progression establishes the theoretical foundation for analyzing chatbot acceptance factors summarized in Table 2.

Table 1. Summary of Technology Acceptance Model Development.

First Author	Journal	Objective	Theory	Focus
Davis [13], [16]	MIS Quarterly (1985/89)	Explanation of user acceptance	TAM	PU & PEOU
Venkatesh [20]	Decision Sciences (2000)	Expansion to include social factors	TAM 2	Social Influence, Output Quality
Parasuraman [21]	Journal of Service Research (2000)	Measurement of tech readiness	TRI	Scale development with index
Venkatesh [19]	MIS Quarterly (2003)	Integration of multiple models	UTAUT	Unified theory from 8 models
Kulviwat [22]	Psychology & Marketing (2007)	Acceptance in the consumer context	CAT	Emotions, hedonics, social influence
Venkatesh [23]	Decision Sciences (2008)	Explaining PEOU psychologically	TAM 3	Cognitive and emotional effects on PEOU
Venkatesh [24]	MIS Quarterly (2012)	Customisation for consumers	UTAUT 2	Price, habit, hedonics
Parasuraman [25]	TechnoReady Marketing (2015)	Updating of TRI	TRI 2	Technology readiness
Scheuer [26]	Springer Wiesbaden (2020)	AI Acceptance Model	AIAM	Chatbots and dialogue systems

The TAM development shown in Table 1 demonstrates increasing recognition of factors relevant to chatbot acceptance. Davis's original TAM (1985) established perceived usefulness and ease of use as foundational constructs. Models based on the TAM have identified and expanded upon other influencing criteria to include external variables [17]. Subsequent extensions introduced social influence (TAM 2), emotional and hedonic factors (CAT, TAM 3), and consumer-specific contexts (UTAUT 2). Most recently, Scheuer's AI Acceptance Model – AIAM (2020) – specifically addresses AI and dialogue systems, directly relevant to this review's domain. These extensions are particularly significant for the present research gap: emotional and social factors capture user preferences for humanized interaction, AI-specific constructs address the unique characteristics of conversational agents, and consumer-focused models provide frameworks applicable to diverse user populations. However, none of these models explicitly integrate IoT-specific variables such as device interconnectivity, context awareness, and data sensitivity. This research identifies how these theoretical constructs must be adapted and extended specifically for chatbot acceptance within IoT ecosystems.

2.2. Chatbots in IoT ecosystems

Having established the theoretical foundations of technology acceptance models, this section contextualizes these theories within IoT environments. Understanding how chatbots function within connected device ecosystems is essential for applying TAM constructs to this specific domain. The term IoT was coined by Kevin Ashton in 1999. He describes it as a system in which objects in the physical world are connected to the internet by sensors [27]. Contemporary IoT systems are characterized by interoperability across heterogeneous devices, distributed computing capabilities that process data across networks, and cyber physical integration that connects digital systems with physical environments. The IoT era heralds an age of interconnected, intelligent objects that communicate with each other via existing internet infrastructure. The aim is to automate and streamline human-machine communication by processing data from sensors, services, actuators and communication interfaces [28]. In this regard, it has already been established that ‘‘the main strength of the IoT idea is the high impact it will have on several aspects of everyday life and behavior of potential users’’ [29]. Users of IoT systems are finding it increasingly challenging to keep track of all the connected applications in their ecosystem. Standardising IoT interactions in the context of user interfaces is therefore a key challenge [28].

The term chatbot dates back to 1997, when Mauldin invented the name chatterbot. Mauldin used this term to describe how machines communicate with people. A variety of synonyms are used, including agent, dialogue system, conversational interface, virtual assistant and personal assistant. Chatbots enable users to query complex content and complete specific tasks. The process often simulates human interaction [30]. The use of AI agents depends on the user's intentions. Therefore, it is important to generate an overview of existing utilisation models [9].

In a smart home, users can control all connected devices, such as lighting, heating and security cameras, via voice or text commands using the chatbot [31]. In this context, IoT becomes visible in smart cities, smart homes, and smart multimedia applications [32]. In an industrial IoT context, chatbots can efficiently monitor machines. For example, they can plan maintenance based on the probability of failure and recognise deviations at an early stage [31]. IoT therefore has the potential to transform smart factories by reducing operational costs [33].

