# Extending the UTAUT Model for Artificial Intelligence Adoption: A Systematic Review of the Role of Perceived Intelligence and Trust

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## ABSTRACT

The Unified Theory of Acceptance and Use of Technology (UTAUT) has been widely used to explain technology adoption, although its suitability for complex, learning-oriented systems such as Artificial Intelligence (AI) is contested. This systematic literature review, following PRISMA 2020, reviews 71 empirical and review articles published from 2020 to 2025 that apply UTAUT or its extensions to AI adoption in a variety of domains such as education, healthcare, finance and banking, public administration, and retail and services. The review identifies three common limitations of traditional UTAUT in the AI context: little attention to the opaque “black box” decision-making of AI, little consideration of relational user AI interactions, and little consideration of ethical issues such as algorithmic bias and fairness. To address these shortcomings, it proposes an integrated framework where Perceived Intelligence captures users’ evaluation of an AI system’s learning ability, adaptability, and predictive accuracy. Perceived Intelligence is positioned as an intermediary between core UTAUT constructs, in particular Performance Expectancy and Effort Expectancy, and Behavioural Intention. Trust in AI is positioned as a critical antecedent of Perceived Intelligence and disaggregated into competence-based, transparency-based, and privacy-based dimensions. The review offers a theoretically grounded UTAUT extension for AI adoption, specifies hypothesized structural paths, and examines sectoral variation in ethical and competency concerns, providing a testable model for future structural equation modelling and practical guidance for trust-centred AI implementation.

**Keywords:** Artificial Intelligence, AI Adoption, UTAUT, Perceived Intelligence, Technology Acceptance Model

## INTRODUCTION

AI is reshaping the way organisations operate, govern and deliver services. National initiatives such as the European Union’s AI Act and Malaysia’s AI Roadmap are underway to embed AI into the public and private sectors to enhance efficiency, innovation and quality of service. AI is an omnipresent technology that has the capability to revolutionise industries as stated in (Dwivedi et al., 2021). But the potential can only be realized through continued and significant end user adoption, which continues to be a challenge.

UTAUT is one of the most influential models of technology acceptance that has been in use for over 20 years. It has been developed by Venkatesh et al. (2003), which combines eight previous models into four major constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. The constructs predict Behavioural Intention and Use Behaviour, which are moderated by gender, age, experience and voluntariness of use. Later Venkatesh et al. (2012) revised the model as UTAUT2, which incorporated price value, habit and hedonic motivation in consumer context. In a meta-analysis of 60 studies investigating UTAUT2, Tamilmani et al. (2021) informed that the model was found to be robust, and the most prevalent extension constructs in the body of AI-adoption studies were perceived risk, trust, and personal innovativeness.

Technology acceptance models today are applied in other systems than the organizational system, such as in nature-based services and sustainable tourism. The UTAUT model was used by Musa et al. (2016) to study the adoption of mobile marketing by SMEs, and by Jumaat et al. (2025) to investigate the adoption of AI marketing tools among SMEs as well as the adoption of sustainable technology among tour operators (Musa et al., 2025). These developments show how adaptable the model is, but they also highlight the necessity of tailoring it to situations. This is further demonstrated by the adoption of sustainable technology by tour operators (Musa et al., 2025) and AI marketing tools by SMEs (Jumaat et al., 2025). Additionally, studies on service perceptions, such as hikers' satisfaction with forest guides (Shafeeq et al., 2026), have shown that, like the human-AI interaction (2016), trust and perceived competence are predictors of pleasure and re-engagement.

However, UTAUT is not entirely adequate to capture the unique characteristics of AI systems even though it is useful. Conventional technologies are typically deterministic while AI systems, particularly machine learning technologies, are often opaque, probabilistic and adaptive. The users therefore do not only judge the usefulness and usability, but also the reliability of the independent judgment, the transparency of the reasoning and the fairness of the results. The accountability, transparency and misuses were increasingly influencing the users and organisations' reaction to the spread of generative and conversational AI systems (Dwivedi et al., 2023). These concerns are more than just the original UTAUT constructs.

This review will focus on the "intelligence gap" of existing technology-adoption theory. It traces the application of UTAUT in AI-adoption studies, examines its conceptual shortcomings, and presents an extension of UTAUT that is theoretically grounded. To that end, it seeks to: (1) summarize the use and extension of UTAUT in empirical studies of AI-adoption; (2) identify the theoretical and documented limitations of UTAUT in the context of intelligent systems; and (3) incorporate new constructs into UTAUT framework, notably Perceived Intelligence and Trust. The review is based on three research questions:

### Research Questions

1. **RQ1:** In what ways has the UTAUT model been utilised and extended in empirical research on AI adoption?
2. **RQ2:** What are the documented and theoretical constraints of UTAUT in explaining the adoption of AI systems?
3. **RQ3:** How might the incorporation of Perceived Intelligence and Trust address these constraints and enhance the model's explanatory power?

The article follows the outline below: In this second section, an overview of UTAUT and AI-adoption research is provided. The PRISMA guided review process is described in Section 3. The descriptive and thematic synthesis is included in section 4 along with the proposed framework, hypothesized paths, and sectoral variation. The finding of the study is interpreted in Section 5, theoretical and practical implications are presented in Section 6, limitations and future research are discussed in Section 7 and conclusions are presented in Section 8.

