# What factors contribute to the acceptance of artificial intelligence? A systematic review

Kelly, Sage; Kaye, Sherrie Anne; Oviedo-Trespalacios, Oscar

**DOI**
10.1016/j.tele.2022.101925

**Publication date**
2023

**Document Version**
Final published version

**Published in**
Telematics and Informatics

Telematics and Informatics 77 (2023) 101925

Contents lists available at ScienceDirect

Telematics and Informatics

journal homepage: www.elsevier.com/locate/tele

# What factors contribute to the acceptance of artificial intelligence? A systematic review

Sage Kelly [a], Sherrie-Anne Kaye [a], Oscar Oviedo-Trespalacios [b,*]

[a] Queensland University of Technology (QUT), Centre for Accident Research and Road Safety – Queensland (CARRS-Q), School of Psychology & Counselling, Kelvin Grove, Queensland 4059, Australia

[b] Delft University of Technology, Faculty of Technology, Policy and Management, Section of Safety and Security Science, Jaffalaan 5, 2628 BX Delft, The Netherlands

A R T I C L E  I N F O

*Keywords:*
AI
User acceptance
Psychosocial models
Human factors
Social robotics
Machine learning

A B S T R A C T

Artificial Intelligence (AI) agents are predicted to infiltrate most industries within the next decade, creating a personal, industrial, and social shift towards the new technology. As a result, there has been a surge of interest and research towards user acceptance of AI technology in recent years. However, the existing research appears dispersed and lacks systematic synthesis, limiting our understanding of user acceptance of AI technologies. To address this gap in the literature, we conducted a systematic review following the Preferred Reporting Items for Systematic Reviews and meta-Analysis guidelines using five databases: EBSCO host, Embase, Inspec (Engineering Village host), Scopus, and Web of Science. Papers were required to focus on both user acceptance and AI technology. Acceptance was defined as the behavioural intention or willingness to use, buy, or try a good or service. A total of 7912 articles were identified in the database search. Sixty articles were included in the review. Most studies ($n = 31$) did not define AI in their papers, and 38 studies did not define AI for their participants. The extended Technology Acceptance Model (TAM) was the most frequently used theory to assess user acceptance of AI technologies. Perceived usefulness, performance expectancy, attitudes, trust, and effort expectancy significantly and positively predicted behavioural intention, willingness, and use behaviour of AI across multiple industries. However, in some cultural scenarios, it appears that the need for human contact cannot be replicated or replaced by AI, no matter the perceived usefulness or perceived ease of use. Given that most of the methodological approaches present in the literature have relied on self-reported data, further research using naturalistic methods is needed to validate the theoretical model/s that best predict the adoption of AI technologies.

## 1. Introduction

### 1.1. Background

Artificial Intelligence (AI) is the defining technology of the next decade due to its ability to increase human capability at a low-cost (Liu, 2017; Mott et al., 2004; Schwab, 2017). It is predicted that AI will saturate most industries, with an estimated US $15.7 trillion

* Corresponding author.
*E-mail addresses:* sage.kelly@hdr.qut.edu.au (S. Kelly), s1.kaye@qut.edu.au (S.-A. Kaye), O.OviedoTrespalacios@tudelft.nl (O. Oviedo-Trespalacios).

https://doi.org/10.1016/j.tele.2022.101925
Received 27 March 2022; Received in revised form 10 November 2022; Accepted 9 December 2022
Available online 14 December 2022

contribution to the global economy by 2030 (Murphy et al., 2021). The assistance of this technology may enhance humans' everyday lives through the advancement of technology in health care (e.g., early detection; Becker, 2018), customer service (e.g., personalised assistants; Murphy et al., 2021), education (e.g., individualised teaching aids; Kashive et al., 2021), and transportation (e.g., automated vehicles; Kaye et al., 2020), to name a few. To facilitate the broad adoption of this technology, research is required to understand the factors contributing to user acceptance of AI.

In response to the technological advancement of AI, there has been a recent increase in studies that have investigated the antecedents of AI acceptance and created, or extended, various acceptance frameworks. Despite this, there is a lack of synthesis of the current literature surrounding user acceptance of AI. User acceptance can be defined as the behavioural intention or willingness to use, buy, or try a good or service. As AI may benefit society through advances in industries such as transportation (Xia et al., 2020), mental health care (Doraiswamy et al., 2019), and education (Ramu et al., 2022), it is essential to understand what factors facilitate the acceptance and adoption of this technology (Schmidt et al., 2021; Sohn and Kwon, 2020a; Taddeo and Floridi, 2018; Turner et al., 2010). To date, no paper has synthesised the literature to provide a comprehensive overview of the frameworks and factors influencing user acceptance of AI. Understanding previous research will also allow us to systematically assess the similarities, differences, and gaps in acceptance research across the multiple industries, countries, and frameworks that the extant papers highlight.

### 1.2. Definition of AI

There is an issue in defining AI at an academic, government, and community level. The definition of AI is highly contested, and little consensus has been drawn across the range of fields in which the terminology is used. For instance, many "smart" technologies (e.g., smart fridges, smartphones, smart speakers) are referred to as AI in the same vein as autonomous cars (Ghorayeb et al., 2021; Park et al., 2021). The lack of an appropriate definition prevents us from fully understanding if people accept real AI or their idea of AI.

AI acceptance depends on the context in which the agent is being utilised (Barkhuus and Dey, 2003; Luo et al., 2010; Sheng et al., 2008). Thus, the current paper aims to review and synthesise the factors influencing participants' intentions to use AI systems across industries and sectors. This research is essential and often results in recommendations for stakeholders that directly affect technology production. However, few researchers have comprehensively drawn on systematic research to understand the contributing factors of AI acceptance. Further, this systematic review will categorise the context of the AI being examined in each paper. Defining and categorising AI is vital in synthesising the available literature to understand user acceptance.

For this review, AI is defined as an 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 (Bringsjord, 2011; Dobrev, 2012; McLean and Osei-Frimpong, 2019; Omohundro, 2014). AI can be divided into Artificial General Intelligence (AGI), Artificial Narrow Intelligence (ANI), and Artificial Super Intelligence (ASI; see Fig. 1; Antonov, 2011; Gill, 2016). ANI includes modern AI systems, such as voice recognition software (e.g., Apple's Siri), which assists users via machine learning and cannot transfer knowledge across systems or tasks (McLean et al., 2021; Salmon et al., 2021). AGI is currently theoretical and will be able to achieve goals autonomously and transfer leanings within a wide range of scenarios (McLean et al., 2021; Mitchell, 2019). Such abilities will enable AGI agents to possess intelligence far beyond human capability and may lead to developments in complex issues, such as human health and global warming (Salmon et al., 2021). Finally, ASI involves agents that will function on a higher level of intelligence than capable by human beings. Cabrera-Sanchez et al. (2021) stated that ASI is the most accurate form of AI, as it will be capable of pioneering discoveries in general, scientific, academic, creative, and social fields, potentially leading to the redundancy of human beings.

### 1.3. User acceptance of AI

User acceptance of technology is fundamental to the successful uptake of devices (Davis, 1989). As AI can benefit many people, users must accept this technology to embrace it and use it adequately. Low acceptance may decrease user uptake of AI, resulting in the disuse of resources, an excess of AI devices, and a potential decline in technological innovation to the detriment of consumers (Kirlidog

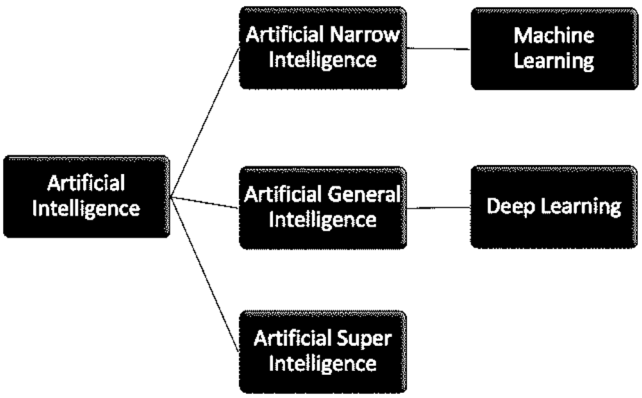


**Fig. 1.** Hierarchy of AI.

and Kaynak, 2013; Lee and See, 2004; Parasuraman and Riley, 1997). Acceptance is a predictive measure that encapsulates a personal choice, such as the knowing purchase of AI devices. Put another way, buying a technological device with the knowledge that it contains a form of AI. Alternatively, acceptance can be an involuntary action, such as using AI chatbots that may present as non-AI agents. For instance, an online banking AI chatbot may present itself as a customer service agent, invoking the customer's sense of talking with a human rather than an AI chatbot. Therefore, there are differing agency levels involved in user acceptance. Assessing user acceptance is fundamental for stakeholders to understand the variables required to maximise the technology uptake in various circumstances. There are several models which have been used to assess user acceptance of AI, including the Technology Acceptance Model (TAM; Davis, 1985, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), and more recently, the AI Device Use Acceptance model (AIDUA; Gursoy et al., 2019).

### *1.4. Technology acceptance model (TAM)*

The TAM (Davis, 1985, 1989) was adapted from the Theory of Reasoned Action (Fishbein et al., 1975) and postulated that external variables, such as the media and social references, inform humans' *perceived usefulness* (PU) and *perceived ease of use* (PEOU), which contribute to their intentions to use technology, ultimately driving their actual system usage (Davis, 1985, 1989). PU is the degree to which a user perceives the technology as useful to their everyday life (Davis, 1989). PU is often the strongest positive predictor of an individual's behavioural intention to use new technology (Davis, 1989; Rafique et al., 2020; Wu et al., 2011). Meanwhile, PEOU refers to a user's perception of how effortless a technological device would be to use (Davis, 1989). PEOU is reasoned to have a weaker influence on technology acceptance than PU as it is only relevant to the technical use of a device, which has become less important as users have acquired increasing familiarity with using technology in their daily lives (Davis, 1985, 1989; Lunney et al., 2016). Alternatively, some studies have demonstrated that PEOU is an insignificant predictor of behavioural intention (Liu et al., 2016; Mun et al., 2006; van Eeuwen, 2017). It may be that when the technology is frequently used (e.g., a mobile recommendation application; Liu et al., 2016), the importance of PEOU is reduced when appraising technology adoption. The TAM is also frequently extended with additional variables, such as trust and knowledge, to enhance its predictive power (Kashive et al., 2021; Lin and Xu, 2021).

#### *1.4.1. Trust*

Trust is the subjective attitude that allows individuals to make a vulnerable decision (Chang et al., 2017; Zerilli et al., 2022). Trust in technology allows users to believe that using a device will achieve the desired goal, for instance, asking Google Maps for directions to a restaurant and successfully arriving at the restaurant (Chang et al., 2017). Trust is a significant antecedent of use behaviour and has been adopted into technology acceptance models to predict behavioural intentions. For instance, Choung et al. (2022) extended the TAM and found that trust positively predicted PU. In another study, trust was the strongest predictor of behavioural intentions to use an AI for iris scanning, weakening the influence of PU on behavioural intention (Miltgen et al., 2013). As such, trust in AI and the technology provider is a driving factor in AI acceptance.

#### *1.4.2. Unified theory of acceptance and use of technology (UTAUT)*

The Unified Theory of Acceptance and Use of Technology (UTAUT) was formulated based on eight theoretical acceptance models, including the TAM (Venkatesh et al., 2003). The UTAUT suggests that performance expectancy, social influence, effort expectancy, and facilitating conditions predict behavioural intentions, which informs use behaviour (Venkatesh et al., 2003). Performance expectancy is the degree to which the user believes the device will help them achieve their task (similar to the construct of PU). Social influence can be defined as perceptions that significant others would approve or disapprove of the behaviour. Effort expectancy refers to the degree of ease associated with using the device (similar to the construct of PEOU). Facilitating conditions are the support available to use the technology. Further, the model also proposes that gender, age, voluntariness of use, and prior experience moderate the effects of these predictors on intentions and behaviour (Venkatesh et al., 2003). The predictors of the UTAUT have been found to explain approximately 60–70 % of the variance in behavioural intentions across cultures (Thomas et al., 2013; Venkatesh et al., 2003).