3. Methodology

This section describes the systematic literature review methodology used to identify chatbot acceptance factors in IoT contexts. To implement chatbots successfully, it is essential to develop a comprehensive understanding of acceptance models and usage [34]. For this purpose, a systematic literature review (SLR) will be conducted based on relevant databases. This will involve analysing peer-reviewed articles from the last 5 years (since 2020) and summarising them in a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flowchart. The analysis methodology reflects current, state-of-the-art research theory [35]. The research area should cover the acceptance of chatbots by users, as well as the acceptance models and adaptation factors involved. Articles without empirical modelling or with a one-sided focus on technical development without considering the user perspective will be excluded [36]. The four methodical steps are shown chronologically below:

- **Research Design:** Presentation of the research design to answer the research question and achieve the research objective (SLR)
- **Data Collection:** Transparent presentation of the procedure and origin of the data collection (Reference criteria)
- **Data Criteria:** Summary of the inclusion and exclusion criteria for data collection (Peer-reviewed articles)
- **Data Analysis:** Justified selection of the data analysis instrument (PRISMA flowchart)

3.1. Research design

A SLR was selected as the appropriate research methodology for this study because it enables comprehensive synthesis of existing evidence across multiple peer-reviewed sources, reduces bias through transparent and replicable procedures and provides a structured foundation for identifying patterns and gaps in acceptance research. Given the broad range of TAM-based models and their application across diverse technologies, an SLR allows for systematic evaluation of how these models have been adapted and applied to chatbots. This approach is particularly suitable for synthesizing evidence from heterogeneous study designs and identifying factors that consistently influence user acceptance across different applications. So a research methodology is chosen that does justice to the challenges of AI and chatbots in IoT ecosystems [37].

The chosen research design is intended to answer the key research question: “What key factors derived from theoretical acceptance models influence the use of chatbots and could these findings be applied to AI-driven conversational interfaces within IoT ecosystems?” This, in turn, will enable the chosen goal of closing the current research gap concerning the factors influencing user acceptance of chatbots in IoT context to be approached.

Therefore, a systematic literature search of existing sources is carried out in order to obtain an overview of data that is as comprehensive as possible. The source data is primarily reduced to peer-reviewed sources. The SLR methodology is used for a “process for assembling, arranging, and assessing existing literature in a research domain” [37]. Data extraction follows a standardized protocol recording study characteristics, theoretical frameworks, and acceptance factors. Selection bias is minimized through consistent application of inclusion criteria and transparent documentation via the PRISMA flowchart. The aim of the analysis is to identify and analyse relevant articles and to present the results in a bundled form. An SLR analysis can be applied to a specific topic, research question or purely scientific phenomenon. The aim is to bundle scientific endeavours so as not to re-develop existing knowledge [38]. In this context, SLR studies are also a common practice in the field of artificial intelligence [39]. The categorizations for the data collection are discussed in more detail below.

3.2. Data collection

First, a detailed literature review was conducted. This establishes the basis of the research on the basis of thematically suitable literature. The following search algorithm was used and continuously expanded: ("artificial intelligence" OR "conversational interface" OR "chatbots" OR "agents") NEAR/5 ("technology acceptance model" OR "customer acceptance" OR "IoT ecosystem" OR "user interface")

The search criteria were expanded, particularly in the case of missing or neighboring subject areas and frequently used synonyms. Adaptive adjustment during data collection is crucial and determines the quantity of sources that can ultimately be compiled. While synonyms for chatbots (such as conversational agents and virtual assistants) were included to ensure comprehensive coverage, the search criteria maintained focus on studies addressing technology acceptance and user interaction. This narrowed approach ensures that the methodology directly addresses the research question rather than capturing broadly related studies on AI or interfaces in general. The initial search across all databases yielded 585 records. The search was conducted across six academic databases: Google Scholar, Springer Link, Web of Science, IEEE Xplore, Elsevier ScienceDirect, and supplemented with physical data sources.

Furthermore, the filter function is limited to a period of the last five years (since 2020). The literature search was systematically conducted between October 2024 and December 2025 across the six identified databases using the specified search algorithm. Although this limits the search radius, it is assumed that progressive research processes and published articles build on and influence the results of previously published studies. This comprehensive search strategy resulted in 585 initial records. After systematic removal of duplicates (n=87) and application of the screening criteria, 498 records were reviewed, ultimately yielding 11 studies that met all inclusion criteria. It is therefore expected that this approach will lead to the discovery of a large number of already known articles and authors, as well as those that are less well known, and that these will be incorporated into the overall picture.

3.3. Data criteria

The inclusion and exclusion criteria are defined as part of the data criteria. This part of the methodological design is crucial in order to demonstrate the replicability and transparency of the present study. The criteria were specifically designed to capture recent research on user acceptance of AI-driven conversational interfaces. The five-year timeframe (2020-2025) was selected to reflect the accelerated development and adoption of chatbot technologies and IoT ecosystems during this period, while remaining focused on contemporary research practices and current theoretical frameworks. Firstly, the inclusion criteria are as follows:

- Studies in the context of user acceptance models based on the models presented in section 2.1
- Technical reference to chatbots, conversational agents, user assistance or synonyms
- Use cases of chatbots in the context of networked systems that could be part of IoT
- Within the publication period of 2020-2025 defined in section 3.2
- Published peer-reviewed articles in English

The inclusion criteria ensure a clear focus on the core research objective – understanding user acceptance factors for chatbots in IoT contexts – thereby preventing scope creep and ensuring analytical coherence. Secondly, the exclusion criteria are defined as follows:

- Exclusive focus on technical development without reference to user acceptance
- Use cases without reference to chatbots, IoT ecosystem or user interactions
- Theoretical studies without methodological part and empirical analysis
- Studies without complete publication of data generation and lack of transparency
- Non-peer-reviewed articles, such as white papers, internet articles or theses

The exclusion criteria maintain focus on user acceptance factors and exclude purely technical or theoretical work without empirical validation. These exclusion criteria specifically target studies that lack empirical validation of user perspectives, as such studies cannot contribute to understanding acceptance factors. By excluding purely technical studies and theoretical work without methodological rigor, the review maintains focus on empirically-grounded acceptance models applicable to IoT-chatbot integration. The sources found are then summarised and analysed as part of the data analysis.