## LITERATURE REVIEW

### Theoretical Foundations of UTAUT

In this section, the theoretical background of UTAUT is reviewed. UTAUT is a model designed to predict users' attitude towards adopting technology and then using it. It integrates eight previous models into four constructs: Performance Expectancy (PE) which refers to the belief that use of a system will improve performance; Effort Expectancy (EE) which is perceived ease of use; Social Influence (SI) which is perceived pressure from important others; and Facilitating Conditions (FC) which is perceived organisational and technical support. These constructs are used to predict Behavioural Intention (BI) and Use Behaviour, while gender, age, experience and voluntariness are used as moderators (Venkatesh et al., 2003). Venkatesh et al. (2012) introduced hedonic motivation, price value, and habit to enhance the explanatory power of the UTAUT2 model for consumer-technology relationships.

**Extending UTAUT to Complex and Intelligent Technologies**

UTAUT has been expanded to explain the complexities of technology like the Internet of Things, big data analytics, and robotics, in which researchers have introduced additional constructs. Tamilmani et al. (2021) demonstrate that some of the most prevalent extensions of the UTAUT2 model are trust, personal innovativeness and perceived risk. This comes as a precedent for the use of AI. As evident in the literature review of AI adoption in education (Xue, 2025) and that of generative AI adoption among teaching academics (Nikolic et al., 2024), most studies involving the adoption of AI in education present non-core constructs such as trust, perceived risk, or anxiety in addition to the basic model.

The study's findings support the addition of contextual factors to the UTAUT. According to the findings of research by Musa et al. (2016) and Jumaat et al. (2025), trust and perceived compatibility boost UTAUT's explanatory power in the areas of SMEs' adoption of mobile marketing and AI marketing technologies, respectively. These studies suggest that as technologies are becoming more autonomous and intelligent, users are more likely to make decisions based on relational and trust-based judgments. This is in line with research from the service industry showing that consumer satisfaction is influenced by perceived competence and trust (Shafeeq et al., 2026).

The adaptivity, autonomy, opacity and personalisation are what set AI systems apart from previous technologies. They can learn from new data, function at a reduced level of human supervision and adapt outputs specifically for each user. However, decision logic is sometimes hard to understand and can create the “black box” problem (Shin, 2021). These features give rise to user perceptions and concerns not completely addressed by the original UTAUT constructs.

**Perceived Intelligence and Trust in AI**

This gap has led to new constructs appearing in the literature. Perceived Intelligence (PI) is the user's expectations for the system's learning, reasoning, problem solving and adaptation capabilities. Unlike traditional assessments, PI examines the attributes that users assign to AI that may be more related to cognition. Trust in AI is a willingness to be vulnerable due to positive expectations of the AI’s behavior or motivations (Kauttonen et al., 2025). It is usually multidimensional comprising competence-based trust, and integrity-based trust, along with benevolence. Explainability research enhances this connection: Shin (2021) shows that explainability and causability influence the trust in algorithms, the perceived performance of the algorithm, and the adoption of the algorithm. Also, at the core is algorithmic bias; its impact can be to reduce perceptions of fairness and trust (Pasipamire & Muroyiwa, 2024).

Since the involvement of Trust in AI is a key element of the proposed framework, the dimensions of this trust must be clearly specified. The three dimensions are identified based on the studies reviewed. Competence-based trust is the confidence in the reliability and accuracy of an AI system, achieved over time and typically quantified by modified ability benevolence integrity trust scales. The trust based on transparency relies on explainability and interpretability. It refers to the ability of users to understand the output of the system and how it works. It is measured using explainability and causability scales (Shin, 2021).

Privacy-based trust relates to the level of trust in the collection, storage, and utilization of personal information, and is typically quantified using information-privacy instruments customized for AI. Each of these dimensions can be prevalent in different applications; in diagnostics or financial applications, competence-based trust might be most important, in the high-stakes or regulated applications, transparency-based, privacy processing, and privacy-based. Identifying them allows future studies to operationalise what is Trust in AI as a multidimensional latent construct. Overall, the literature indicates a mutually reinforcing relationship between Perceived Intelligence and Trust. If users feel the system is intelligent, they tend to feel more competent in using the system and this can enhance user trust and intention to use. This paper extends that understanding by incorporating PI and Trust in an extended UTAUT framework for AI adoption.

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# REVIEW METHOD

The review was conducted in accordance with PRISMA 2020 guidelines (Page et al., 2020) to ensure a transparent, reproducible, and rigorous way of doing the review. It was created to support the conceptual variety found in research on the adoption of AI and to keep the reporting standards of systematic reviews.

## Search Strategy and Database Selection

Four databases were searched: Scopus, Web of Science, ScienceDirect, and the ACM Digital Library, selected for their coverage of information systems and technology-adoption research. The search string, adapted to each database, was: TITLE-ABS-KEY ("UTAUT" OR "unified theory of acceptance and use of technology") AND TITLE-ABS-KEY ("artificial intelligence" OR "AI" OR "machine learning" OR "intelligent system") AND TITLE-ABS-KEY ("adoption" OR "acceptance" OR "use"). Search was limited to peer-reviewed journal articles published between January 2020 and May 2025. An additional 18 records were identified through reference-list snowballing. The search returned 1,250 records; after duplicate removal, 968 records proceeded to title and abstract screening.