#### *1.4.3. AI device use acceptance model (AIDUA)*

While there is strong support for the superiority of the TAM in evaluating technology acceptance, the rapid advancement of AI devices has reduced the predictability of this model (Sohn and Kwon, 2020a). It is, therefore, necessary to consider theoretical models designed for the specific purpose of measuring the acceptance of AI to enhance the accuracy of our predictions. Gursoy et al. (2019) stated that traditional technology acceptance models (i.e., TAM and UTAUT) should only be utilised to study non-intelligent technology, as their predictors were irrelevant for AI usage. They developed the AI Device Use Acceptance model (AIDUA) to investigate user acceptance of AI technology (Gursoy et al., 2019). The AIDUA extends on previous acceptance models to explore user acceptance of AI agents by studying user experience in three stages (i.e., primary appraisal, secondary appraisal, and outcome stage). In the primary appraisal stage, Gursoy et al. (2019) propose that consumers assess the importance of using the AI device based on social influence, hedonic motivation, and anthropomorphism. Hedonic motivation is the perceived pleasure one would derive from using the AI device. Anthropomorphism refers to human qualities that the device may replicate (e.g., human appearance). Based on this appraisal, consumers will then deliberate the benefits and costs of the AI device based on its perceived performance expectancy and effort expectancy, resulting in developing emotion towards the AI (Gursoy et al., 2019). The previous appraisal process determines the outcome stage and results in the users' willingness to accept or object to the technology (Gursoy et al., 2019). Objection refers to the unwillingness to use the AI device in preference for human service. This two-prong outcome stage is dissimilar to traditional acceptance models and is helpful to researchers who do not view acceptance and rejection as oppositional constructs. For instance, a user may reject Amazon due to ethical reasoning, however, they demonstrate acceptance via the use of the website.

### 1.5. The present research

This paper presents the first comprehensive systematic synthesis of user acceptance of AI. This review will show the characteristics of the research investigating user acceptance of AI technologies and the critical factors reported to predict the acceptance of AI technologies across the different studies. This paper offers four contributions to the existing literature on AI acceptance. First, it provides a comprehensive review of the study characteristics of the extant research on user acceptance of AI. Second, this review summarises the current definitional usage of the term AI, which is beneficial to understanding the current state of AI in the literature. Third, this review contextualises the factors that predict AI acceptance across multiple industries, enabling stakeholders to gain a greater insight into the predictors of AI acceptance across different contexts. Finally, the paper synthesises the use and extension of acceptance theories in the literature and highlights which acceptance model/s and predictors are suitable for assessing user acceptance of AI.

A group of research questions were formulated to structure the review. Using research questions in a systematic review can help focus and organise the literature. Firstly, this paper sought to find relevant literature and synthesise the types of research designs and paradigms considered in the published literature studying user acceptance of AI technologies. This highlights the sophistication of the research conducted and the empirical limitations to be addressed in future work.

RQ1: What are the methodological characteristics of the previous research investigating user acceptance of AI?

i. What type of research design was used?

Given the wide range of AI technologies described in section 1.2, the following questions were formulated to understand the types of AI that have been considered in acceptance research. Arguably, different forms could have different levels of acceptance in the community. As such, it is essential to identify what AI types have been investigated.

RQ2. How is AI technology conceptualised in previous research?

i. How do the authors distinguish and operationalise AI technology?

ii. How do the authors distinguish and operationalise AI technology for the participants?

iii. What is the readiness of the technology?

iv. What are the industries/context?

Many theories have been used to study user acceptance of AI technology (see section 1.3). However, there is a lack of synthesis of the theories and their factors associated with the acceptance of AI technology. As such, the following questions were formulated:

RQ3: What factors are associated with the adoption of AI?

i. What theories are used?

ii. How are the theories modified?

## 2. Overview of research methodology

### 2.1. Search strategy and eligibility criteria

The search followed the Preferred Reporting Items for Systematic Reviews and meta-Analysis (PRISMA) guidelines (Liberati et al., 2009). The authors developed the search strategy, which was undertaken in September 2021. Five databases were searched: EBSCO host, Embase, Inspec (Engineering Village host), Scopus, and Web of Science (see Table 1 for the keywords). Search limits were only applied to Scopus (i.e., search within abstract, title, keywords). This limit was deemed appropriate as Scopus does not offer full texts.

### 2.2. Screening and selection

A total of 7,912 articles were identified, and 5,552 records remained after duplicates were removed (see Fig. 2 for the study selection process). These articles were then screened for inclusion via a title search based on pre-determined inclusion criteria. They were required to: (i) be written in English, (ii) focus on acceptance, as defined in the introduction, and (iii) include human participants. The first author undertook the title search. Following the title search, 858 articles remained. The remaining records were exported to Abstrackr, a collaborative web-based screening tool designed to review abstracts. Abstrackr has been successfully employed in similar systematic reviews (Giummarra et al., 2020; Wallace et al., 2012). Abstracts were screened for inclusion criteria identified above. Of the 858 abstracts reviewed, 89 were excluded, and 769 articles remained for full-text review. The first author screened the full-text

**Table 1**
Search Terms.

| | |
|---|---|
| Artificial Intelligence | "artificial intelligen*" OR "AI" OR "machine learning" OR "big learning" OR "deep learning" OR automation OR "cognitive computing" OR "neural networks" OR "intellig* computing" OR "natural language processing" |
| | AND |
| Acceptance | "technology accept*" OR "user accept*" OR "technology acceptance model" OR tam OR "Theory of Planned Behavio?r" OR "Unified Theory of Acceptance and Use of Technology" OR tpb OR utaut |

*Note.* Quotation marks were used around terms that consisted of two or more words to ensure that results were returned that included these phrases rather than articles that contained each word individually.

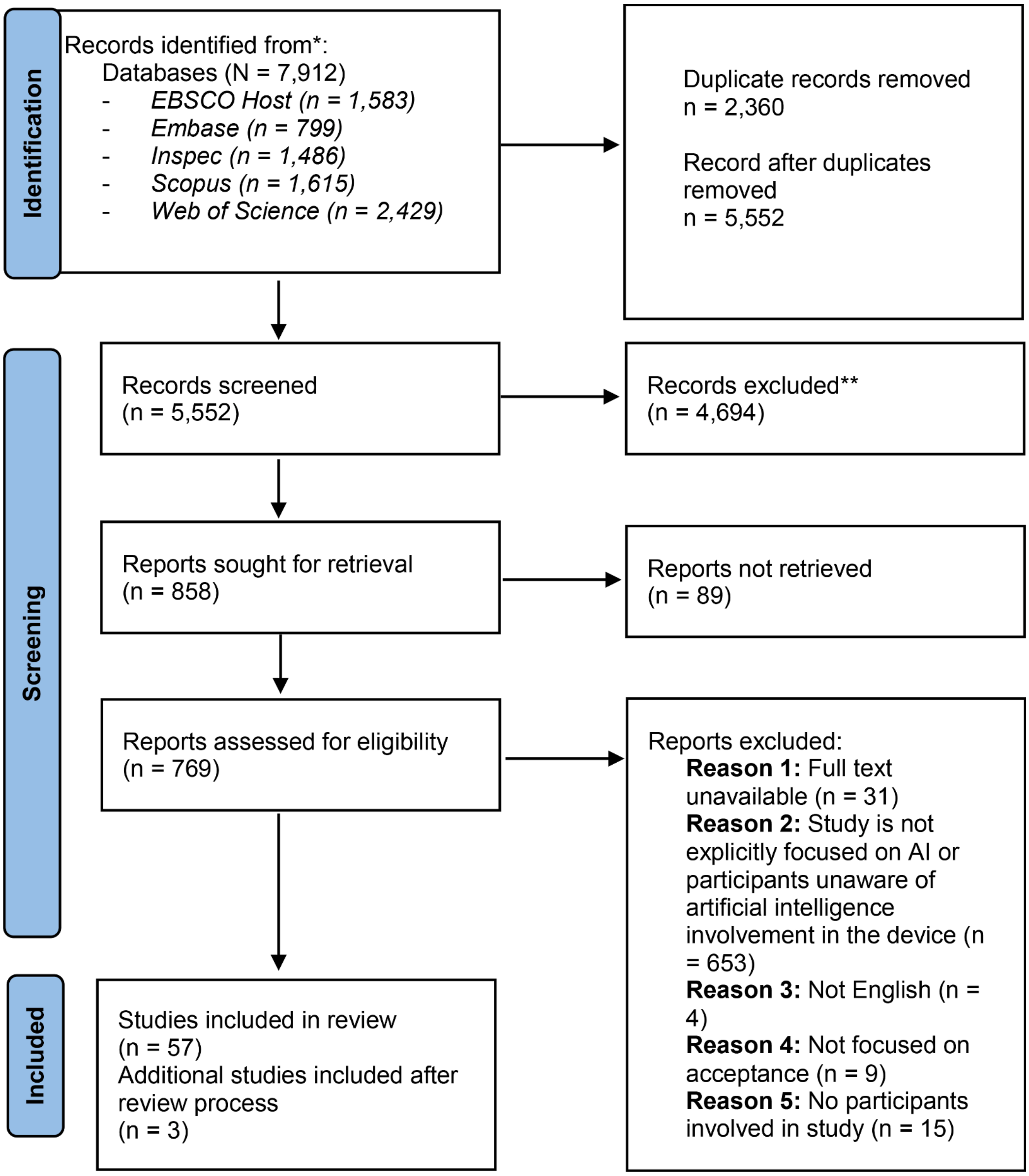


**Fig. 2.** Flow Diagram of Literature Search.

articles using the pre-determined checklist (see Table 2). The second and third authors were consulted to ensure that the full-text articles met the inclusion criteria.

Of the 769 articles, 713 were excluded as they did not meet the criteria. These articles were excluded as they: (i) were not available in full-text, (ii) were not explicitly focused on AI and/or the participants were unaware of AI, (iii) were not available in English, (iv) were not focused on acceptance, (v) no participants involved in the study. Four authors were contacted via email to verify if participants in their studies knew that the focus was on AI, as acceptance of other non-AI technology would negate the purpose of the review. Of the four authors contacted, two responded and confirmed that their articles did not refer to the technology in question as AI. The other two authors did not respond. As such, all four articles were excluded. Consequently, 56 articles remained after this review process.

Following Liberati et al. (2009), the references of the included papers and studies that cited these papers were also reviewed. This step revealed another relevant study (Floruss and Vahlpahl, 2020). The initial review was finalised on November 19, 2021, and a title search of any pertinent new papers was undertaken between September and November in Google Scholar. Three recent papers were identified (Ali and Freimann, 2021; Dieter, 2021; Memon and Memon, 2021). As such, data from 60 articles were extracted.

**Table 2**
Inclusion and Exclusion Criteria.

| | *Inclusion criteria* | *Exclusion criteria* |
|---|---|---|
| Publication type | Original research published in peer-reviewed publications and grey literature | Narrative reviews, letters, editorials, commentaries, unpublished manuscripts, meeting abstracts and consensus statements |
| Study design | Qualitative and qualitative studies | Reviews and meta-analyses |
| Case definition | Studies must clearly assess user acceptance of AI | Studies in which participants were not aware of AI involvement in the device they were being questioned about |
| Dependent variable | Intention, usage, acceptance, adoption, willingness | Other dependent variables |
| Publication period | Up to September 2021 (including in press) | Nil |
| Publication language | English | If an English translation is not available after contacting author or available using translation methods |

### 2.3. Data extraction

Data were extracted according to a pre-determined checklist. The checklist included: study aims, objectives, research question/s, the field of research, experiment design, the definition of AI, participant characteristics (gender and age), the definition provided to participants, measures of acceptance, analysis, and results (see Table 2). The first author extracted the data for the systematic analysis, which the second and third authors reviewed.

## 3. Results

### 3.1. RQ1: what are the study characteristics?

#### 3.1.1. Study characteristics

All articles included in the review were written in English and published between 2019 and 2022. In total, there were 58,179 participants, 48.4 % women,[1] aged 10–60 years and older. Most studies ($n = 50$) used online surveys and questionnaires (i.e., self-reports). Seven papers were qualitative studies comprising structured and semi-structured interviews. One study used secondary data from surveys. The remaining two studies were mixed-method studies. In terms of the sample, 30 studies recruited participants from specific groups (e.g., health care professionals, managers who would potentially use AI), 19 studies recruited participants from the general population, seven studies comprised of university students, and four studies recruited participants via Amazon Mechanical Turk. Behavioural intention/intention to use/intentions to adopt was the most popular measure of acceptance (listed 26 times), followed by actual use behaviour (7), willingness to use (4), and actual system use (2). Other acceptance measures, such as technology acceptance and actual purchase, were all listed once.

Concerning the qualitative studies, the average number of participants was 22, and participants ranged from 20 to 61 years of age. Both Lin and Xu (2021) and Xu and Wang (2019) devised their questions around the TAM constructs (i.e., PU and PEOU). Meanwhile, Lin and Xu (2021) and Ochmann and Laumer (2020) both utilised attitudes as a predictor of intention to use. Specifically, attitudes directly influenced behavioural intentions, while the other independent variables indirectly influenced intention via attitudes. Table 9 provides further information on each study's characteristics.

### 3.2. RQ2: How is AI technology conceptualised in previous research?

#### 3.2.1. AI definition used in the acceptance research

The operationalisation of AI has two dimensions: (i) the author's definition in the paper and (ii) the definition given to the study's participants. Although all papers focused on AI (as per the inclusion criteria), over half ($n = 31$) of the studies did not define AI in their papers. Fortuna and Gorbaniuk (2022) conducted an online study that surveyed IT professionals' and laypeople's interpretations of the concept of AI. They found that AI conceptualisations differed among professionals and between professionals and laypeople (Fortuna and Gorbaniuk, 2022). Lack of consistency in individuals' ideation of AI is a limitation when researching intentions of AI, as cognitive evaluations impact attitudes and intentions towards using a particular technology (Savela et al., 2021).