3.4. Data analysis

The schematic data analysis was conducted using the PRISMA flowchart, as illustrated in Figure 1. This systematic approach, developed by an international group of experts, structures the research process from initial identification through final inclusion, ensuring transparent and replicable methodology. The flow diagram documents all study selection stages, including the number of records identified, screened, assessed for eligibility, and ultimately included in the review [35]. The procedure to date is recorded in the article and thus enables a transparent presentation of the research design. This includes analysing the data with a suitable protocol tool [40].

AI and IoT are relevant for consideration in an SLR analysis as landmarks of the fourth industrial revolution. Schematic analyses of such disruptive technologies lead to a quick and at the same time detailed overview of the current state of research [41]. This approach is particularly valuable for synthesizing fragmented literature on emerging chatbot-IoT intersections, where traditional acceptance models require contextual adaptation. The results design shown in section 4.1 is based on the PRISMA flowchart analysis and was adapted to the research subject and the feasibility of the article format. The methodology ensures these complex technology interactions are systematically captured and rigorously evaluated. The PRISMA flowchart diagram showing the systematic study selection process from identification (n=585) through final inclusion (n=11), including removal of duplicates and reasons for exclusion at each stage.

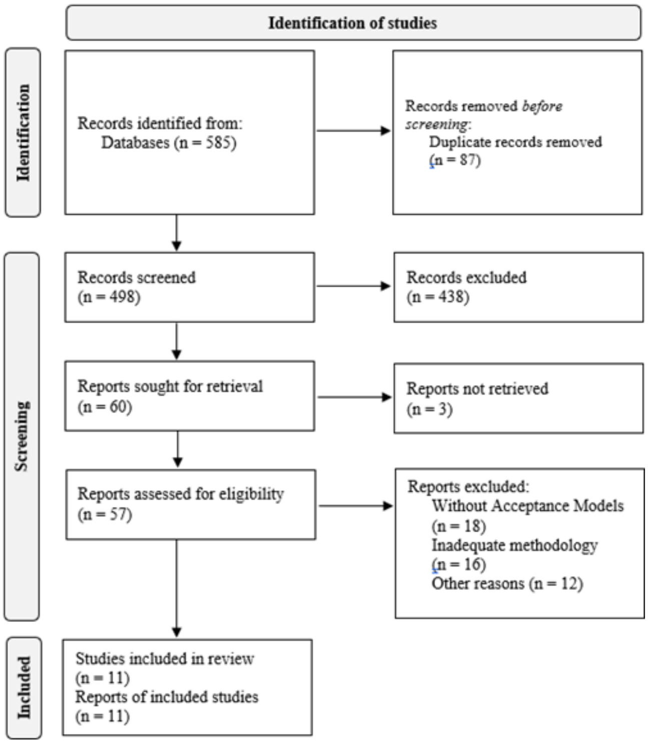

Figure 1. PRISMA Flowchart Diagram.

Figure 1 establishes methodological rigor by systematically documenting the PRISMA selection process, which reduced 585 initial records through duplicate removal, title/abstract screening, full-text eligibility assessment, and quality criteria application to yield 11 empirically robust studies suitable for synthesis. This transparent procedure provides the empirical foundation for the TAM-based acceptance factors systematically analyzed in Table 2 and comprehensively discussed throughout Section 4.

Section 4.1 summarises the results based on acceptance models and chatbots, creating a basis for IoT-integrative research. After the results have been categorized in section 4.2, the typology transfer takes place in section 4.3.

4. Results

The presentation of the results is based on the methodological approach defined in Section 3. It is important to note that only the models and extensions listed in Section 2.1 are included. The inclusion and exclusion criteria presented in Section 3.2 have been applied accordingly to ensure that the studies included in the report form part of the results presentation.

4.1. Overview of studies

The results of the SLR study are used as the basis for the presentation of the results. This is limited to the relevant studies that remained at the end of the PRISMA flowchart process. This ensures a robust presentation of the research results. The second part of the section looks at the key factors that lead to acceptance. The third part connects the IoT-specific context with a general framework proposal.

Table 2 summarizes the 11 studies selected through the PRISMA process (Figure 1), presenting their theoretical frameworks, sample sizes and key acceptance factors. These results provide the empirical foundation for the factor categorization and IoT-specific implications discussed in Section 4.2.