## Eligibility Criteria

Inclusion and exclusion criteria were established prior to the study, and the aim was to limit the chosen studies to those relevant to the aims of the review (Table 1). They included studies that utilized or expanded UTAUT in the context of the adoption and/or acceptance of AI, machine learning or other intelligent technologies that were published in an English-language, peer-reviewed journal article from January 2020 to May 2025. Studies were excluded if they did not focus on non-AI technologies, were purely conceptual or editorial, existed as a book, chapter, or conference paper, or were not available in full text, or were not central to UTAUT.

**Table 1. Inclusion and Exclusion Criteria**

| Criterion | Inclusion | Exclusion |
|---|---|---|
| Publication period | This publication will be updated on a quarterly basis from January 2020 to May 2025 to reflect recent conversations about AI-adoption in the years after 2020. | Studies published before 2020. |
| Subject of study | Empirical studies related to the adoption or acceptance of AI, machine learning or intelligent systems using UTAUT. | Research of non-AI systems or research without UTAUT as a core concept. |
| Language | English | Non-English |
| Publication type | Peer-reviewed journal articles | Books, conference proceedings, editorials, and non-peer-reviewed literature |
| Methodology | Empirical (quantitative, qualitative or mixed-methods) research in peer-reviewed journal articles. | Opinion pieces, editorials, white papers, and non-empirical research. |

## Study Selection

Figure 1 shows the flow diagram of the PRISMA 2020. The 968 unique records identified were removed if not related to AI-related technology or if they did not use UTAUT (790). The remaining 178 full-text articles were assessed against the eligibility criteria. Of these, 107 were excluded, primarily where they were not empirical or conceptual (n = 34), where they did not center on UTAUT in a central role (n = 22), or where they did not include UTAUT at a peripheral level (n = 19). There were 71 studies that were selected for qualitative synthesis in the five sectors (education, healthcare, finance and banking, public administration, and retail and services).

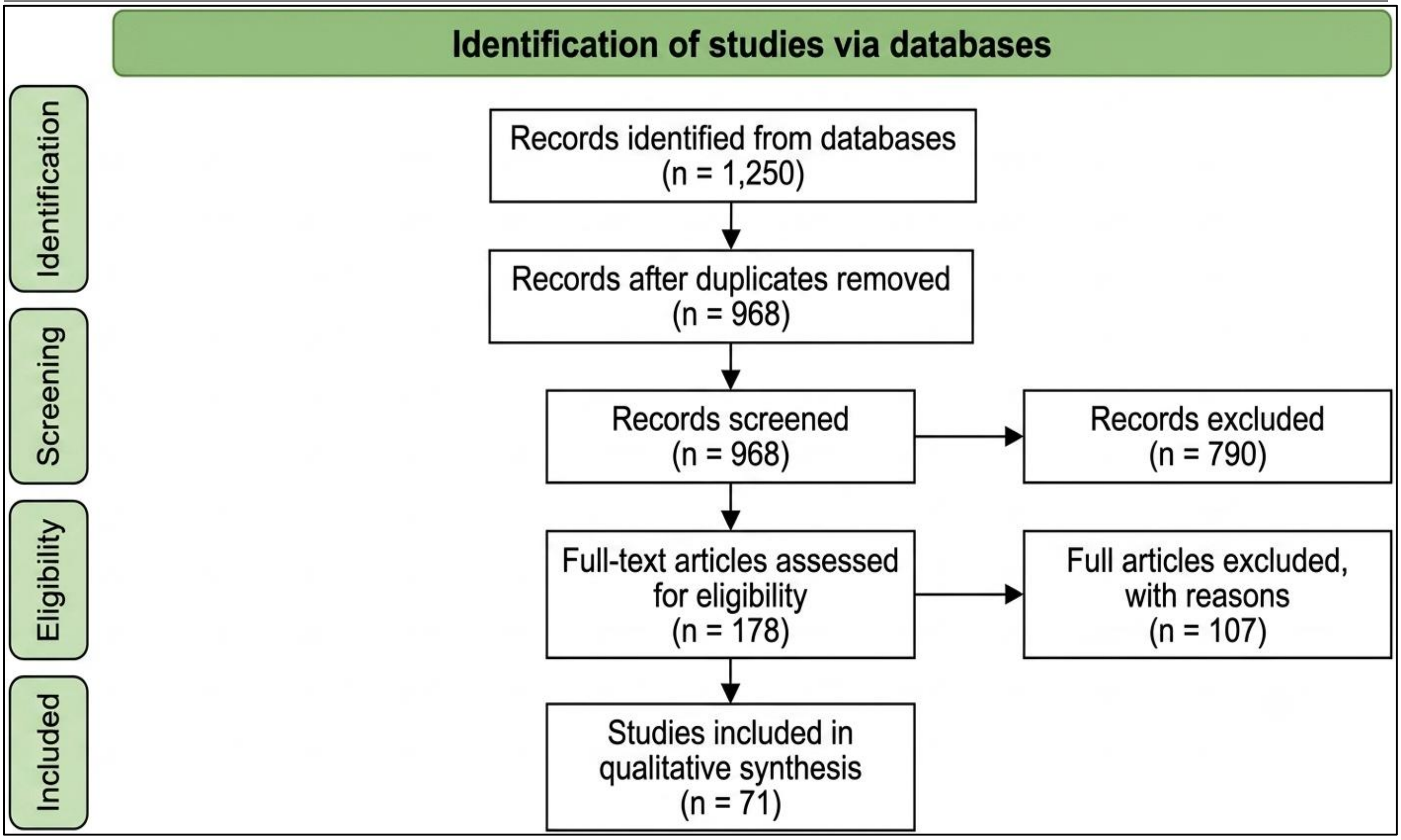


Figure 1. PRISMA 2020 flow diagram of the study identification, screening, eligibility, and inclusion process.