Three papers divided AI into levels (Cabrera-Sanchez et al., 2021; Huang et al., 2019; Lee et al., 2021). For instance, both Huang et al. (2019) and Lee et al. (2021) use the term 'weak AI' to define narrow AI. Huang et al. (2019) stated that weak AI could solve specific problems, such as evaluating what song performs well on a music website. Lee et al. (2021) postulate that AI is split into 'strong' and 'weak' AI, with weak AI currently existing and replacing the role of workers performing repetitive tasks. Strong AI is currently used in areas that demand high intelligence (e.g., self-driving cars; Lee et al., 2021). Cabrera-Sanchez et al. (2021) outlined

[1] Eleven studies did not report the participants' gender (Cao et al., 2021; Chatterjee et al., 2021a; Chatterjee et al., 2021b;Chatterjee et al., 2021c; Chatterjee & Bhattacharjee, 2020; Damerji & Salimi, 2021; Gansser & Reich, 2021; Kim & Kim,2021; Lee et al., 2021; Pelau et al., 2021; Vu & Lim, 2019).

**Table 3**

| *Customer Service* | Technology Acceptance Model | Unified Theory of Acceptance and Use of Technology | Theory of Planned Behaviour | AI Device Use Acceptance | Other |
|---|---|---|---|---|---|
| **Total number** | 7 | 3 | 0 | 3 | 3 |
| **Extra Constructs** | 1. Subjective norms and attitude (Ali and Freimann, 2021)<br>2. Trust and Attitude (Chatterjee et al., 2021a)<br>3. Perceived risk and perceived value (Huang et al., 2019)<br>4. Performance risk, technology attitudes, fashion involvement and attitudes towards AI (Liang et al., 2020)<br>5. Optimism, innovativeness, discomfort, insecurity, perceived enjoyment, customization, interactivity (Pillai et al., 2020)<br>6. Trust, perceived risk and customer satisfaction (Seo and Lee, 2021)<br>7. Interpretability, procedural fairness and trust (Wang et al., 2020a) | 1. Compatibility, CRM quality and CRM satisfaction (Chatterjee et al., 2021c)<br>2. Anthropomorphism (Kuberkar and Singhal, 2020)<br>3. Personal wellbeing concern, personal development concern, perceived severity, perceived susceptibility, attitude, perceived threat, intention (Cao et al., 2021) | NA | 1. NA (Gursoy et al., 2019)<br>2. NA (Lin et al., 2020)<br>3. NA (Roy et al., 2020) | 1. Advantage, disadvantage, perceived value, intention to use (Meidute-Kavaliauskiene et al., 2021)<br>2. Perceived empathy, interaction quality, perceived anthropomorphism, acceptance and trust towards AI (Pelau et al., 2021)<br>3. Usefulness, dependability, social intelligence, knowledgeableness, attractiveness, human-likeness, collaborativeness, ease of use, anxiety toward robots, negative social influence, perceived risk, innovativeness, desire for control, technological self-efficacy (Song and Kim, 2020) |

$n = 16$.

the three levels of AI: ANI, AGI, and ASI. They stated that ANI is a task-specific device that currently exists and can be found in smartphones and weather forecasting devices. AGI is the next stage of AI which can apply its knowledge to multiple areas, similar to or better than human intelligence (Cabrera-Sanchez et al., 2021). Cabrera-Sanchez et al. (2021) report that ASI is the most accurate form of actual AI, defined as "a system or application that is capable of correctly interpreting both internal and external data" (p.1). As such, ASI should be able to outperform humans in all areas.

The semantics of a definition is critical to interpretation. A text analysis tool (Voyant) was used to analyse the definitions available to readers. Voyant was selected as it was freely available and has been successfully used to analyse text in previous studies (Eddine, 2018; Rambsy, 2016). The text analysis found that 'intelligence' was the term used most frequently in the definitions (included 17 times), followed by human (15), artificial (8), and data (8). The frequent use of the terms 'artificial' and 'intelligence' in defining 'artificial intelligence' is autological, providing a circular definition. Due to the use of both 'artificial' and 'intelligence' in the title of the phrase, it seems as though 'human' and 'data' are keywords used to define AI. The term 'human' is frequently used to contrast the capabilities of AI (e.g., AI machines "exhibit human intelligence"; Chi et al., 2020). However, 'human intelligence' is not defined. This research highlights that there is no consistent definition of AI across sectors; however, key themes can be found when analysing the classification of AI in each paper.

### 3.2.2. AI definition provided to participants

Over half ($n = 38$) of the studies included in the current review did not provide (or state that they offered) a definition of AI to their participants. Of the 22 studies that informed participants that the focus was on AI, seven studies provided a written definition of AI (Chi et al., 2020; Gansser and Reich, 2021; Kashive et al., 2021; Kim and Kim, 2021; Liu and Tao, 2022; Meyer-Waarden and Cloarec, 2021; Mohr and Kühl, 2021). The remaining 15 studies defined AI through video snippets, readings (e.g., news articles), and other examples.

Voyant was also utilised to analyse the definition of AI provided to the participants. The authors used the term human five times, followed by learning (4) and environment (3). Learning is used as an example of the human-like intelligence that AI exhibits (i.e., that AI is capable of learning). In contrast, environment refers to the surrounding setting that the AI responds to.

Some studies, such as Ali and Freimann (2021) and Gao and Huang (2019), recruited participants who were familiar with the

**Table 4**

| *Education* | Technology Acceptance Model | Unified Theory of Acceptance and Use of Technology | Theory of Planned Behaviour | AI Device Use Acceptance | Other |
|---|---|---|---|---|---|
| **Total Number** | 3 | 2 | 1 | 0 | 1 |
| **Extra Constructs** | 1. Perceived effectiveness, attitude, satisfaction (Kashive et al., 2021)<br>2. Self-efficacy, attitudes towards use and anxiety (Wang et al., 2021)<br>3. Attitude toward new technology and Attitudes toward AITA (Kim et al., 2020) | 1. NA (Tran et al., 2021)<br>2. NA (Chatterjee and Bhattacharjee, 2020) | 1. Self-efficacy in learning AI, AI readiness, perceptions of the use of AI for social good, AI literacy (Chai et al., 2021) | NA | 1. Perceived social norm, PEOU, PU, perceived knowledge on AI, attitude towards AI, intention to use AI (Gado et al., 2021) |

$n = 7$.

technology the study was assessing (e.g., developers and users of AI technology and household users of AI televisions). As such, the researchers relied on the participant's knowledge and experience with AI technology. Other studies, such as Pelau et al. (2021), assessed users' intentions based on their current understanding of AI. In these studies, a lack of definition may demonstrate the users' acceptance in a real-world setting.

#### 3.2.3. *Technology readiness*

Most reviewed papers ($n = 44$) stated that the AI technology they assessed already existed. For instance, Ye et al. (2019) studied potential end users' acceptance of ophthalmic AI devices. The authors stated that this technology currently exists and can surpass the performance of medical experts. Similarly, Kim et al. (2020) asked participants to respond to a news article describing an AI teaching assistant used in a university setting. As such, most of the papers assessed existing ANI in specialised areas. The current report categorised each use of AI based on the definitions provided of ANI, AGI, and ASI (see Appendix A). However, some papers' definitions could not be classified (e.g., fashion robot advisors). Therefore, restricting verification of the readiness of the technologies.

#### 3.2.4. *Industries*

The 60 papers reviewed were categorised into the industry of use. The industries were defined as customer service (27 %), education (11 %), healthcare (17 %), organisations (15 %), consumer product (15 %), and other (15 %). Tables 3 to 8 present the theories utilised in each study within the six industries. Consumer use was coded as devices that would be used for personal use by the consumer for their services (e.g., smart speakers, virtual assistants). Customer service was coded as consumers' devices for business use (e.g., customer relation management, fashion advisors). Healthcare was differentiated from organisational use because the technology is/would be used in hospital or medical settings or purposes (e.g., healthcare insurance). The other category included uses of AI that did not fit into the existing five industries. Of note, Gansser and Reich (2021) surveyed 21,841 respondents in a within-subjects study that investigated the acceptance of AI appliances across three industries: mobility, household, and health. They found that the extended UTAUT (see Table 7 for additional variables) was a relevant model that can measure acceptance across multiple industries, such as mobility, household, and health (Gansser and Reich, 2021).

Of the qualitative studies, three focused on AI use in organisations (Greiner et al., 2021; Ochmann and Laumer, 2020; Xu and Wang, 2019), while Atwal et al. (2021) and Lin and Xu (2021) focused on other industries (i.e., wine and architecture, respectively). Tran et al. (2021) investigated attitudes towards AI in Christian education. Finally, Gansser and Reich (2021) studied AI acceptance in mobility, household, and health applications.

### 3.3. *RQ3: What factors are associated with the adoption of AI?*

#### 3.3.1. *Theories*

Tables 3 to 8 show that the revised TAM[2] was the most frequently used theory to assess the acceptance of AI technologies. However, most authors used an extended model by adding additional variables to the two TAM predictors of PU and PEOU. The AIDUA was the least frequently applied model, used only in four studies. However, no scholars extended the AIDUA with additional constructs to investigate the participants' willingness or objection to the use of AI devices.

[2] Davis's (1989) definition of the TAM was used. Any additional variables (e.g., attitudes) are listed as additional variables.

**Table 5**

*Healthcare*

| | Technology Acceptance Model | Unified Theory of Acceptance and Use of Technology | Theory of Planned Behaviour | AI Device Use Acceptance | Other |
|---|---|---|---|---|---|
| **Total Number** | 5 | 4 | 0 | 0 | 1 |
| **Extra Constructs** | 1. Managerial factors, technological factors, operational factors, strategic factors, IT infrastructure factors and attitudes (Alhashmi et al., 2020)<br>2. Attitudes towards use and subjective norm (Lin et al., 2021)<br>3. Personalisation, loss of privacy, anthropomorphism, trust, age, gender, usage experience (Liu and Tao, 2022)<br>4. Attitudes and subjective norm (Memon and Memon, 2021)<br>5. Trust in AI, personal information privacy concerns, purchase of health insurance (Zarifis et al., 2021) | 1. Attitude, trust, value, social influence, health technology self-efficacy, willingness (Dieter, 2021)<br>2. Task complexity, personal innovativeness, technology characteristics, performance expectancy, effort expectancy, propensity to trust, initial trust, social influence, perceived substitution crisis, BI (Fan et al., 2020)<br>3. Personal innovativeness and trust (Floruss and Vahlpahl, 2020)<br>4. Trust theory (disposition to trust technology, initial trust), inertia, medico-legal risk, performance risk, perceived threat, resistance to change, behavioural intention (Prakash and Das, 2021) | NA | NA | 1. Mixed: TAM (PU, PEOU) + TPB (subjective norms, perceived behavioural control) + eye health consciousness, trust, perceived risk, resistance bias, intention to use (Ye et al., 2019) |

$n = 10$.

### 3.3.2. Modifications

Attitudes ($n = 15$) and trust ($n = 12$) were the most included variables to extend upon the TAM and UTAUT. Seven studies found that attitudes positively predicted behavioural intention when included as direct measures of intentions in the TAM (Alhashmi et al., 2020; Chatterjee et al., 2021a; Kim et al., 2020; Liang et al., 2020; Memon and Memon, 2021; Wang et al., 2020b; Wang et al., 2021) and four studies found no direct or indirect effect of attitudes on intentions (Ali and Freimann, 2021; Kashive et al., 2021; Lin et al., 2021; Mohr and Kühl, 2021). This finding fits with the original TAM, which included attitudes as a predictor of behavioural intention (Davis, 1985). While Greiner et al. (2021) included attitudes to code their variables, their study was qualitative so that no correlations could be made between variables. Surprisingly, no apparent theme was found between the industries in which the variable of attitudes was significant or non-significant. Kim et al. (2020) found that attitudes towards new technology positively predicted PU, influencing attitudes towards teaching assistants and positively predicting behavioural intentions. Attitudes were also found to be a significant positive predictor of intentions when added as an extra predictor in the UTAUT (Cao et al., 2021; Dieter, 2021). Further, Ochmann and Laumer (2020) included attitudes alongside other UTAUT variables as a construct in their qualitative study. Interestingly, Tran et al.'s (2021) study investigated attitudes towards AI in Christian education and found that most participants accepted using AI in religious education. However, the non-acceptance responses were all collected from participants' who identified as Christian. Following the UTAUT, Tran et al. (2021) found that those who were not accepting had doubts about the performance expectancy of such devices in conveying the spiritual capacity of Christianity. While Ochmann and Laumer (2020) found millennials (Gen Y[3]) to be accepting of AI technology, Tran et al. (2021) found that Gen Y and X[4]participants struggled with the technical facilitating conditions, while the

[3] Individuals born between 1981 and 1996.
[4] Individuals born between 1965 and 1980.