4.1. Identified acceptance factors

The key factors of the theoretical models for determining user acceptance and its influencing factors can be summarised into five categories. User acceptance is primarily influenced by cognitive and affective factors. Furthermore, humanised and empathic agents are favoured and used more frequently. In this context, reliability, data protection and transparency are key acceptance criteria. Additionally, social components such as recommendations and reputation are becoming increasingly important.

Across the 11 included studies, cognitive and affective factors appear consistently significant. Perceived usefulness and enjoyment were reported in all studies, while perceived ease of use and trust appeared in 9-10 studies. Personalization and empathy factors were present in 8 studies and reliability or privacy concerns in 9 studies.

Social factors appeared in 7 studies, suggesting growing but not yet universal emphasis. This variation indicates that while core TAM variables remain foundational, the importance of extended factors depends on application context.

Table 2. Summary of Technology Acceptance Model Development

First Author	Journal	Sample Size	Theory	Key Factors
Akram [42]	Personal and Ubiquitous Computing (2024)	146 (+ 38 qualitative)	TAM	Usefulness, ease of use, transparency, trust, efficiency, ethical concerns, personalization
Ayanwale [43]	Computers in Human Behavior Reports (2024)	842	TAM	Relative advantage, compatibility, trialability, trust, usefulness, ease of use, intention
Durak [44]	Current Psychology (2024)	926	UTAUT with moderators	Performance expectancy, effort expectancy, attitude, self-efficacy, anxiety, confirmation, usage continuance, system quality, satisfaction
Myin [45]	Journal of Consumer Marketing (2024)	353	TAM	Optimism, innovativeness, relative advantage, complexity
Wang [46]	Digital Health (2024)	259	TAM 2	Subjective norms, user image
Andrés-Sánchez [47]	Journal of Organizational Computing and Electronic Commerce (2024)	226	UTAUT with trust	Performance expectancy, effort, social influence, trust, age, gender
Goli [48]	International Journal of Technology and Human Interaction (2023)	378	UTAUT	Perceived enjoyment, innovativeness, information quality, customization
Chocarro [49]	Educational Studies (2021)	225	TAM	Usefulness, ease of use, conversational design, age, digital skills
De Cicco [50]	Computer Science (2021)	208	TAM	Attitude, intention, trust, compatibility, enjoyment
Pillai [51]	IJCHM (2020)	36 managers, 1.480 customers	UTAUT	Perceived trust, intelligence, anthropomorphism, technological anxiety
Rese [52]	Journal of Retailing and Consumer Services (2020)	205	TAM	Authenticity of conversation, perceived usefulness, enjoyment, privacy concerns, technology immaturity

Cognitive and affective dimensions form the foundation of user acceptance. Usefulness, ease of use, enjoyment, and trust emerge as primary drivers that influence whether users engage with chatbot systems. Beyond these individual factors, empathy and personalization prove essential to acceptance, as users consistently prefer chatbots that demonstrate human-like qualities and respond with empathy to their concerns. Reliability and privacy protections remain equally crucial, as they directly affect user confidence in the system. Transparent data management practices build trust by addressing user concerns about how their information is collected, stored, and utilized. Finally, social influence and considerations of user image affect adoption decisions, reflecting the broader social context in which technology use occurs.

Trust emerges as a cross-cutting theme that moderates the relationship between other factors and usage intention. Studies that explicitly measured trust consistently reported stronger predictive power for adoption, suggesting that trust-building mechanisms should be prioritized alongside functional usability improvements.

Based on this analysis of the main trends in chatbot acceptance research, further measures can be derived for use in chatbot programming and application. It is crucial to proactively influence future changes in user behaviour by monitoring it. This suggests that adaptive chatbot models could be promising in the context of the IoT.

4.2. Typology of IoT context and conceptual framework

The connection of smart devices through IoT is clearly evident in everyday life. Applications include medicine, healthcare, agriculture, manufacturing, transport, energy management, and building and home automation [28]. Traditional IoT interfaces use standardised graphical user interfaces (GUIs) and mobile systems, in which users control commands to the device via menu navigation. However, with large language models (LLMs) and natural language processing (NLP), contextualised and interpretable commands can be fed into the IoT network, influencing the user experience [53].

Generative AI can create new content that supposedly resembles human writing, such as through chatbots. It offers the opportunity to process large amounts of data from IoT infrastructure and act as a communication interface [54]. Despite continuous developments in chatbot technology, LLMs and NLP, their potential remains largely untapped for IoT applications [53].

Based on the five acceptance factor categories identified in this review, a conceptual framework emerges for understanding chatbot acceptance in IoT contexts. This framework builds on the traditional TAM foundation of perceived usefulness and perceived ease of use while extending it to incorporate the five contemporary acceptance variables: cognitive and affective factors, empathy and personalization, reliability and privacy, transparency and data management, and social influence. IoT-specific contexts introduce additional considerations that are not typically addressed in standard TAM research. These include device interconnectivity, referring to the chatbot's ability to manage interactions across multiple connected devices. Context-awareness is another critical variable, as the chatbot must understand user and environmental context to provide appropriate responses. Data sensitivity represents users' concerns about data transmission and security across IoT networks. Finally, device complexity captures the challenge of managing interactions with heterogeneous device types and interfaces. An integrated perspective addressing both psychological acceptance factors and IoT-specific technical considerations appears necessary for predicting and enhancing chatbot adoption in IoT ecosystems.