**Data Extraction and Thematic Synthesis**

A data extraction structured form was developed and pilot tested to ensure that the studies were coded in the same way. It collected bibliographic data, context, application of AI, research design, sample size, analysis method, UTAUT constructs, UTAUT extensions, and key findings regarding AI-related barriers and facilitators. Data from the various studies were amalgamated on a master spreadsheet for comparison across studies.

Then a structured thematic analysis was conducted. Findings and discussion paragraphs were coded to look for common patterns and themes, including those related to extensions to UTAUT, the role of trust as a mediator, and opacity as a barrier. Themes were developed by continually comparing with the data to match the three research questions. Thematic synthesis is used along with descriptive summaries of construct usage across the corpus in section 4.

## RESULTS AND SYNTHESIS

The 71 studies in the compilation reveal an expanding and varied Research literature on AI-adoption in education, healthcare, finance, public administration, and retail. Figure 2 presents the annual distribution of included studies; Figure 3 provides a summary of the sectoral distribution of included studies and Figure 4 outlines the proposed research framework for organising the synthesis of the included studies. There was a significant boost in research output following the mainstream adoption of generative AI from 2022 and onwards, and the domains with the highest number of papers were education (n = 22) and healthcare (n = 17).

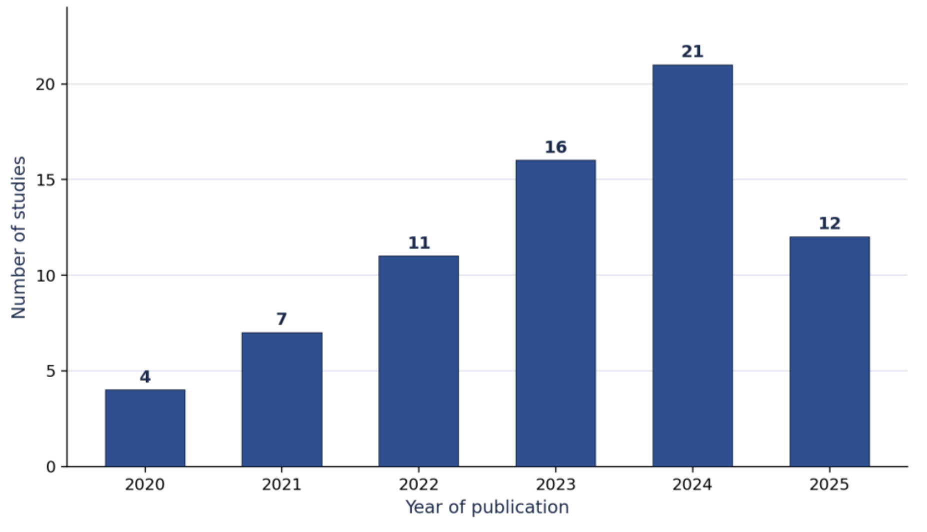


Figure 2. Distribution of included studies by publication year (2020–2025, n = 71)

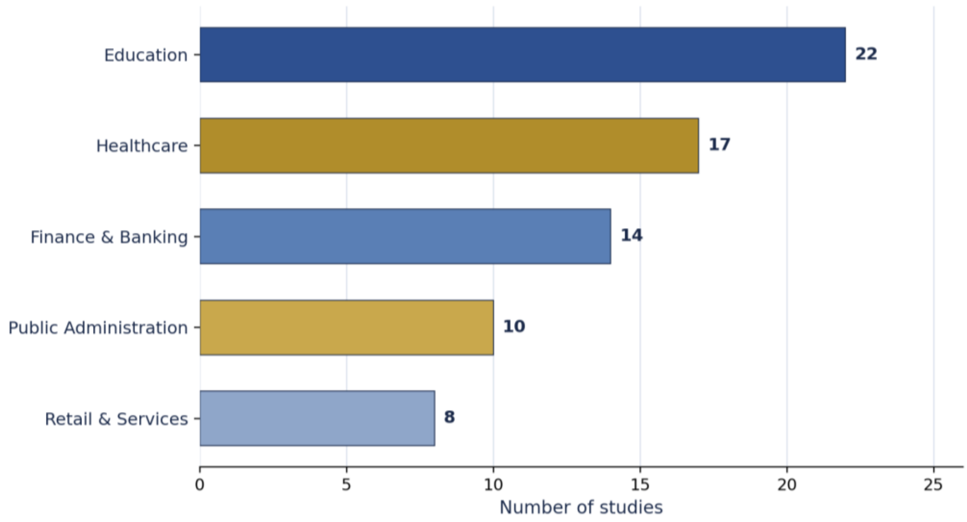


Figure 3. Distribution of included studies by application sector (n = 71).