**Table 6**

| *Organisational* | Technology Acceptance Model | Unified Theory of Acceptance and Use of Technology | Theory of Planned Behaviour | AI Device Use Acceptance | Other |
|---|---|---|---|---|---|
| **Total Number** | 4 | 3 | 0 | 0 | 3 |
| **Extra Constructs** | 1. Technological context (reliability, security, conformity, technical novelty), organisational context (ubiquity, innovativeness, readiness), environmental context (legal and policy environment), number of employees, (Lee et al., 2021)<br>2. Technological readiness (Damerji and Salimi, 2021)<br>3. Legal use, sense of trust (Xu and Wang, 2019)<br>4. Digital technology efficacy, perceived threat of general job loss, techno-social environment (Vu and Lim, 2021) | 1. Hedonic motivation, price value and habit (Fleischmann et al., 2020)<br>2. Habit, privacy risk expectancy, innovation expectancy, attitude, intention to apply (Ochmann and Laumer, 2020)<br>3. NA (Andrews et al., 2021) | NA | NA | 1. Employee knowledge of AI, perceived cognitive capabilities of AI, anticipated adverse outcomes of AI, affective attitude toward AI, cognitive attitude toward AI, intention to use enterprise AI, intention to leave organisation (Chiu et al., 2021)<br>2. Role clarity, extrinsic motivations, intrinsic motivations, privacy risk, trust, willingness to accept AI (Choi, 2020)<br>3. Openness, affordances, generativity, social influence, hedonic motivation, effort expectancy, performance expectancy, attitude, uncertainty, inconvenience, AI acceptance intention (Upadhyay et al., 2021) |

$n = 10$.

younger (Gen Z[5]) participants reported feeling surer of their capabilities, leading to heightened acceptance.

Trust was found to be a significant positive indirect, and direct predictor of behavioural intentions in the extended TAM (Liu and Tao, 2022; Seo and Lee, 2021; Wang et al., 2020a; Xu and Wang, 2019; Zarifis et al., 2021; Zhang et al., 2021). Interestingly, trust did not predict PU or adoption of AI customer relationship systems in Chatterjee et al.'s (2021a) study. These authors claimed that the participants might not have enough information on the product to inform their trust beliefs. Trust was also found to positively predict use behaviour when included alongside other variables in the UTAUT (Dieter, 2021; Fan et al., 2020; Floruss and Vahlpahl, 2020; Meyer-Waarden and Cloarec, 2021; Prakash and Das, 2021). For instance, Prakash and Das (2021) found that disposition to trust technology positively predicted initial trust, which positively predicted intentions to use intelligent diagnostic systems. Appendix A outlines what other predictors significantly affected the dependent variable in the included studies.

A total of 29 papers[6] included in this review assessed technology that will, seemingly, replace human employees. Authors such as Fan et al. (2020) and Choi (2020) assessed AI technology that will potentially replace the role of assistants and human resource employees, respectively. As such, while many of these papers stated that variables such as trust (Seo and Lee, 2021; Ye et al., 2019; Zarifis et al., 2021) and subjective norms (Memon and Memon, 2021; Song, 2019) were significantly positive predictors of AI acceptance, only one study included fear of potential job loss as potentially influential variable (Vu and Lim, 2021). Specifically, Vu and Lim (2021) studied public attitude towards the use of AI / Robots across 28 European countries and found that participants were significantly frightened by the potential threat of job loss due to AI ($M = 3.09$ on a 4-point scale). Ultimately, Vu and Lim (2021) found that the perceived threat of job loss negatively predicted acceptance of AI. These authors stated that the inclusion of technophobia in the TAM was pertinent when reviewing acceptance of AI agents due to the significant impact of this factor on acceptance (Vu and Lim, 2021).

## 4. Synthesis and discussion

This paper identified and described the published literature on user acceptance of AI. The researchers conducted searches of the

[5] Individuals born from 1997 onwards.
[6] Technology that the authors were unsure of were marked as 'no'.

**Table 7**

*Consumer Product*

| | Technology Acceptance Model | Unified Theory of Acceptance and Use of Technology | Theory of Planned Behaviour | AI Device Use Acceptance | Other |
|---|---|---|---|---|---|
| **Total Number** | 5 | 1 | 0 | 0 | 2 |
| **Extra Constructs** | 1. Two-way communication, personalisation, co-creation and user-experience type (Gao and Huang, 2019)<br>2. Subjective norm (Song, 2019)<br>3. Anxiety, self-efficacy, attitude towards use (Wang et al., 2021)<br>4. Perceived humanity, perceived social interactivity, perceived social presence, trust (Zhang et al., 2021)<br>5. Attitude (Greiner et al., 2021) | 1. Health, convenience comfort, sustainability, safety security, habit, hedonic motivation, price value, personal innovativeness, (Gansser and Reich, 2021) | NA | NA | 1. Mixed: TAM, UTAUT, VAM and TPB (Sohn and Kwon, 2020b)<br>2. Mixed: UTAUT+UTAUT2+TAM (Cabrera-Sanchez et al., 2021) |

$n = 8$.

peer-reviewed and grey literature to address questions related to the study characteristics, study definitions, and what factors were associated with the adoption of AI. In total, 60 publications were included in the review. This systematic review offers a synthesis for researchers to find papers relevant to their research interests (e.g., industry, country of study).

### 4.1. *Types of AI considered in previous research*

Most studies classified their use of AI as ANI because the authors state that the technology currently exists (see Table 9). For example, Choi (2020) and Lin et al. (2021) studied the use of AI tools that were available to the participants. Arguably, most studies in the current literature assess behavioural intention to use AI that is currently available to consumers. A potential reason for this finding is that the present research reviewed papers that explicitly focused on AI. Future research should carefully outline the AI capabilities and communicate this to the readers and participants to create a consistent understanding between research assessing acceptance of ANI, AGI, and ASI. As such, there is value in prospective studies of acceptance (a priori acceptance) for futuristic AI (AGI and ASI). Such research could help avoid potential inequities in the development of technology.

### 4.2. *Theoretical considerations when assessing AI acceptance*

AI research has actively adopted theoretical models to assess acceptance. Each theoretical model has its positive attributes and reasoning for usage. The TAM is the most flexible of the included models, as demonstrated by the frequent extension of this theory in the reviewed studies. As such, the TAM is best used to test existing technology or when researching acceptance amongst multiple contexts due to its ability to include additional variables. The AIDUA is the most recently developed of the theoretical models and was used in fewer studies included in this review than other more familiar models of acceptance (i.e., the TAM). However, the studies cited herein show promising results (i.e., significant predictive power). The AIDUA has been primarily used to study user acceptance of AI devices in customer service roles (e.g., hotel service and hospitality) that could seemingly replace humans. Future research should endeavour to apply this model in other industries to see if the findings are similar (e.g., using AI alongside humans in education). Furthermore, studies have demonstrated that the TAM is not generalisable across industries (Ali and Freimann, 2021; Kelly et al., 2022). A multi-industry analysis using the AIDUA would interest researchers to confirm if the AIDUA is a comprehensive acceptance model across sectors. Despite its limited applications, the AIDUA appears to be a promising acceptance model for AI as it considers both willingness to accept and objection to use. The AIDUA can be particularly useful when researching AI technology that could replace the need for human workers in the customer service industry or other more controversial AI applications. This is a beneficial insight for future researchers looking to apply an acceptance model to a given scenario.

### 4.3. *Factors that influence acceptance of AI*

Based on the published literature, there has been agreement on the importance of psychosocial factors related to the acceptance of

**Table 8**

*Other Industries*

| | TAM | UTAUT | AIDUA | Other |
|---|---|---|---|---|
| **Total Number** | 3 | 2 | 1 | 3 |
| **Industry** | Agriculture | Self-driving cars | Tourism | Disaster management |
| **Extra Constructs** | Personal innovativeness, personal attitude, perceived behavioural control, perceived social norm, expectation of property rights over business data (Mohr and Kühl, 2021) | User well-being, privacy concerns, technology security, trust social recognition and hedonism (Meyer-Waarden and Cloarec, 2021) | NA (Chi et al., 2020) | Resources, voluntariness, organisational culture, BI, actual usage (Behl et al., 2021) |
| **Industry** | Architecture | Leisure | | Journalism |
| **Extra Constructs** | Socialised field diversity and controllable flexibility (Lin and Xu, 2021) | Expected performance of AI, effort expectancy, social circle, facilitating conditions, hedonic motivation, price value, user habit and personal innovativeness and income (Xian, 2021) | | Prior expectation, Perceived quality, positive disconfirmation, satisfaction, uncertainty avoidance, intention to accept news stories written by robot journalists (Kim and Kim, 2021) |
| **Industry** | Manufacturing | | | Wine Industry |
| **Extra Constructs** | Organisational competency, organisational complexity, organisational readiness, organisational compatibility, competitive advantage, partner support, leadership support (Chatterjee et al., 2021b) | | | Perceived benefits, organisational readiness, external pressure (Atwal et al., 2021) |

$n = 9$.

**Table 9**
A brief overview of included studies in the systematic review.

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| Alhashmi et al. (2020) | Advances In Intelligent Systems And Computing | Explore the critical success factors required to implement AI projects in the health sector in providing services for patient monitoring | $N = 53$ health care employees in Dubai<br><br>(74% women; aged 18-45) | United Arab Emirates | Online questionnaire | Extended TAM (adding managerial factors, technological factors, operational factors, strategic factors, IT infrastructure factors and attitudes) | Not provided | Managerial, organizational, operational and IT infrastructure factors have a positive impact on (AI) projects PEOU and PU which contributes to behavioural intention | The simulation of different processes of human intelligence by machines, more so computer-related systems | ANI |
| Ali and Freimann (2021) | Thesis | To understand the challenges of using AI in the Telecom sector. | $N = 190$ Swedish staff developing AI and non-AI applications, users of AI and non-AI application and staff outside of technology like marketing, HR etc.<br><br>(10% women; aged 21-61) | Sweden | Online questionnaire | Extended TAM (adding subjective norms and attitude) | Not provided | TAM model cannot be generalised across the sectors | AI is any program that does something that we would think of as intelligent in humans | ANI |
| Andrews et al. (2021) | Journal Of Academic Librarianship | Investigate librarians' intentions to adopt AI | $N = 236$ American and Canadian academic and public librarians<br><br>(76.7% women; aged 24-64) | North America | Online questionnaire | UTAUT + TAM | Not provided | Performance expectancy and attitude toward use have significant impact on librarians' intention to adopt AI | Revolves around the idea of creating computers and machines that mimic human behaviour and ultimately "think" like humans. These machines are meant to perform simple tasks and make decisions based on data they have gathered. | ANI |
| Atwal et al. (2021) | Strategic Change-Briefings In Entrepreneurial Finance | Identify which factors enable or inhibit artificial intelligence adoption within the wine sector | $N = 41$ students in a wine business program at university<br><br>(41.46% women; $M$ age= 28) | France | Case study (via qualitative interviews) | BOE (perceived benefits, organisational readiness, external pressure = AI adoption) | Respondents were introduced to the general concept of AI and the wine sector value chain. | Perceived benefits, such as disease treatment and cost efficiencies, positively influenced AI adoption. Lack of control was seen to decrease adoption of AI. | Not provided | ANI |