To illustrate how these factors apply in practice, consider two IoT scenarios. In a smart home environment [31], users must perceive the chatbot as useful for managing multiple devices (perceived usefulness) while finding voice commands intuitive (perceived ease of use). Simultaneously, they require assurance that their home automation data remains secure and transparent (reliability and privacy). The chatbot must demonstrate context-awareness by understanding that evening voice commands differ from morning routines and it must handle the interconnectivity of devices across different manufacturers.

In industrial IoT settings, such as predictive maintenance systems [33] the chatbot's ability to interpret complex sensor data (device interconnectivity and context-awareness) becomes critical, while data sensitivity intensifies due to operational security concerns. These examples demonstrate that the five acceptance factor categories identified in Section 4.2 must be operationalized differently depending on IoT context, and that IoT-specific variables fundamentally shape how users evaluate chatbot systems.

The research area of user acceptance models in artificial intelligence-driven conversational interfaces for IoT ecosystems is very limited [55]. Therefore, the conceptual framework presented here offers a structured approach for understanding how traditional TAM factors, contemporary acceptance variables and IoT-specific considerations interact to shape chatbot adoption. The results of this review could be transferred to IoT infrastructure due to the similarity between chatbots and standardised application development with a similar architecture, as well as the development of cloud platforms and their interlinking [28]. This framework provides a foundation for future empirical validation across IoT applications, thereby advancing both theoretical understanding of acceptance dynamics and practical design of chatbots in connected ecosystems.

5. Discussion

This systematic research on acceptance criteria for chatbots provides a detailed basis for subsequent research work. The study includes chatbot TAM, in particular to provide an overview of the respective factors for the use of ICT. At the same time, it is clear that this is a new field of research that combines established technologies and models. Due to the broad range of research, numerous insights could be generated.

The literature reveals important contradictions regarding factor importance. While traditional TAM emphasizes perceived usefulness and ease of use as primary drivers, several studies in this review found that trust and privacy concerns override usability considerations, particularly in IoT contexts where data sensitivity is high. For example, Akram et al. (2024) reported that ethical concerns and transparency ranked equally with usefulness in predicting adoption. This suggests that the relative importance of acceptance factors is context-dependent: in consumer smart home applications, usability may dominate, while in healthcare or industrial IoT, trust and privacy are paramount. Additionally, the role of social influence varies considerably, being significant in some studies but negligible in others, potentially reflecting differences in research methodology, demographic characteristics, or application domain rather than theoretical inconsistency. These tensions highlight that acceptance models for IoT chatbots cannot be universally applied without considering domain-specific requirements. These extensions represent a theoretical shift where emotional factors such as empathy, social influences like reputation, and contextual elements including data sensitivity become necessary to explain acceptance in IoT environments. They address dimensions absent from classical TAM but critical for chatbot design in connected ecosystems.

It is evident that the areas of user acceptance of chatbots in the context of AI and the IoT overlap, with the latter often being implicitly referenced in scientific literature. However, research on chatbots in an IoT environment using the TAM is clearly underrepresented. While the results of general TAM studies can be transferred to the IoT, they must be critically scrutinised on a case-by-case basis with regard to the respective application reference.

The acceptance factors identified in this review manifest distinctly across IoT domains. In smart home contexts, perceived usefulness relates directly to managing multiple devices simultaneously, while ease of use becomes critical for elderly users. In industrial IoT settings such as predictive maintenance systems, trust and data transparency dominate because operational failures carry severe consequences. This demonstrates that acceptance factors operate contextually – IoT-specific characteristics such as data sensitivity and device interconnectivity reshape which factors drive adoption. Therefore, chatbot design must align with domain-specific acceptance priorities rather than applying generic TAM approaches.

Therefore, the idea of designing a chatbot acceptance model specifically IoT arises from the research discussion. To this end, further empirical research will be conducted based on the current state of TAM research. The aim is to advance understanding of chatbots in IoT ecosystems by developing a comprehensive model that explains user expectations regarding the integration of technologies.

6. Conclusion and Future Work

The results show that acceptance models have become established and are being expanded to include additional factors such as emotional as well as rational focal points. In particular, the influencing components of trust, social influence and ease of use were determined. This study specifically addressed the research question by identifying how these factors apply to chatbots in IoT ecosystems, revealing that IoT-specific variables such as device interconnectivity and data sensitivity reshape traditional TAM models in ways prior reviews have not examined. However, the limited number of included studies (n=11) reflects the nascent state of IoT-specific chatbot research, potentially limiting the generalizability of findings to broader IoT contexts. Further research is needed to explore personalisation factors and long-term usage intentions across diverse IoT applications.