**RQ1: Application and Extension of UTAUT in AI-Adoption Research**

According to the assessment, UTAUT is often insufficient to be employed in its conventional form, even though it provides a useful basis for AI-adoption studies in the context of RQ1. More than 80% of the evaluated studies added one or more extra characteristics to the original model, which is in accordance with UTAUT2 literature (Tamilmani et al., 2021), and the most common constructs added were trust, perceived risk, anxiety and perceived transparency. Numerous industries exhibit this tendency. The expansion of use, trust, and perceived danger are similar areas of AI extensions in education (Xue, 2025; Nikolic et al., 2024). The main UTAUT parameters do not account for a substantial amount of the variation in behavioral intention, according to research on the application of generative AI in businesses (Kim et al., 2024).

Similar studies on the acceptance of technology are equivalent to this. In evaluating a scale of acceptance for AI marketing tools, Jumaat et al. (2025) concluded that the model should incorporate trust and perceived intelligence for an appropriate-fit model. Likewise, Musa et al. (2025) found additional structures in addition to the standard TAM and UTAUT were needed to explain the adoption of sustainable technology in tourism. The results reported here underline the argument for enhancing the models of acceptance for intelligent, autonomous, and ethically important technology.

**RQ2: Documented Limitations of UTAUT in AI Contexts**

This resulted from a thematic analysis of the findings and discussion sections of the reviewed studies, where three common problems with the conventional UTAUT system emerged with respect to RQ2.A thematic analysis of the findings and discussion section of the reviewed studies came up with three recurring problems of the conventional UTAUT system in relation to RQ2.

**a) The Black Box Problem.** UTAUT's construct of Performance Expectancy is about the outcomes of technology use but not about understanding why an AI system made its decision. When results are positive, this transparency can lead to reduced acceptance and trust. Explainability and causability are independent factors that led to trust and perceived performance, which is not captured by the base UTAUT model as shown by Shin (2021).

**b) Neglect of the Relational Dynamic.** In general, UTAUT sees technology as a tool. On the other hand, human users frequently anthropomorphize AI to varied degrees and assign quasi-sociality to it. Regardless of an AI system's effectiveness, adoption is anticipated to be influenced by trust in high-stakes contexts like healthcare, where the results of the system's use are crucial (Kauttonen et al., 2025). This relationship indicates that, although not quantified in UTAUT, the adoption choice is heavily influenced by an AI system's perceived intelligence.

**c) Insufficient Attention to Ethical Considerations.** UTAUT may not always consider the problematic concerns of algorithmic fairness, accountability, and data privacy that commonly surface in the literature on AI adoption. Users' reluctance to use a system they perceive to be prejudiced or unethical cannot be explained by Effort Expectancy and Social Influence as originally defined (Pasipamire & Muroyiwa, 2024).

**RQ3: A Proposed Conceptual Framework**

At this point, the design activity will be followed by a proposed conceptual design framework. In RQ3, the findings from these are synthesized into a conceptual framework with Perceived Intelligence as a mediator between core UTAUT constructs and Behavioural Intention (Figure 4). If an AI system is easy to use and produces correct and useful outputs, users are more likely to perceive the system as intelligent. The next factor, Perceived Intelligence, affects Behavioural Intention. Perceived Intelligence is outlined as a crucial antecedent of trust in AI: Users only trust and attribute intelligence to a system when they believe it has competence, integrity, and transparency. Social Influence and Facilitating Conditions are kept as direct predictors of Behavioural Intention. The framework is designed to solve the black box problem (RQ2.1), relationships (RQ2.2) and ethical issues (RQ2.3).