(continued on next page)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| Behl et al. (2021) | International Journal Of Manpower | Explore the readiness of government agencies to adopt artificial intelligence (AI) to improve the efficiency of disaster relief operations | $N = 184$ Indian government agents<br><br>(28.26% women; age not reported) | India | Online questionnaire | UTAUT + Civic Voluntarism Model | Not provided | Resources (e.g., time, money, skills) significantly influence adoption of AI. | Not provided | ANI |
| Cabrera-Sanchez et al. (2021) | Telematics And Informatics | Examine the relevant factors of AI adoption | $N = 740$ Spanish participants<br><br>(49.86% women; *M* age = 27.9) | Spain | Questionnaire | UTAUT2 (adding technology fear and consumer trust) | Not provided | Performance expectancy and hedonic motivations were the strongest contributors to behavioural intention towards AI apps. | AI is a system or application that is capable of correctly interpreting both internal and external data, learning from such data, and using those learnings to achieve specific individual or organization-wide goals. | ANI |
| Cao et al. (2021) | Technovation | To research managers' attitudes and intentions to use AI for decision making | $N = 269$ managerial employees from construction, wholesale, manufacturing and finance<br><br>(Gender and age not reported) | United Kingdom | Online survey | IAAAM (UTAUT + TTAT) | Not provided (basic knowledge assumed) | Peer influence, facilitating conditions and effort expectancy did not influence intentions. Personal wellbeing and development concerns negatively influenced intentions. | AI enables machines and systems to do things that would require intelligence if done by humans. | Unable to classify |
| Chai et al. (2021) | Educational Technology And Society | To measure intentions to learn AI amongst primary school students | $N = 682$ primary school students in China (48.95% women; *M* age = 9.87 years) | China | Online questionnaire | TPB (self-efficacy in learning AI, AI readiness, perceptions of the use of AI for social good, AI literacy, and behavioural intention) | The participants were enrolled in an AI course covering basic AI knowledge. | Intention to learn AI was influenced by self-efficacy in learning AI, AI readiness, and perceived use of AI for social good. | Not provided | Unable to classify |
| Chatterjee and Bhattacharjee (2020) | Education And Information Technologies | Explore how stakeholders would adopt AI in higher education | $N = 329$ (205 students; 80 teachers; 44 administrative staff) | India | Online questionnaire | UTAUT | Not provided | Perceived risk (negative) and effort expectancy (positive) impact attitude for adoption. | Not provided | ANI |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | (Gender and age not reported) | | | | | | | |
| Chatterjee et al. (2021a) | Technological Forecasting And Social Change | To identify the factors impacting the adoption of an AI-integrated CRM system (AICS) in agile organizations | $N = 357$ Indian employees from a range of companies<br><br>(Gender and age not reported) | India | Questionnaire | TAM2 (PU, PEOU, Trust, Attitude) | Not provided | PU impacts behavioural intention which impacts adoption. PEOU impacts PU. Trust impacts attitude. | Not provided | ANI |
| Chatterjee et al. (2021b) | Technological Forecasting And Social Change | To understand AI adoption in manufacturing and production firms | $N = 340$ Indian employees of small, medium and large firms<br><br>(Gender and age not reported) | India | Online survey | TAM-TOE | Not available | Organizational competency positively influences PU. Organizational complexity negatively impacts PU and PEOU. TAM is supported | Not provided | ANI |
| Chatterjee et al. (2021c) | Information Systems Frontiers | To develop theoretical model that explains behavioural intentions of Indian employees to use AI integrated CRM system. | $N = 315$ (Indian employees)<br><br>(Gender and age not reported) | India | Online questionnaire | Extended UTAUT (adding compatibility, CRM quality and CRM satisfaction) | Not provided | CRM quality and satisfaction significantly influences an organization's employees' attitudes and intentions to use AI integrated CRM system | AI is a modern technological genre. | ANI |
| Chi et al. (2020) | Journal Of Travel Research | To examine tourists' attitudes toward the use of artificially intelligent (AI) devices in hedonistic and utilitarian services | $N = 423$ Amazon Mechanical Turk workers (58.4% women; aged 18-65) | Not provided | Online survey | AIDUA | Artificial intelligence devices can simulate human behaviours (e.g., talk, walk, express emotions) and/or intelligence (e.g., learning, analysis, independence consciousness | Acceptance in both contexts is influenced by social influence, hedonic motivation, anthropomorphism, performance and effort expectancy, and emotions. Social influence was a stronger determinant in hedonic services | Artificial intelligence refers to a series of technologies that enable electronic devices to exhibit human intelligence such as sensing, perceiving, interpreting, or learning | ANI |
| Chiu et al. (2021) | International Journal Of Information Management | To explore the nature of AI and the role of affective attitudes in employees' responses to AI. | $N = 363$ Taiwanese employees<br><br>(55% women; aged 30-39 years) | Taiwan | Online questionnaire | Appraisal + Attitudes = Behavioural responses (intention to use AI or intention to leave organisation) | Not provided | Cognitive and affective attitudes towards AI were positively associated with intentions to use AI. | AI represents the ability of a machine to learn from experience and adjust to new inputs to execute human-like tasks | ANI |
| Choi (2020) | | | | South Korea | Online survey | | Not provided | | Not provided | ANI |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | European Journal Of Management And Business Economics | Examine how employees adopt AI-based self-service technology. | $N = 454$ Korean employees<br><br>(52.4% women; 25.7% aged 30-39) | | | Role clarity + extrinsic motivations + intrinsic motivations + privacy risk + trust = willingness to accept AI | | Clarity of user and AI's roles, user's motivation to adopt AI-based technology and user's ability increases their willingness to accept AI technology | | |
| Damerji and Salimi (2021) | Accounting Education | To investigate adoption of AI in accounting | $N = 101$ American accounting students<br><br>(Gender and age not reported) | America | Questionnaire | Technology readiness & TAM | Not provided | Technology readiness significantly influences technology adoption via PU and PEOU | AI focuses on building intelligent systems that can learn and reason and function like human beings | ANI |
| Dieter (2021) | Thesis | To identify consumer perception of HCAI use in their diagnosis and treatment and to describe the factors that influence the perception that leads to acceptance or non-acceptance. | $N = 401$ healthcare consumers or potential healthcare consumers based in the U.S.<br><br>(50.4% women; aged 18-55+) | America | Online survey | eUTAUT (attitude, trust, value, social influence, health technology self-efficacy = willingness to use) | Respondents were provided with minimal information needed to answer questions, and the survey avoids more extensive descriptions of the technology and its uses, because the study design aims to produce a baseline of healthcare consumer acceptance of HCAI. | Most consumers were willing to undergo diagnosis and treatment by HCAI within specified limits. Trust strongly influenced perception | AI is a general term that implies intelligent behaviour from a computer without explicit human programming | ANI |
| Fan et al. (2020) | Annals Of Operations Research | Examining the factors contributing to behavioural intention to use an AI-based medical diagnosis system | $N = 191$ healthcare professionals<br><br>(62.83% women; aged under 30-50+) | China | Questionnaire | UTAUT + Trust theory (task complexity, personal innovativeness, technology characteristics, performance expectancy, effort expectancy, propensity to trust, | Specific to AI-based medical diagnosis system | Initial trust and performance expectancy both have significant effects on behavioural intention. There was no significant influence of effort expectancy and social influence. | Not provided | ANI |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | initial trust, social influence, perceived substitution crisis, BI) | | | | |
| Fleischmann et al. (2020) | Proceedings Of The Annual Hawaii International Conference On System Sciences | Investigate whether differences in acceptance of Smart Communication Technology exist across cultures, and how the use of SCTs influences communication effectiveness. | $N$ = 643 students from 14 universities in nine countries<br><br>(55.2% women; age not reported) | United States, India, Canada, Lithuania, Finland, Spain, France, Germany, and Singapore | 2 online surveys (7 weeks apart, post project) | UTAUT2 (performance expectancy, effort expectancy, hedonic motivation, uncertainty avoidance, future orientation, humane orientation, individualism/ collectivism, performance orientation) | Not provided | Team members from individualistic, future oriented cultures generally had more positive expectations towards the performance and enjoyment of using the technology. | Not provided | ANI |
| Floruss and Vahlpahl (2020) | Thesis | To investigate the reasons why AI-based systems are not yet widely used in the healthcare sector | $N$ = 258 German healthcare professionals<br><br>(65.5% women; aged 18-55+) | Germany | Online survey | eUTAUT (performance expectancy, effort expectancy, social influence, facilitating conditions = BI = use behaviour) | Informed the respondents about the research topic to ensure that they have a basic understanding of the topic and to stimulate their interest in participating. | Trust was the most influential determinant of the BI to use AI-based systems. Social influence had no effect on BI. | A computer algorithm that performs cognitive tasks associated with human performance and intelligence | ANI |
| Gado et al. (2021) | Psychology Learning And Teaching | Gain insights into psychology students' perceptions, acceptance and intentions to use AI technology in the health and therapy sector. | $N$ = 218 German psychology students (75.9% women; $M$ age = 24.2) | Germany | Online questionnaire | TAM + TRA + UTAUT (perceived social norm, PEOU, PU, perceived knowledge on AI, attitude towards AI, intention to use AI) | Not provided | Intention to use AI was predicted by PU, perceived social norm regarding AI, and attitude towards AI. PEOU did not predict intentions. | Autonomous or semi-autonomous analysis, interpretation, and utilization of large amounts of data | Unable to classify |
| Gansser and Reich (2021) | Technology in Society | To investigate the influential factors in an acceptance model on behavioural intention and use behaviour for products containing AI in mobility, household and health | $N$ = 21,841 German students (Gender not reported; aged 17-61+)<br><br>(Mobility $n$ = 7,260; Household $n$ = 7,261; Health $n$ = 7,320) | Germany | Face-to-face interview/ questionnaire | Extended UTAUT2 | AI is the imitation of human behaviour (ability to think, solve problems, learn, correct oneself, etc.) by computer | Convivence comfort the strongest predictor of performance expectancy in the mobility and household segments. Social influence was the strongest predictor of intentions in the health scenario. | Not provided | ANI |

(*continued on next page*)