Future research should focus on developing a holistic chatbot acceptance model to advance scientific understanding and practical application. Furthermore, it is recommended that specific IoT applications are differentiated, such as those in the smart home or smart industry sectors, in order to assign user expectations specifically and investigate whether there are significant differences.

The results presented can create new possibilities in the area of adaptive user interfaces. The role of IoT chatbots, particularly in data-sensitive areas, is worthy of further research. It is recommended that a long-term study be conducted on an AI-driven conversational interface in IoT ecosystems in order to observe user expectations over time. This could help validate and expand existing models, as well as recognise changing acceptance criteria due to technological and social dynamics.

Competing Interest Statement

The author declares no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability Statement

Supplementary materials and data used in this research are accessible upon request. For access, please contact the corresponding author.

References

[1] 1. P. B. Brandtzaeg and A. Følstad, "Chatbots: changing user needs and motivations," *interactions*, vol. 25, pp. 38-43, 2018. https://doi.org/10.1145/3236669

[2] 2. M. Adam, M. Wessel, and A. Benlian, "AI-based chatbots in customer service and their effects on user compliance," *Electron. Markets*, vol. 31, pp. 427-445, 2021. https://doi.org/10.1007/s12525-020-00414-7

[3] 3. F. Ibrahim, J.-C. Münscher, M. Daseking, and N.-T. Telle, "The technology acceptance model and adopter type analysis in the context of artificial intelligence," *Front. Artif. Intell.*, vol. 7, 2025. https://doi.org/10.3389/frai.2024.1496518

[4] 4. A.-M. Seeger, J. Pfeiffer, and A. Heinzl, "Texting with humanlike conversational agents: Designing for anthropomorphism," *J. Assoc. Inf. Syst.*, vol. 22, pp. 931-967, 2021. https://doi.org/10.17705/1jais.00685

[5] 5. J. De Andrés-Sánchez and J. Gené-Albesa, "Not with the bot! The relevance of trust to explain the acceptance of chatbots by insurance customers," *Humanit. Soc. Sci. Commun.*, vol. 11, 2024. https://doi.org/10.1057/s41599-024-02621-5

[6] 6. S. Ekundayo and C. N. Arasanmi, "Drivers of generative AI acceptance in an ODFL institution through the lens of the technology acceptance model (TAM)," in *Proc. ACIS 2024*, 2024.

[7] 7. A.-K. Kleine, I. Schaffernak, and E. Lermer, "Exploring predictors of AI chatbot usage intensity among students: Within- and between-person relationships based on the technology acceptance model," *Comput. Hum. Behav. Artif. Humans*, vol. 3, 100113, 2025. https://doi.org/10.1016/j.chbah.2024.100113

[8] 8. A. S. Almogren, W. M. Al-Rahmi, and N. A. Dahri, "Exploring factors influencing the acceptance of ChatGPT in higher education: A smart education perspective," *Heliyon*, vol. 10, e31887, 2024. https://doi.org/10.1016/j.heliyon.2024.e31887

[9] 9. S. Kelly, S.-A. Kaye, and O. Oviedo-Trespalacios, "What factors contribute to the acceptance of artificial intelligence? A systematic review," *Telemat. Inform.*, vol. 77, 101925, 2023. https://doi.org/10.1016/j.tele.2022.101925

[10] 10. S. Na, S. Heo, S. Han, Y. Shin, and Y. Roh, "Acceptance model of artificial intelligence (AI)-based technologies in construction firms: Applying the technology acceptance model (TAM) in combination with the technology-organization-environment (TOE) framework," *Buildings*, vol. 12, 90, 2022. https://doi.org/10.3390/buildings12020090

[11] 11. N. Marangunić and A. Granić, "Technology acceptance model: A literature review from 1986 to 2013," *Univ.*

Access Inf. Soc., vol. 14, pp. 81-95, 2015. https://doi.org/10.1007/s10209-014-0348-1

[12] 12. D. Marikyan and S. Papagiannidis, "Technology acceptance model: A review," in *TheoryHub Book*, 2025.

[13] 13. F. D. Davis, "A technology acceptance model for empirically testing new end-user information systems: Theory and results," Ph.D. dissertation, 1985.

[14] 14. M. Fishbein and I. Ajzen, *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Reading, MA: Addison-Wesley, 1975.

[15] 15. I. Ajzen, "The theory of planned behavior," *Organ. Behav. Hum. Decis. Process.*, vol. 50, pp. 179-211, 1991. https://doi.org/10.1016/0749-5978(91)90020-T

[16] 16. F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Q.*, vol. 13, p. 319, 1989. https://doi.org/10.2307/249008

[17] 17. C. Sagnier, E. Loup-Escande, D. Lourdeaux, I. Thouvenin, and G. Valléry, "User acceptance of virtual reality: An extended technology acceptance model," *Int. J. Hum.-Comput. Interact.*, vol. 36, pp. 993-1007, 2020. https://doi.org/10.1080/10447318.2019.1708612

[18] 18. D. Marikyan and S. Papagiannidis, "Unified theory of acceptance and use of technology: A review," in *TheoryHub Book*, 2025.