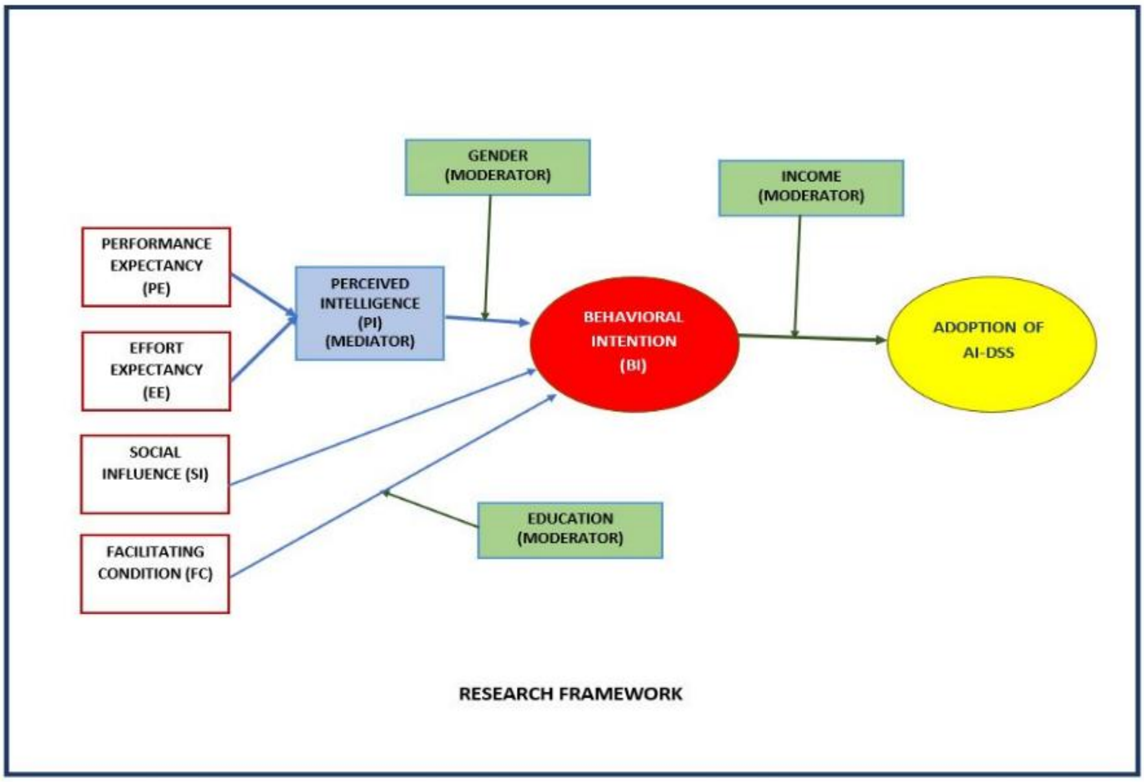


Figure 4. Proposed research framework for AI adoption, in which Perceived Intelligence mediates the relationship between core UTAUT constructs and Behavioural Intention.

**Table 2. Synthesis of Key AI-Specific Constructs from Reviewed Literature**

| Construct | Definition | Relevance to AI Adoption |
| --- | --- | --- |
| Perceived Intelligence | User's subjective view of the capacity of an AI system to learn, reason, adapt, and solve problems. | Tackles the relationship and how to see AI as a competent agent, not just a tool. |
| Trust in AI | User's willingness to be vulnerable to the actions of an AI system, depending on user expectations of competence, integrity and benevolence. | Resolves the black box problem and ethical issues; one of the basic requirements for the acceptance of autonomous decisions. |
| Perceived Transparency / Explainability | How easy or difficult the user finds it to understand how an AI system made their decision | Solves the black-box and opacity problem directly, which relates to both trust and perceived intelligence (Shin, 2021). |
| Algorithmic Bias / Fairness | User concerns about the systematic unfairness or discrimination of an AI system | Reflects an important ethical aspect that negatively affects Social Influence and Performance Expectancy (Pasipamire & Muroyiwa, 2024). |

### Hypothesized Structural Paths for Future Model Testing

Table 3 provides the specific hypothesized paths and their directions, and the rationale for each path in a form that can be directly translated to a structural equation model for future researchers to operationalise the framework presented in Figure 2.

**Table 3. Hypothesized Paths in the Proposed Framework**

| No | Relationship | Direction | Theoretical Rationale |
| --- | --- | --- | --- |
| H1 | Performance Expectancy → Perceived Intelligence | Positive (+) | Users gain an impression of intelligence from the usefulness and accuracy of the system's performance. |
| H2 | Effort Expectancy → Perceived Intelligence | Positive (+) | Ease of use influences users attributions of adaptive, intelligent behaviour. |
| H3 | Trust in AI → Perceived Intelligence | Positive (+) | U users to recognise and credit a system's intelligence, as they must also have trust in the AI, which can be competence, transparency, and privacy based. |
| H4 | Perceived Intelligence → Behavioral Intention | Positive (+) | The higher the perceived intelligence is, the more willing user are to use and keep using the system. |
| H5 | Social Influence → Behavioral Intention | Positive (+) | Retained as a direct predictor as outlined in the original UTAUT specification. |
| H6 | Facilitating Conditions → Behavioral Intention | Positive (+) | Retained as a direct predictor as outlined in the original UTAUT specification. |
| H7 | Trust in AI → Behavioral Intention (indirect, via Perceived Intelligence) | Positive (+), mediated | Perceived Intelligence and should be tested directly and indirectly from Trust to Behavioral Intention. |

These pathways are not universal and do not have to be equally strong in all contexts. The dimensions of trust that are salient in each domain, and the importance of each demonstrated competence will vary by sector, and should be discussed and moderated accordingly, particularly for H3 and H4.

### Sectoral Variation in the Proposed Framework

The proposed framework is presented as a single nomological structure, however, as revealed by the 71 reviewed studies, the constructs of the framework do not have equal weight across the five application sectors covered in this review. Table 4 presents, by sector, the trust dimension that is most highlighted in the literature and the points in the model where ethical concerns and system competency are most critical to adoption.

**Table 4. Sectoral Variation in Trust Dimensions, Ethical Salience, and Competency Salience**

| Sector | Dominant Trust Dimension | Where Ethical Concerns Matter Most | Where System Competency Matters Most |
|---|---|---|---|
| Education | Transparency-based trust | Fairness in automated grading, feedback, and admissions decisions | Perceived accuracy and adaptivity of personalised learning recommendations |
| Healthcare | Competence-based and privacy-based trust | Life-critical decisions, diagnostic bias, and protection of sensitive patient data | Reliability and accuracy of diagnostic or clinical decision-support outputs |
| Finance and Banking | Privacy-based and integrity-based trust | Discriminatory credit-scoring or lending decisions and data security | Predictive accuracy of risk-assessment and fraud-detection models |
| Public Administration | Trust based on transparency and integrity in decision making | Algorithmic accountability and fairness in resource allocation or eligibility decisions | Consistency and reliability of automated decision systems |
| Retail and Services | Competence-based trust | Data-driven personalisation and consumer-privacy concerns | Perceived usefulness and accuracy of recommendation and personalisation systems |

Two patterns emerge. Ethical issues are most relevant on the path Trust-to-Perceived-Intelligence (H3), particularly in domains where AI-driven decisions impact life outcomes, financial status, and public entitlements, such as healthcare, finance and banking, and public administration. Here, the failure to act fairly and to protect data could prevent the development of Trust before the development of Perceived Intelligence and Behavioural Intention. Second, in sectors in which adoption is primarily task performance-based, i.e., education, retail and services, system competency is most salient on the Performance-Expectancy-to-Perceived-Intelligence path (H1). Future studies of the framework should thus be undertaken as a multi-group study, where the path coefficients of the framework may differ across sectors, especially H1, H3, and H4.