Table 9 (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | systems. | | | |
| Gao and Huang (2019) | Heliyon | To explore intentions to use smart media content services | $N = 585$ Chinese owners of an AI TV (50.8% women; aged 18-46+) | China | Questionnaire | TAM + two-way communication, personalisation, co-creation and user-experience type | Not provided | Smart service belief factors, including perceived two-way communication and personalization are found to be critical determinants of a user's attitude toward behaviour and intention to purchase in the extended TAM. Co-creation is an antecedent for PU. | Not provided | ANI |
| Greiner et al. (2021) | Advances In Intelligent Systems And Computing | Investigate acceptance of AI as co-workers | $N = 14$ German participants (gender and age not reported) | Germany | Interviews | eTAM (attitude) | Four snippets of differing levels of AI were presented to participants | Acceptance of AI can be increased through transparency and perceptible interaction (i. e., seeing, hearing, feeling) | Not provided | Unable to classify |
| Gursoy et al. (2019) | International Journal Of Information Management | To develop and test a new theoretical model to explain consumers' use of AI devices. | $N = 439$ Amazon Mechanical-Turks (57.5% women; aged 18-65+) | America | Online questionnaire | AIDUA | Not provided | Social norms and attitudes predict consumer acceptance of AI devices. Hedonic motivation was positively related to effort expectancy and anthropomorphism increased the perception of effort required to use AI devices. | Tasks that used to be performed by humans only, such as driving vehicles, processing human language, recognising faces in photos, analysing big data or conducting online searches, now can be easily accomplished by AI devices | Unable to classify |
| Huang et al. (2019) | Acm International Conference Proceeding Series | Measure participants' behavioural intentions to use AI for customer service | $N = 411$ Taiwanese (46.7% women; age not reported) | Taiwan | Questionnaires | eTAM (perceived risk and perceived value) | Not provided | Perceived value is the most significant factor contributing to acceptance. Perceived risk negatively affects women intentions to use this technology (more so than males) | Weak AI refers to the focus that can only solve the artificial wisdom of specific problems | ANI |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| Kashive et al. (2021) | International Journal Of Information And Learning Technology | Identifying the factors that influence user acceptance of AI enabled e-learning | *N* = 100 Indian participants<br><br>(59% students, 41% professionals)<br><br>(52% women; aged 21-34) | India | Questionnaire | eTAM (adding perceived effectiveness, attitude, satisfaction) | Personal learning profile has four items like "A.I. can recommend material and methodology," and "A.I. can provide personalised feedback and self-evaluation". Personal learning network has three items like "A.I. can connect the learner with people with similar interests," and "A.I. can help learners exchange knowledge with similar others." While personal learning environment has two items like "A.I. can make the learning environment more conducive" and "A.I. can make learning more enjoyable." | Results did not support that a learner's attitude or satisfaction toward AI e-learning impacts their intention to use it | Not provided | ANI |
| Kim and Kim (2021)<br><br>*Survey conducted in 2017 | Technological Forecasting And Social Change | Explore users' intentions to accept news stories written by robot journalists | *N* = 388 South Korean participants<br><br>(Gender not reported; aged 20-50+) | South Korea | Online survey | eUTAUT | "In Korea as well as in other countries, AI that collects and organises data, and writes news articles is wide spreading. It is | Perceived quality was positively associated with satisfaction which led to a higher intention to accept news articles written by robot journalists | Not provided | ANI |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | called "robot journalism" | | | |
| Kim et al. (2020) | International Journal Of Human-Computer Interaction | To understand students' perceptions of AI teaching assistants in online education | $N = 321$ American undergraduate communication students (65.1% women; *M* age = 21.52) | America | Online survey | eTAM (adding attitude toward new technology and Attitudes toward AITA) | Participants were led to read an article about an AI teaching assistant in higher education | PU and PEOU positively affect students' attitudes towards AI teaching assistants which positively influences intentions to adopt | Not provided | ANI |
| Kuberkar and Singhal (2020) | International Journal On Emerging Technologies | To investigate what factors impact the adoption of AI chatbots in public transport information services? | $N = 463$ public transport commuters in and around Pune smart city (India) (42% women; aged 21-50+) | India | Online survey | UTAUT + Anthropomorphism + Trust | A simulated AI based Chatbot as shown in Fig. 2 was presented to respondents before collecting the survey feedback to familiarise them with this emerging technology solution. | Performance expectancy, effort expectancy, social influence, facilitating conditions, anthropomorphism, and trust positively explain future adoption intention of an AI Chatbot | Not provided | ANI |
| Lee et al. (2021) | Studies In Computational Intelligence | Investigate the factors affecting the intention of use of AI-based recruitment system | $N = 187$ South Korean participants (Gender and age not reported) | South Korea | Online survey | TOE + TAM | Not provided | PEOU, PU and legal and policy environment influence behavioural intention | Artificial intelligence is divided into strong and weak artificial intelligence depending on the autonomy of cognitive abilities. weak AI to replaces repetitive tasks | ANI |
| Liang et al. (2020) | Clothing And Textiles Research Journal | Examine consumers' attitudes and purchase intention toward an AI device (Echo Look) | $N = 313$ Americans (61% women; aged 18-65) | America | Online questionnaire | eTAM (adding performance risk, technology attitudes, fashion involvement and attitudes towards AI) | Participants viewed a 30-s commercial video advertising Amazon's Echo Look (labelled as AI technology) | PU and PEOU significantly positively influenced attitudes. Performance risk was a negative predictor of attitudes. Attitude had a positive significant influence on behavioural intentions to purchase. | Not provided | ANI |
| Lin and Xu (2021) | Technology Analysis & | Explore the factors affecting intention to | $N = 12$ (16.67% women; *M* age = 39.83) | Taiwan | Interviews | RTAM (robotic TAM; adding socialised field diversity and | Not provided | All interviewees intended to use AI robotic architect. They stated | AI has been devoted to building the | Unable to classify |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | Strategic Management | use AI robotic architects for design | | | | controllable flexibility) | | that big data analysis, seamless exchange of information, and human–computer interaction would enhance PEOU | capability to reason, understand, plan, learn, communicate, perceive, move, and manipulate objects that are similar to or even beyond humans | |
| Lin et al. (2020) | Journal Of Hospitality Marketing And Management | To validate and extend the applicability of the AIDUA model in explaining customers' AI service device acceptance in the hospitality service context. | $N = 605$ Mechanical-Turks 292 full- service hotel samples and 313 limited-service hotel samples<br><br>(63% women; aged 18=65+) | Not provided | Online customer panel | AIDUA | Not provided | Compared to limited-service hotel customers, full-service hotel customers rely less on their social groups when evaluating artificially intelligent robotic devices; their emotions toward the use of artificially intelligent devices are less likely to be influenced by effort expectancy; and their emotions cause less impact on their objection to the use. | Not provided | ANI |
| Lin et al. (2021) | Journal Of Educational Technology & Society | To explore how medical staff's attitudes, intentions, and relevant influencing factors in relation to AI application learning. | $N = 285$ Taiwanese medical staff (245 nursing staff, 40 physicians)<br><br>(86.7% women; 29.8% 41-50 years old) | Taiwan | Questionnaires | Extended TAM (adding attitudes towards use and subjective norms) | All participants completed two training modules, "AI and robotics in the New Health era" and "New era of medical education: AI-supported precision medicine" for 2 hours; following that, they were allowed to experience the use of an AI-based diagnosis system | The intentions of medical staff to learn to use AI applications to support precision medicine can be predicted by SN, PEU, PU, and ATU | AI not only emulates the decision-making process of human experts but can also make a detailed analysis and objective predictions based on a large set of data. | ANI |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| Liu and Tao (2022) | Computers In Human Behavior | To examine the roles of trust, personalization, loss of privacy and anthropomorphism in acceptance of smart healthcare services | $N = 769$ members of an online survey company (56.44% women; $M$ age = 30.12) | China | Questionnaire | eTAM (personalisation, loss of privacy, anthropomorphism, trust, age, gender, usage experience) | Smart healthcare services refer to healthcare services that were supported by advanced techniques such as AI, big data, cloud computing, natural language processing, and computer vision | The trust–behavioural intention relationship was found to be even stronger than the perceived usefulness–behavioural intention relationship . | Not provided | ANI |
| Meidute-Kavaliauskiene et al. (2021) | Sustainability | To investigate if people are accepting of service robots in the hospitality industry | $N = 1,408$ Turkish adults<br><br>(57.2% women; aged 18-56+) | Turkey | Online survey | Advantage + Disadvantage + Perceived value = Intention to use | Not provided | The perception of advantage and perceived value affect the intention to use service robots positively and significantly while the perception of disadvantage negatively affects the intention to use service robots | Artificial intelligence-based systems not only trigger service and process automation but are also used for direct interaction with customers in various pre-service | ANI |
| Memon and Memon (2021) | International Research Journal Of Modernization In Engineering Technology And Science | To investigate the acceptance by healthcare professionals of AI-based systems | $N = 96$ healthcare and related non-healthcare personnel in a specialised private hospital in Kelang Valley.<br><br>(64.6% women; aged 26-55+) | Malaysia | Questionnaire | eTAM (adding attitudes and subjective norm) | Not provided | Only 11.5% of respondents would use artificial intelligence to assist them in decision-making | Not provided | ANI |
| Meyer-Waarden and Cloarec (2021) | Technovation | Investigate antecedents, mediators and consequences of adoption of level-five, AI-automated vehicles. | $N = 207$ French participants<br><br>(47% women; Median age = 27) | France | Online survey (via social networks) | Extended UTAUT (Adding user well-being, privacy concerns, technology security, trust social recognition and hedonism) | A fully autonomous, level-five, AI-powered vehicle with different decisions made by the AI system with no human intervention required at all. | Positive relationship between behavioural intention to use AI-powered AVs and performance-/effort expectancy, social recognition, well-being, hedonism and technology trust, as well as security. Privacy concerns | Machines and systems that can perform tasks that normally require human intelligence—is rapidly changing the marketing landscape | AGI/ ASI |

(*continued on next page*)

Table 9 (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | The automated AI-based system takes over all functions and will never need to ask for human intervention. The AV senses the environment and operates without human involvement. It controls the steering, acceleration and deceleration, it monitors the driving environment, and it has a fallback performance, as the driver cannot place his or her hands on the steering wheel (there is no steering wheel). The driver can take his or her eyes off the street and can even sleep. | negatively influence technology trust. | | |
| Mohr and Kühl (2021) | Precision Agriculture | Explore what factors influence the acceptance of AI in agriculture | $N = 84$ German farmers<br><br>(Age and gender not reported) | Germany | Online (group 1) and paper (group 2) survey | TAM + TPB | AI systems was described by the term self-learning systems to avoid negative and dystopian associations with the term AI. | Perceived behavioural control and personal attitude have the most influence on acceptance, respectively | AI can be described as learning systems that originate from the field of computer science and independently process data, learn to recognise patterns in the data, and independently solve specific | AGI |

(*continued on next page*)

Table 9 (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | tasks | |
| Ochmann and Laumer (2020) | Proceedings Of The 15th International Conference On Business Information Systems 2020 "Developments, Opportunities And Challenges Of Digitization." | To investigate why and under which circumstances do job seekers accept AI recruitment methods used by organizations? | $N = 23$ German millennials<br><br>(43.5% women; aged 20-34) | Germany | Semi-structured interviews | UTAUT2 (Habit, privacy risk expectancy, innovation expectancy, attitude, intention to apply) | Not provided | Use is not an appropriate measure of acceptance in a passive use context such that we imply to consider attitude toward the technology [53] as mediating variable that explains the influence of several perceptions about a technology. | AI means any intelligent agent that automates activities by acting rational | ANI |
| Pelau et al. (2021) | Computers In Human Behavior | To determine the influence of the psychological anthropomorphic characteristics of an AI device on the perceived empathy and interaction quality, and thereafter on the consumer's acceptance and trust towards AI | $N = 188$ Romanian college students<br><br>(Gender and age not reported) | Romania | Online survey | Perceived empathy + Interaction quality + Perceived anthropomorphic = acceptance and trust towards AI | Not provided | Anthropomorphic characteristics alone do not influence the interaction quality unless the AI device is able to show empathy. Perceived empathy and interaction quality mediate the relation between anthropomorphic characteristics and acceptance | Not provided | ANI |
| Pillai et al. (2020) | Journal Of Retailing And Consumer Services | To study user intention to shop at AI-powered automated retail stores | $N = 1250$ Indian consumers of retail shops in Mumbai and Pune city<br><br>(41% women; aged 21-60) | India | Survey | TRAM (PU, PEOU, optimism, innovativeness, discomfort, insecurity, perceived enjoyment, customization, interactivity = BI) | A video about the AIPARS concept and an information leaflet was provided | Innovativeness and Optimism affects the PEOU and PU. PEOU, PU, perceived enjoyment, customization and interactivity are significant predictors of shopping intention | Is that activity devoted to making machines intelligent and intelligence is that quality that enables an entity to function appropriately and with fore-sight in its environment | Unable to classify |
| Prakash and Das (2021) | Information And Management | To investigate the determinants of medical practitioner's intention to use an "intelligent" clinical diagnostic decision support system | $N = 183$ Indian medical professionals (66% women; younger 30 – 60+ years of age) | India | Study 1: Netnography & interviews<br><br>Study 2: Survey | Disposition to trust technology, effort expectancy, inertia, medico-legal risk, performance expectancy, performance risk, perceived threat, resistance to change, | In-depth session on applications of AI in radiology led by a domain expert Participants were specifically instructed to fill the | Performance expectancy, social influence and initial trust significantly predicted intentions. Inertia, perceived threat, and risks (medico-legal and performance) determined resistance to | Artificial intelligence (AI) is an umbrella term that represents sciences and technologies that use machines to mimic, extend, or | AGI |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | social influence, initial trust = behavioural intention | questionnaire based on their idea of the general collection of ICDDSS rather than any product in particular. | change | improve human intelligence | |
| Roy et al. (2020) | Global Business Review | To validate the AIDUA in the Indian hospitality sector | $N = 129$ Indian luxury hotel customers (38.6% women; aged 20-40+) | India | Survey | AIDUA | Not provided | Performance and effort expectancy influenced customer emotion which influenced willingness and objection to use AI devices among hotel customers | AI concerns intelligence as demonstrated by machines, that reacts and responds to its surrounding environment and customer requirements by using deep learning algorithms, offering robust services that are considered relatively superior to the ones that are offered by its human counterparts | ANI |
| Seo and Lee (2021) | Sustainability (Switzerland) | Investigate the drivers of customers' behavioural intention of having robot restaurants at business hotels | $N = 338$ restaurant consumers in Korea<br><br>(51.2% women; aged 20-59) | South Korea | Online survey | eTAM (adding trust, perceived risk and customer satisfaction) | A scenario was provided which defined the service robot as AI | Trust was a crucial antecedent variable of TAM. There is a positive influence of PU on intention to revisit robot service restaurants. | Not provided | Unable to classify |
| Sohn and Kwon (2020a), Sohn and Kwon (2020b) | Telematics And Informatics | To determine which model best explains consumer acceptance of AI-based intelligent products and which factors have the greatest impact in terms of | $N = 378$ Korean participants interested in using products such as the smart speaker, voice assistant services, and AI-based home | South Korea | Online survey | TAM, UTAUT, VAM and TPB | Not provided | VAM performed best in modelling user acceptance. Interest in technology influences acceptance of AI technology more strongly than utilitarian aspects. | Not provided | Unable to classify |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | | purchase intention. | appliances<br><br>(53.4% women; aged 20-50+) | | | | | | | |
| Song (2019) | Thesis | Extending the TAM to explore user acceptance of an AI virtual assistant | $N = 433$ Mechanical Turks (50% women; $M$ age = 39.71) | America | Online survey | eTAM (adding subjective norm) | Not provided | Subjective norm did not influence behavioural intention. The TAM was supported. | Not provided | ANI |
| Song and Kim (2020) | Clothing And Textiles Research Journal | Investigate the factors behind adoption (or non-adoption) of fashion robot advisors | $N = 464$ American consumers<br><br>(51.7% women; Aged 18-81) | America | Online survey | Usefulness, dependability, social intelligence, knowledgeableness, attractiveness, human-likeness, collaborativeness, ease of use, anxiety toward robots, negative social influence, perceived risk, innovativeness, desire for control, technological self-efficacy | Participants first were exposed to a short video clip, which provided information about AI service robots with big-data knowledge. | How consumers perceive FRAs socially, aesthetically, and intellectually and their capability to use technology are the key to their adoption of FRA | Not provided | Unable to classify |
| Tran et al. (2021) | Religions | To generate insights on Vietnamese Christian and non-Christian people's readiness and acceptance toward AI innovation in religious education and practices. | $N = 32$ Vietnamese participants<br><br>(47% women; 53%; Gen X, Y and Z; 53% Christian and 28% Atheist) | Vietnam | Semi-structured interviews (via Zoom) | UTAUT | The researchers asked whether the respondents understand the concept of AI clearly and how this technology can impact education and religious practices. | Only Generation Z participants were fully prepared to adopt this innovation.<br>The non-acceptance responses only came from the Christian respondents | Not provided | ANI |
| Upadhyay et al. (2021) | International Journal Of Entrepreneurial Behaviour And Research | To determine the entrepreneur's intention to accept artificial intelligence (AI) | $N = 476$ participants recruited from AI entrepreneurship focused groups<br><br>(25.21% women; aged 19-40+) | America, China, Britain, Italy, Russia, France, Germany, India, Australia, Spain, Netherlands, and Canada | Online survey | AIADE (openness, affordances, generativity, social influence, hedonic motivation, effort expectancy, performance expectancy, attitude, uncertainty, inconvenience = AI acceptance intention) | Not provided | All factors (but effort expectancy and openness) influenced acceptance intentions. Inconvenience was a negative predictor while the rest were positive. | Not provided | Unable to classify |
| Vu and Lim (2021) | | Study the factors influencing public | $N = 16,672$ participants | 28 European countries | Secondary survey data | TAM + (Digital technology efficacy, | Not provided | Respondents' willingness to accept AI/Robot was | The use of algorithms to | |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | Behaviour And Information Technology | attitude towards the use of AI / Robots | (52.1% women; *M* age = 28) | (specific countries not provided) | (Responses to Eurobarometer surveys, which have generated nationally representative public opinion data on a regular basis since 1974, were used) | Perceived threat of general job loss, Usefulness, and Acceptance of AI/ Robot and one single-question variable, Prior knowledge of AI) | | low. Acceptance differed across cultures (indicating the influence of national policies and developments) | make a computer perform complex functions that require human intelligence | Unable to classify |
| Wang et al. (2020a) Wang et al. (2020b) | Acm International Conference Proceeding Series | To study the influence of interpretability of AI recommendation systems on behavioural intention | *N* = 244 individuals from online communities<br><br>(61.9% women; aged 18-40+) | Not provided | Online survey | eTAM (adding interpretability, procedural fairness and trust) | Not provided | Interpretability has a significant positive influence on trust, PU and PEOU. There is no relationship between procedural fairness and trust, but PF does have an affect PU. PEOU and PU influences BI. | Not provided | ANI |
| Wang et al. (2021) | Educational Technology And Society | Investigate teachers' continuance intention to teach with AI. | *N* = 311 university teachers in China (experience in using AI technologies (e.g., Mosoteach, Smart Class, Youdao Translation, HappyClass Smart Classroom System)<br><br>(45.02% women; aged younger than 30-50+) | China | Questionnaires | Extended TAM (added self-efficacy, attitudes towards use and anxiety) | Not provided | Teachers' SE would positively influence their PEOU and attitudes towards use about adopting AI technologies, and it could further affect PU through PEOU | AI has been described as computers being used to mimic human minds to perform cognitive tasks (e.g., thinking, learning, problem solving) | ANI |
| Wang et al. (2021) | The 2020 2nd International Conference On Management Science And Industrial Engineering | To explore the factors that influence consumers' use of smart speakers | *N* = 237 Taiwanese participants<br><br>(58% women; aged 21-51+) | Taiwan | Questionnaire | TPB + TAM | Not provided | PEOU and PU have positive indirect effects on behavioural intentions through attitudes. | Not provided | ANI |
| Xian (2021) | Journal Of Internet Technology | To measure the determinants of consumers' acceptance of AI in leisure activities | *N* = 560 individuals<br><br>(43.04% women; over 50% aged 20-29) | Mainland China, Hong Kong, Macau, and Taiwan | Online survey | UTAUT2 (expected performance of AI, effort expectancy, social circle, facilitating conditions, hedonic motivation, price | Not provided | Expected performance of AI, social circle, facilitating conditions, pleasure derived from using AI, price value, and user habit significantly influenced AI adoption | Artificial Intelligence (AI) is the ability for a machine to collect information and use sophisticated | Unable to classify |