[19] 19. V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Q.*, vol. 27, p. 425, 2003. https://doi.org/10.2307/30036540

[20] 20. V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," *Manage. Sci.*, vol. 46, pp. 186-204, 2000. https://doi.org/10.1287/mnsc.46.2.186.11926

[21] 21. A. Parasuraman, "Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies," *J. Serv. Res.*, vol. 2, pp. 307-320, 2000. https://doi.org/10.1177/109467050024001

[22] 22. S. Kulviwat, G. C. Bruner II, A. Kumar, S. A. Nasco, and T. Clark, "Toward a unified theory of consumer acceptance technology," *Psychol. Mark.*, vol. 24, pp. 1059-1084, 2007. https://doi.org/10.1002/mar.20196

[23] 23. V. Venkatesh and H. Bala, "Technology acceptance model 3 and a research agenda on interventions," *Decis. Sci.*, vol. 39, pp. 273-315, 2008. https://doi.org/10.1111/j.1540-5915.2008.00192.x

[24] 24. V. Venkatesh and X. Thong, "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology," *MIS Q.*, vol. 36, p. 157, 2012. https://doi.org/10.2307/41410412

[25] 25. A. Parasuraman and C. L. Colby, "An updated and streamlined technology readiness index: TRI 2.0," *J. Serv. Res.*, vol. 18, pp. 59-74, 2015. https://doi.org/10.1177/1094670514539730

[26] 26. D. Scheuer, "Development of a theoretical model for the acceptance of artificial intelligence," in *Acceptance of Artificial Intelligence*, Wiesbaden, Germany: Springer Fachmedien, pp. 57-65, 2020. https://doi.org/10.1007/978-3-658-29526-4_4

[27] 27. K. Rose, S. Elridge, and L. Chapin, "The internet of things: An overview: Understanding the issues and challenges of a more connected world," 2015.

[28] 28. R. Kar and R. Haldar, "Applying chatbots to the Internet of Things: Opportunities and architectural elements," *Int. J. Adv. Comput. Sci. Appl.*, vol. 7, 2016. https://doi.org/10.14569/ijacsa.2016.071119

[29] 29. L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A survey," *Comput. Netw.*, vol. 54, pp. 2787-2805, 2010. https://doi.org/10.1016/j.comnet.2010.05.010

[30] 30. A. López, J. Sànchez-Ferreres, J. Carmona, and P. Padró, "From process models to chatbots," in *Lecture Notes in Computer Science*, Cham, Switzerland: Springer, pp. 383-398, 2019. https://doi.org/10.1007/978-3-030-21290-2_24

[31] 31. N. Rane, S. Choudhary, and J. Rane, "Artificial intelligence (AI), Internet of Things (IoT), and blockchain-powered chatbots for improved customer satisfaction, experience, and loyalty," *SSRN J.*, 2024. https://doi.org/10.2139/ssrn.4847274

[32] 32. Y. B. Zikria, R. Ali, M. K. Afzal, and S. W. Kim, "Next-generation Internet of Things (IoT): Opportunities, challenges, and solutions," *Sensors*, vol. 21, 1174, 2021. https://doi.org/10.3390/s21041174

[33] 33. M. Soori, B. Arezoo, and R. Dastres, "Internet of things for smart factories in industry 4.0, a review," *Internet Things Cyber-Phys. Syst.*, vol. 3, pp. 192-204, 2023. https://doi.org/10.1016/j.iotcps.2023.04.006

[34] 34. B. T. Khoa, "The triple helix of digital engagement: Unifying technology acceptance, trust signaling, and social contagion in Generation Z's social commerce repurchase decisions," *J. Theor. Appl. Electron. Commer. Res.*, vol. 20, pp. 145, 2025. https://doi.org/10.3390/jtaer20020145

[35] 35. M. J. Page et al., "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *PLoS Med.*, vol. 18, e1003583, 2021. https://doi.org/10.1371/journal.pmed.1003583

[36] 36. H. Li, R. Zhang, Y.-C. Lee, R. E. Kraut, and D. C. Mohr, "Systematic review and meta-analysis of AI-based conversational agents for promoting mental health and well-being," *npj Digit. Med.*, vol. 6, 2023. https://doi.org/10.1038/s41746-023-00979-5

[37] 37. J. Paul and M. Barari, "Meta-analysis and traditional systematic literature reviews—What, why, when, where, and how?" *Psychol. Mark.*, vol. 39, pp. 1099-1115, 2022. https://doi.org/10.1002/mar.21657

[38] 38. R. Van Dinter, B. Tekinerdogan, and C. Catal, "Automation of systematic literature reviews: A systematic literature review," *Inf. Softw. Technol.*, vol. 136, 106589, 2021. https://doi.org/10.1016/j.infsof.2021.106589