## DISCUSSION

The results indicate that UTAUT is useful but needs conscious extension in the field of AI. Perceived Intelligence and Trust explain the user's perception of intelligence based on usefulness and ease of use, and their confidence in the dependability of the system. This moves UTAUT from an instrumental approach to technology and emphasizes on the cognitive and relationship processes associated with AI adoption. The use of AI technology also seems to be a prerequisite for Perceived Intelligence.

This focus on trust-building is consistent with wider service research. Shafeeq et al. (2026) found that trust in a guide’s competence and benevolence strongly predicted positive service evaluations. Similarly, the proposed role of Trust in AI as an antecedent of Perceived Intelligence suggests that relational trust can shape both human-to-human and human-to-AI service interactions.

The framework also contributes to the understanding of conflicting results that have been reported in previous research. However, the relationship between Performance Expectancy and adoption intention can be different since trust and perceived intelligence affect the understanding of the usefulness of demonstrated features. In low trust environments, performance might not translate to adoption as users are not convinced of the capabilities of the system. In the context of AI adoption, three factors - exhibiting performance, demonstrating intelligence, and building trust - are most useful. This interpretation leads to the following theoretical and practical implications.

# THEORETICAL AND PRACTICAL IMPLICATIONS

### Theoretical Implications

This is the first review to offer a cognitive mediator, Perceived Intelligence, and a relational antecedent, Trust, to the UTAUT nomological network. It responds to requests for theoretically grounded expansions of the UTAUT model that incorporate constructs specific to the context rather than ad hoc (Tamilmani et al., 2021). The emergent construct is concise, testable and suitable for structural equation modelling.

The framework also adds to the development of the technology-acceptance theory for various non-organisational application scenarios. In this review the same approach was adopted as Musa et al. (2025) who showed that the use of context-specific constructs can improve baseline models in the tourism sector. This review extended UTAUT by integrating Perceived Intelligence and Trust in various AI fields such as education, health care, public administration, and retail services.

### Practical Implications

The study results indicate that the design, installation, and interaction of AI interfaces should convey professionalism and reliability to the practitioners and managers. Trust and privacy concerns are the determinants of purchase intention for apparel retail with AI-powered chatbots, the Malaysian context (Taib et al., 2025). Transparency and explainability need to be seen as not only compliance, but also infrastructure for adoption for policymakers.

# LIMITATIONS AND FUTURE RESEARCH

There are some limitations in this review. Firstly, only publications written in English and four databases Second, the proposed conceptual framework, while grounded in thematic synthesis of the reviewed literature, has not yet been empirically tested through structural equation modelling; this represents an important direction for future research. Third, the categorisation of studies by sector and year, while informative for mapping the field, necessarily simplifies studies that span multiple sectors or AI applications.

Future research should prioritise operationalising and empirically testing the proposed Perceived Intelligence – Trust – UTAUT framework across diverse cultural and organisational contexts, including public-sector settings where algorithmic accountability and trust-building. Researchers should confirm the multidimensionality of the construct Trust in AI and estimate the paths in Table 3, as well as test the sectoral patterns of Table 4 using multi-group structural equation modelling. Longitudinal designs would also help answer the question of whether trust and perceived intelligence will remain constant or change over the long term when using AI.

# CONCLUSION

This systematic literature review has critically analyzed the use of the UTAUT model in AI-adoption research and identified important theoretical gaps associated with AI's opacity, relational nature, and ethical aspects. To address these gaps, the review contributes to technology-acceptance literature by proposing a new conceptual framework, in which Perceived Intelligence is an important mediator and Trust is a critical antecedent. The framework provides a more sophisticated view for understanding the psychological processes underlying AI acceptance and lays the groundwork for future empirical studies. Future studies should focus on operationalising and quantitatively testing this extended model through structural equation modelling across diverse organisational and cultural contexts to establish its predictive validity.