(*continued on next page*)

**Table 9** (*continued*)

| First author | Journal | Objective | Participants | Country | Design | Theory | AI definition provided to participants | Key related significant findings[7] | Definition of AI in the paper | AI[8] |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | value, user habit and personal innovativeness and income) | | | algorithms and logical functions to learn from it, thereby adapting future capabilities based on additional information to increase knowledge | |
| Xu and Wang (2019) | Journal Of Management And Organization | To explore the relationship between AI robot lawyers and human lawyers and to identify the elements of AI robot lawyers that are accepted by human users | $N = 10$ (four lawyers, two judges, two AI experts and two potential customers in Taiwan)<br><br>(10% women; *M* age = 36) | Taiwan | Secondary data collection and semi structured in-depth interviews | Extended TAM for robot lawyers (RLTAM; legal use, PEOU, sense of trust, PU) | Not provided | Legal use and trust perception were proposed to add value to the RLTAM. Participants stated that mutual trust between the AI lawyers and the clients drive behavioural intention. | The theory and application of systems used to simulate, extend, and expand human intelligence | Unable to classify |
| Ye et al. (2019) | Journal Of Medical Internet Research | Explore psychosocial factors determining adoption of AI in medical settings | $N = 474$ potential end users of ophthalmic AI devices in China<br><br>(64.3% women; aged under 18-60+) | China | Online survey | TAM + TPB + eye health consciousness + trust + perceived risk + resistance bias = intention to use | Not provided | Subjective norm plays a more important role than PU through both direct and indirect paths. Resistance bias of new technology reduced intention, whereas perceived risk did not influence public IU | Not provided | Unable to classify |
| Zarifis et al. (2021) | Journal Of Internet Commerce | To evaluate whether a consumer purchasing health insurance without visible AI will have higher trust and lower personal information privacy concerns (PIPC) compared to when there is visible AI in the interaction | Group 1 $N = 221$ UK residents (44.34% women)<br><br>Group 2 $N = 217$ UK residents (48.85% women)<br><br>Aged under 18-60+ | United Kingdom | Survey | TAM + trust + PIPC | Not provided | Trust is higher without visible AI involvement. | Not provided | ANI |
| Zhang et al. (2021) | Frontiers In Psychology | To research user acceptance of AI virtual assistants | $N = 240$<br><br>(57.92% women; 46.25% aged under 20-40+) | Not provided | Online questionnaire | TAM + perceived humanity + perceived social interactivity + perceived social presence + trust = acceptance | Not provided | There was a positive effect of trust on the acceptance of AI virtual assistants. PU and PEOU positively influenced trust. | Not provided | ANI |

[7] The focus is on individuals' attitudes towards or intentions and/or willingness to use artificially intelligent devices in the future. Other measures and findings may have been reported in these studies, however only those key findings which relate to this review's objective were included. Interested readers are encouraged to review the original articles for further details.

[8] AI was classified based on whether or not it was currently in use.

AI technologies. Fitting with the most common theories (i.e., TAM and UTAUT), most studies concluded that independent variables, such as perceived usefulness, performance expectancy, and effort expectancy, significantly and positively predicted behavioural intention, willingness, and use behaviour of AI across multiple industries. The frequent inclusion and significance of both trust and attitudes highlight the relevance of these additional variables in understanding what factors influence user acceptance of AI. Furthermore, the influence of trust and attitudes across different industries and demographics reveals their flexibility and emphasises their importance in the extended TAM and UTAUT. Thus, it can be suggested that traditional base theories matter, but idiosyncrasies, such as trust and attitudes, must be captured to understand user acceptance completely. As such, it is recommended that when using traditional acceptance models, future studies extend upon them to include trust and/or attitudes. This insight is informative for advancements in theory-building.

Another point to note is that variables regarding social norms and social influence positively predicted intentions across various industries, such as customer service and healthcare (Gursoy et al., 2019; Lin et al., 2021). These variables may have been significant in these industries due to high levels of social contact. Researchers studying AI acceptance among adolescents and young adults should consider this variable since these cohorts may be highly susceptible to influence by their peers (Knoll et al., 2015). Future studies in these industries are recommended to extend traditional technology models to account for these variables or use acceptance models that contain these predictors (e.g., AIDUA).

Culture appears to play a role in the acceptance/rejection of AI in some of the reviewed studies. For example, Tran et al. (2021) studied the acceptance of AI involvement in Christian education in Vietnam, a secular state. Responses indicated that the non-acceptance of AI in religious teaching came from Christian respondents, particularly the church staff (Tran et al., 2021). Tran et al. (2021) stated that this was because most individuals sought religious learning to cultivate spiritual and emotional comfort, which AI could not replace. Cultural implications can also be demonstrated in Atwal et al.'s (2021) study of the adoption of AI in the wine industry. The results indicated that Burgundy wine producers were reluctant to use AI technology due to a preference for tradition rather than cultural disruption (Atwal et al., 2021). Tradition enables the continuance of community and culture. It may be that if tradition is not addressed in the research and development of AI agents, there will always be rejection due to cognitive biases. Nevertheless, it is essential to sit with the cultural implications that some individuals seek services purely for a sensory experience in contrast to academic or financial motivations. In these scenarios, it appears that the need for human contact cannot be replicated or replaced by AI, no matter the PU or PEOU. It is recommended that more research consider cultural implications when addressing the reasoning behind the acceptance of AI in different contexts.

### 4.4. Actual use behaviour

A criticism of the literature is that only seven papers studied actual use behaviour (Alhashmi et al., 2020; Behl et al., 2021; Cabrera-Sanchez et al., 2021; Chatterjee et al., 2021c; Floruss and Vahlpahl, 2020; Gansser and Reich, 2021; Tran et al., 2021). Furthermore, none of the seven studies measured use behaviour as item purchase. However, this may be due to the chosen technology's function and the role of the participants (e.g., medical professionals' willingness to use AI in the healthcare sector; Alhashmi et al., 2020). Instead, many studies defined their dependent variable as willingness to use, behavioural intention, or acceptance. As most ($n = 50$) of the studies reviewed were questionnaires, it is fitting that very few researched the actual uptake of AI technology. However, given that most of the studies assessed existing applications of AI, it would be helpful to consider how acceptance, intentions, and willingness to use translates to actual behavioural use.

While models such as the TAM indicate that preferences directly predict behaviour, Cocosila (2013) states that a priori views (i.e., an individual's perception of the technology before use) on a targeted technology should not be confounded for actual use. This is particularly relevant as some papers investigated technology that does not exist (e.g., AGI). For instance, Keung et al. (2004) conducted two studies a year apart. They found that while the TAM variables predicted that the employees of a company would adopt technology, the technology was not being used a year later (Keung et al., 2004). Consequently, some of the reviewed literature in the present study is speculative. It is recommended that future studies examine the use of existing AI adoption models with use behaviour as the dependent variable.

### 4.5. Limitations and implications for future research

Several limitations must be considered when interpreting the outcomes of the current review. First, papers were only included in the review if they were accessible in English and clearly stated that they studied AI, potentially minimising the scope of the research. Second, some authors did not respond to emails asking for clarification; therefore, their papers were not included as part of this review. Finally, the review comprised 51 papers where participants were asked to complete an online survey, restricting the involvement of many offline individuals. This holds particular significance when studying technology acceptance.

Understanding perceptions of AI can help stakeholders better discern where it is most beneficial to invest their resources in the everchanging development of AI. As such, it is a weakness that most of the available literature was inconsistent in how it distinguished and operationalised AI to the participants. Previous research shows that individuals have difficulty understanding what AI is. For instance, Liang and Lee (2017) found that their participants could not distinguish between autonomous robots and AI. Hence, it is difficult to report the similarities and differences between studies and extract themes and learnings for stakeholders regarding how to influence the acceptance of AI technologies. Based on these findings, future research must ensure participants' consistent understanding of AI technology. Furthermore, researchers citing AI papers should critically determine if the technology meets the standard to be classified as AI, as we found this is unclear in many cases.

## 5. Conclusion

The existence of ANI and the emergence of more advanced AI agents have resulted in an increased number of studies in the last two years that have assessed user acceptance of AI. Many studies have been reviewed, but the conceptual underpinnings were not always well established. From a theoretical perspective, the TAM and UTAUT were the models most commonly applied to assess behavioural intentions. Perceived usefulness, performance expectancy, attitudes, trust, and effort expectancy significantly and positively predicted behavioural intention, willingness, and use behaviour of AI across multiple industries. Cultural factors are also an important consideration when comparing acceptance research across different demographics. The TAM was the model most commonly adopted to measure acceptance and was found to have the most predictive success in measuring behavioural intentions. Nonetheless, there have been new theoretical developments in the AI field. The AIDUA is an emerging model that offers a more comprehensive analysis of use behaviour due to the inclusion of two outcome stages (willingness and rejection) and its consideration of advanced technology (e.g., AI). Future applications should consider that willingness and rejection might co-exist rather than rely on traditional models (e.g., TPB, TAM) that view willingness as the absence of rejection. An important limitation of the research is that actual behaviour has been mainly evaluated using the TAM, so the external validity of the other theories is vastly unexplored. This is unsurprising considering actual behaviour is an outcome variable in the TAM, but not in other theoretical models, such as the AIDUA. Researchers should consider the different outcome variables when comparing user acceptance or rejection of AI. The lack of naturalistic studies is a limitation of the current literature, and more research is required to assess the actual uptake of AI. AI research is a rich field that contains many studies, with applications ranging from religious services to automated retail stores. By systematically mapping the predicting factors of AI acceptance, this paper can be utilised to guide future research and development of AI.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

No data was used for the research described in the article.

## Appendix A

See Table 9

## References

Alhashmi, S.F.S., Salloum, S.A., Abdallah, S., 2020. Critical success factors for implementing artificial intelligence (AI) Projects in Dubai Government United Arab Emirates (UAE) health sector: applying the extended technology acceptance model (TAM) [Conference Paper]. Adv. Intelligent Syst. Comp. 1058, 393–405. https://doi.org/10.1007/978-3-030-31129-2_36.