[39] 39. L. Labadze, M. Grigolia, and L. Machaidze, "Role of AI chatbots in education: Systematic literature review," *Int. J. Educ. Technol. High. Educ.*, vol. 20, 2023. https://doi.org/10.1186/s41239-023-00426-1

[40] 40. F. J. García-Peñalvo, "Developing robust state-of-the-art reports: Systematic literature reviews," *Educ. Knowl.*

Soc., vol. 23, e28600, 2022. https://doi.org/10.14201/eks.28600

[41] 41. V.-D. Păvăloaia and S.-C. Necula, "Artificial intelligence as a disruptive technology—A systematic literature review," *Electronics*, vol. 12, 1102, 2023. https://doi.org/10.3390/electronics12051102

[42] 42. S. Akram, P. Buono, and R. Lanzilotti, "Recruitment chatbot acceptance in a company: A mixed method study on human-centered technology acceptance model," *Pers. Ubiquit. Comput.*, vol. 28, pp. 961-984, 2024. https://doi.org/10.1007/s00779-024-01826-4

[43] 43. M. A. Ayanwale and M. Ndlovu, "Investigating factors of students' behavioral intentions to adopt chatbot technologies in higher education: Perspective from expanded diffusion theory of innovation," *Comput. Hum. Behav. Rep.*, vol. 14, 100396, 2024. https://doi.org/10.1016/j.chbr.2024.100396

[44] 44. H. Yildiz Durak and A. Onan, "Predicting the use of chatbot systems in education: A comparative approach using PLS-SEM and machine learning algorithms," *Curr. Psychol.*, vol. 43, pp. 23656-23674, 2024. https://doi.org/10.1007/s12144-024-06072-8

[45] 45. M. T. Myin and K. Watchravesringkan, "Investigating consumers' adoption of AI chatbots for apparel shopping," *J. Consum. Mark.*, vol. 41, pp. 314-327, 2024. https://doi.org/10.1108/jcm-03-2022-5234

[46] 46. A. Wang, Y. Zhou, H. Ma, X. Tang, S. Li, R. Pei, and M. Piao, "Preparing for aging: Understanding middle-aged user acceptance of AI chatbots through the technology acceptance model," *Digit. Health*, vol. 10, 2024. https://doi.org/10.1177/20552076241284903

[47] 47. J. De Andrés-Sánchez and J. Gené-Albesa, "Drivers and necessary conditions for chatbot acceptance in the insurance industry: Analysis of policyholders' and professionals' perspectives," *J. Organ. Comput. Electron. Commer.*, pp. 1-28, 2024. https://doi.org/10.1080/10919392.2024.2435118

[48] 48. M. Goli, A. K. Sahu, S. Bag, and P. Dhamija, "Users' acceptance of artificial intelligence-based chatbots: An empirical study," *Int. J. Technol. Hum. Interact.*, vol. 19, pp. 1-18, 2023. https://doi.org/10.4018/ijthi.318481

[49] 49. R. Chocarro, M. Cortiñas, and G. Marcos-Matás, "Teachers' attitudes towards chatbots in education: A technology acceptance model approach considering the effect of social language, bot proactiveness, and users' characteristics," *Educ. Stud.*, vol. 49, pp. 295-313, 2023. https://doi.org/10.1080/03055698.2020.1850426

[50] 50. R. De Cicco, S. Iacobucci, A. Aquino, F. R. Alparone, and R. Palumbo, "Understanding users' acceptance of chatbots: An extended TAM approach," in *Lecture Notes in Computer Science*, Cham, Switzerland: Springer, pp. 3-22, 2022. https://doi.org/10.1007/978-3-030-94890-0_1

[51] 51. R. Pillai and B. Sivathanu, "Adoption of AI-based chatbots for hospitality and tourism," *Int. J. Contemp. Hosp. Manag.*, vol. 32, pp. 3199-3226, 2020. https://doi.org/10.1108/ijchm-04-2020-0259

[52] 52. A. Rese, L. Ganster, and D. Baier, "Chatbots in retailers' customer communication: How to measure their acceptance?" *J. Retail. Consum. Serv.*, vol. 56, 102176, 2020. https://doi.org/10.1016/j.jretconser.2020.102176

[53] 53. H. Al-Safi, H. Ibrahim, and P. Steenson, "Vega: LLM-driven intelligent chatbot platform for Internet of Things control and development," *Sensors*, vol. 25, 3809, 2025. https://doi.org/10.3390/s25123809

[54] 54. A. Matharaarachchi et al., "Optimizing generative AI chatbots for net-zero emissions energy Internet-of-Things infrastructure," *Energies*, vol. 17, 1935, 2024. https://doi.org/10.3390/en17081935

[55] 55. S. Gallo, F. Paterno, and A. Malizia, "Conversational interfaces in IoT ecosystems: Where we are, what is still missing," in *Proc. 22nd Int. Conf. Mobile Ubiquitous Multimedia*, Vienna, Austria: ACM, pp. 279-293, 2023. https://doi.org/10.1145/3626705.3627775