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# REFERENCES


1. Almarwani, A. M. (2026). Adoption of AI in nursing education - A systematic review of factors influencing student intentions. Nurse Education in Practice.
2. Burton, J. W., Stein, M. K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. Journal of Behavioral Decision Making, 33(2), 220–239. https://doi.org/10.1002/bdm.2155
3. Desouza, K. C., & Jacob, B. (2017). Big data in the public sector: Lessons for practitioners and scholars. Administration & Society, 49(7), 1043–1064. https://doi.org/10.1177/0095399714555751
4. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
5. Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., … Wright, R. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642
6. Grimmelikhuijsen, S. (2022). Explaining why the computer says no: Algorithmic transparency affects the perceived trustworthiness of automated decision-making. Public Administration Review, 83(2), 241–262. https://doi.org/10.1111/puar.13483
7. Janowski, T. (2016). Implementing sustainable development goals with digital government–aspiration-capacity gap. Government Information Quarterly, 33(4), 603–613. https://doi.org/10.1016/j.giq.2016.12.001
8. Jumaat, E. J., Mat Sania, A., & Mohamad, N. (2025). Adoption of AI marketing tools among SMEs: Insights from technology scale validation in Malaysia. Journal of Technology Management and Technopreneurship (JTMT), *13*(3).
9. Kauttonen, J., Rousi, R., & Alamäki, A. (2025). Trust and acceptance challenges in the adoption of AI applications in health care: Quantitative survey analysis. Journal of Medical Internet Research, 27, Article e65567. https://doi.org/10.2196/65567
10. Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of generative AI system adoption and usage behaviour in Korean companies: Applying the UTAUT model. Behavioral Sciences, 14(11), 1035. https://doi.org/10.3390/bs14111035
11. Klievink, B., Romijn, B. J., & Cunningham, S. (2018). The role of public sector entrepreneurship in achieving public sector innovation: A systematic literature review. Public Management Review, *20*(8), 1230–1258.
12. Lean, O. K., Ramayah, T., & Zainal, S. R. M. (2019). E-government implementation in Malaysia: A comprehensive review. International Journal of Public Administration, *42*(10), 802–815.
13. Malaysian Administrative Modernisation and Management Planning Unit (MAMPU). (2021). Digital Government Transformation Framework. Putrajaya, Malaysia: Prime Minister's Department.
14. Ministry of Science, Technology and Innovation (MOSTI). (2021). National Artificial Intelligence Roadmap 2021-2025. Putrajaya, Malaysia.
15. Molnár, L., Nagy, S., & Hajdú, N. (2025). Factors influencing the intention to use robo-advisors: A Hungarian perspective. Acta Polytechnica Hungarica, *22*(7), 263–283.
16. Muhammad Shafeeq, M. S., Thinaraj, B., Zawawi, A. A., & Isai Amutan, K. (2026). Voices from the trails: Hikers' perceptions of Malaysian forest guides. Malaysian Journal of Social Sciences and Humanities (MJSSH), *11*(1), Article e003763. https://doi.org/10.47405/mjssh.v11i1.3763
17. Musa, H., Abdullah, A. R., Othman, M. N., Rashid, N., & Azmi, F. R. (2025). Rethinking the technology acceptance model: A structural analysis of sustainable technology adoption in Malaysian tourism. International Journal of Research and Innovation in Social Science (IJRISS), *9*(1), 6125–6139.
18. Musa, H., Ab. Rahman, A., & Mohd Shariff, M. N. (2016). Adoption of mobile marketing in SMEs: Extending the UTAUT model. European Proceedings of Social and Behavioural Sciences, *15*, 267–276. https://doi.org/10.15405/epsbs.2016.05.02.24

19. Musa, H., Khadar, N. Z. A., & Azmi, F. R. (2026). Enhancing tourist awareness and preferences through eBECA: A digital empowerment approach. International Journal of Research and Innovation in Social Science (IJRISS), *10*(1), 772–783.
20. Nikolic, S., Wentworth, I., Sheridan, L., Moss, S., Duursma, E., Jones, R. A., … Middleton, R. (2024). A systematic literature review of attitudes, intentions and behaviours of teaching academics pertaining to AI and generative AI (GenAI) in higher education: An analysis of GenAI adoption using the UTAUT framework. Australasian Journal of Educational Technology, *40*(6), 56–75. https://doi.org/10.14742/ajet.9643
21. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, Article n71. https://doi.org/10.1136/bmj.n71
22. Pasipamire, N., & Muroyiwa, A. (2024). Navigating algorithm bias in AI: Ensuring fairness and trust in Africa. Frontiers in Research Metrics and Analytics, 9, Article 1486600. https://doi.org/10.3389/frma.2024.1486600
23. Rahim, F. A., Ahmad, K. Z., & Jambari, D. I. (2022). Digital transformation in Malaysian public sector: A systematic review of challenges and opportunities. Journal of Government and Development, *14*(1), 45–62.
24. Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. International Journal of Human-Computer Studies, 146, Article 102551. https://doi.org/10.1016/j.ijhcs.2020.102551
25. Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. Government Information Quarterly, *36*(2), 368–383. https://doi.org/10.1016/j.giq.2018.09.008
26. Taib, M. S. M., Musa, H., Ghani, M. G. A., Abdullah, A. N. H., & Taib, M. S. M. (2025). Trust and privacy concern in AI-powered chatbot: A conceptual framework for customer purchase intention in Malaysia apparel SMEs. International Journal of Research and Innovation in Social Science (IJRISS), *9*(28), 229–238.
27. Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2021). Consumer acceptance and use of information technology: A meta-analytic evaluation of UTAUT2. Information Systems Frontiers, 23(4), 987–1005. https://doi.org/10.1007/s10796-020-10007-6
28. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540
29. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178. https://doi.org/10.2307/41410412
30. Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector—applications and challenges. International Journal of Public Administration, 42(7), 596–615. https://doi.org/10.1080/01900692.2018.1498103
31. Xue, L. (2025). A systematic review of UTAUT and UTAUT2 for AI adoption in education. International Journal of Human-Computer Interaction, 42(8). https://doi.org/10.1080/10447318.2025.2552867
32. Zuiderwijk, A., Chen, Y. C., & Salem, F. (2021). Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda. Government Information Quarterly, 38(3), Article 101577. https://doi.org/10.1016/j.giq.2021.101577