Andrews, J.E., Ward, H., Yoon, J., 2021. UTAUT as a model for understanding intention to adopt AI and related technologies among librarians. J. Acad. Librariansh. 47 (6), 102437 https://doi.org/10.1016/j.acalib.2021.102437.

Antonov, A.A., 2011. From artificial intelligence to human super-intelligence. Artif. Intell. 2 (6), 3560.

Atwal, G., Bryson, D., Williams, A., 2021. An exploratory study of the adoption of artificial intelligence in Burgundy's wine industry. Strategic Change-Brief. Entrepreneurial Finance 30 (3), 299–306. https://doi.org/10.1002/jsc.2413.

Ali, K., Freimann, K., 2021. *Applying the Technology Acceptance Model to AI decisions in the Swedish Telecom Industry* Blekinge Institute of Technology].

Barkhuus, L., Dey, A. K., 2003. Location-based services for mobile telephony: A study of users' privacy concerns. Interact 2003, 9th Ifip Tc13 International Conference On Human-Computer Interaction, Zurich.

Becker, D. (2018). Possibilities to improve online mental health treatment: Recommendations for future research and developments. Future Of Information And Communication Conference, Singapore.

Behl, A., Chavan, M., Jain, K., Sharma, I., Pereira, V.E., Zhang, J.Z., 2021. The role of organizational culture and voluntariness in the adoption of artificial intelligence for disaster relief operations. Int. J. Manpow. https://doi.org/10.1108/IJM-03-2021-0178.

Bringsjord, S., 2011. Psychometric artificial intelligence. J. Exp. Theor. Artif. Intell. 23 (3), 271–277. https://doi.org/10.1080/0952813X.2010.502314.

Cabrera-Sanchez, J.P., Villarejo-Ramos, A.F., Liebana-Cabanillas, F., Shaikh, A.A., 2021. Identifying relevant segments of AI applications adopters – expanding the UTAUT2's variables. Telematics Inform. 58, 101529 https://doi.org/10.1016/j.tele.2020.101529.

Cao, G., Duan, Y., Edwards, J.S., Dwivedi, Y.K., 2021. Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. Technovation 106, 102312. https://doi.org/10.1016/j.technovation.2021.102312.

Chai, C.S., Lin, P.Y., Jong, M.S.Y., Dai, Y., Chiu, T.K.F., Qin, J., 2021. Perceptions of and behavioral intentions towards learning artificial intelligence in primary school students. Educ. Technol. Soc. 24 (3), 89–101. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85110532692&partnerID=40&md5=516a98df37de5eb3cee49fa83fdcdad3.

Chang, S.E., Liu, A.Y., Shen, W.C., 2017. User trust in social networking services: A comparison of facebook and linkedin. Comput. Hum. Behav. 69, 207–217. https://doi.org/10.1016/j.chb.2016.12.013.

Chatterjee, S., Bhattacharjee, K.K., 2020. Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling. Educ. Inf. Technol. https://doi.org/10.1007/s10639-020-10159-7.

Chatterjee, S., Chaudhuri, R., Vrontis, D., Thrassou, A., Ghosh, S.K., 2021a. Adoption of artificial intelligence-integrated CRM systems in agile organizations in India. Technol. Forecast. Soc. Chang. 168, 120783 https://doi.org/10.1016/j.techfore.2021.120783.

Chatterjee, S., Rana, N.P., Dwivedi, Y.K., Baabdullah, A.M., 2021b. Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. Technol. Forecast. Soc. Chang. 170, 120880 https://doi.org/10.1016/j.techfore.2021.120880.

Chatterjee, S., Rana, N.P., Khorana, S., Mikalef, P., Sharma, A., 2021c. Assessing organizational users' intentions and behavior to AI integrated CRM systems: a meta-UTAUT approach. Inf. Syst. Front. https://doi.org/10.1007/s10796-021-10181-1.
Chi, O.H., Gursoy, D., Chi, C.G., 2020. Tourists' attitudes toward the use of artificially intelligent (AI) devices in tourism service delivery: moderating role of service value seeking. J. Travel Res. https://doi.org/10.1177/0047287520971054.
Chiu, Y.T., Zhu, Y.Q., Corbett, J., 2021. Oct). In the hearts and minds of employees: A model of pre-adoptive appraisal toward artificial intelligence in organizations. Int. J. Inf. Manag. 60, 102379 https://doi.org/10.1016/j.ijinfomgt.2021.102379.
Choi, Y., 2020. A study of employee acceptance of artificial intelligence technology. Eur. J. Manag. Bus. Econ. 30 (3), 318–330. https://doi.org/10.1108/EJMBE-06-2020-0158.
Choung, H., David, P., Ross, A., 2022. Trust in AI and its role in the acceptance of AI technologies. Int. J. Human-Comp. Inter. 1–13 https://doi.org/10.1080/10447318.2022.2050543.
Cocosila, M., 2013. Role of user a priori attitude in the acceptance of mobile health: an empirical investigation. Electron. Mark. 23 (1), 15–27. https://doi.org/10.1007/s12525-012-0111-5.
Damerji, H., Salimi, A., 2021. Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting. Acc. Educ. 30 (2), 107–130. https://doi.org/10.1080/09639284.2021.1872035.
Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13 (3), 319–340. https://doi.org/10.2307/249008.
Davis, F. D., 1985. *A technology acceptance model for empirically testing new end-user information systems: Theory and results* Massachusetts Institute of Technology].
Dieter, D. G., 2021. *Consumer Perception of Artificial Intelligence in US Healthcare* Indiana University of Pennsylvania].
Dobrev, D., 2012. A definition of artificial intelligence. *arXiv preprint arXiv:1210.1568*.
Doraiswamy, P. M., London, E., Varnum, P., Harvey, B., Saxena, S., Tottman, S., Campbell, P., Ibáñez, A. F., Manji, H., & Al Olama, M. A. A. S., 2019. Empowering 8 billion minds: enabling better mental health for all via the ethical adoption of technologies. *NAM perspectives, 2019*. https://doi.org/10.31478/201910b.
Eddine, N.A.S., 2018. The idealization and self-identification of black characters in the bluest eyes by Toni Morrison: using voyant text analysis tools. J. Literature, Languages Linguistics 49, 26–31. https://core.ac.uk/download/pdf/234693608.pdf.
Fan, W.J., Liu, J.N., Zhu, S.W., Pardalos, P.M., 2020. Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS). Ann. Oper. Res. 294 (1–2), 567–592. https://doi.org/10.1007/s10479-018-2818-y.
Fishbein, M., Ajzen, I., Belief, A., 1975. Intention and Behavior: An Introduction to Theory and Research. Addison-Wesley, Reading, MA.
Fleischmann, C., Cardon, P., Aritz, J., 2020. Smart collaboration in global virtual teams: The influence of culture on technology acceptance and communication effectiveness. Proceedings Of The Annual Hawaii International Conference On System Sciences.
Floruss, J., Vahlpahl, N., 2020. *Artificial Intelligence in Healthcare: Acceptance of AI-based Support Systems by Healthcare Professionals* Jonkoping University].
Fortuna, P., Gorbaniuk, O., 2022. What is behind the buzzword for experts and laymen: representation of "artificial intelligence" in the IT-professionals' and non-professionals' minds. Europe's J. Psychol. 18 (2), 207–218. https://doi.org/10.5964/ejop.5473.
Gado, S., Kempen, R., Lingelbach, K., Bipp, T., 2021. Artificial intelligence in psychology: How can we enable psychology students to accept and use artificial intelligence? Psychol. Learn. Teach. https://doi.org/10.1177/14757257211037149.
Gansser, O.A., Reich, C.S., 2021. A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. Technol. Soc. 65, 101535 https://doi.org/10.1016/j.techsoc.2021.101535.
Gao, B., Huang, L., 2019. Understanding interactive user behavior in smart media content service: An integration of TAM and smart service belief factors. Heliyon 5 (12), Article e02983. https://doi.org/10.1016/j.heliyon.2019.e02983.
Ghorayeb, A., Comber, R., Gooberman-Hill, R., 2021. Older adults' perspectives of smart home technology: Are we developing the technology that older people want? Int. J. Hum. Comput. Stud. 147, 102571 https://doi.org/10.1016/j.ijhcs.2020.102571.
Gill, K.S., 2016. Artificial super intelligence: Beyond rhetoric. AI & Soc. 31, 137–143. https://doi.org/10.1007/s00146-016-065.
Giummarra, M.J., Lau, G., Gabbe, B.J., 2020. Evaluation of text mining to reduce screening workload for injury-focused systematic reviews. Inj. Prev. 26 (1), 55–60.
Greiner, C., Jovy-Klein, F., Peisl, T., 2021. AI as co-workers: an explorative research on technology acceptance based on the revised bloom taxonomy [Conference Paper]. Adv. Intelligent Syst. Comp. 1288, 27–35. https://doi.org/10.1007/978-3-030-63128-4_3.
Gursoy, D., Chi, O.H., Lu, L., Nunkoo, R., 2019. Consumers acceptance of artificially intelligent (AI) device use in service delivery. Int. J. Inf. Manag. 49, 157–169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008.
Huang, Y.K., Hsieh, C.H., Li, W., Chang, C., Fan, W.S., 2019. Preliminary study of factors affecting the spread and resistance of consumers' use of AI customer service. Acm International Conference Proceeding Series.
Kashive, N., Powale, L., Kashive, K., 2021. Understanding user perception toward artificial intelligence (AI) enabled e-learning. Int. J. Inf. Learn. Technol. 38 (1), 1–19. https://doi.org/10.1108/IJILT-05-2020-0090.
Kaye, S.-A., Lewis, I., Forward, S., Delhomme, P., 2020. A priori acceptance of highly automated cars in Australia, France. and Sweden: A theoretically-informed investigation guided by the PYTPB and UTAUT. Accid. Anal. Prev. 137, 105441.
Kelly, S., Kaye, S.A., Oviedo-Trespalacios, O., 2022. A multi-industry analysis of the future use of AI chatbots. Human Behavior and Emerging Technologies. https://doi.org/10.1155/2022/2552099.
Keung, J., Jeffery, R., & Kitchenham, B., 2004. The challenge of introducing a new software cost estimation technology into a small software organisation. 2004 Australian Software Engineering Conference. Proceedings.
Kim, D., Kim, S., 2021. A model for user acceptance of robot journalism: Influence of positive disconfirmation and uncertainty avoidance. Technol. Forecast. Soc. Chang. 163, 120448 https://doi.org/10.1016/j.techfore.2020.120448.
Kirlidog, M., Kaynak, A. (2013). Technology acceptance model and determinants of technology rejection. In *Information Systems and Modern Society: Social Change and Global Development* (pp. 226-238). IGI Global. https://doi.org/10.4018/jissc.2011100101.
Kim, J., Merrill, K., Xu, K., Sellnow, D.D., 2020. My teacher is a machine: understanding students' perceptions of AI teaching assistants in online education. Int. J. Human-Comp. Inter. 36 (20), 1902–1911. https://doi.org/10.1080/10447318.2020.1801227.
Knoll, L.J., Magis-Weinberg, L., Speekenbrink, M., Blakemore, S.-J., 2015. Social influence on risk perception during adolescence. Psychol. Sci. 26 (5), 583–592. https://doi.org/10.1177/0956797615569578.
Kuberkar, S., Singhal, T.K., 2020. Factors influencing adoption intention of ai powered chatbot for public transport services within a smart city. Int. J. Emerg. Technol. 11 (3), 948–958. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85087363567&partnerID=40&md5=563cfb37d1af156d35db00974c375780.
Lee, J.H., Kim, J.H., Kim, Y.H., Song, Y.M., Gim, G.Y., 2021. Factors affecting the intention to use artificial intelligence-based recruitment system: a structural equation modeling (SEM) Approach [Conference Paper]. Stud. Comput. Intelligence 985, 111–124. https://doi.org/10.1007/978-3-030-79474-3_8.
Lee, J.D., See, K.A., 2004. Trust in automation: designing for appropriate reliance. Hum. Factors: J. Human Factors Ergon. Soc. 46 (1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392.
Liang, Y. L., Lee, S. H., Workman, J. E., 2020. Implementation of Artificial Intelligence in Fashion: Are Consumers Ready? *Cloth. Textiles Res. J., 38*(1), 3-18, Article 0887302x19873437. https://doi.org/10.1177/0887302x19873437.
Liang, Y., Lee, S.A., 2017. Fear of autonomous robots and artificial intelligence: Evidence from national representative data with probability sampling. Int. J. Soc. Robot. 9 (3), 379–384. https://doi.org/10.1007/s12369-017-0401-3.
Liberati, A., Altman, D.G., Tetzlaff, J., Mulrow, C., Gøtzsche, P.C., Ioannidis, J.P., Clarke, M., Devereaux, P.J., Kleijnen, J., Moher, D., 2009. The prisma statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. J. Clin. Epidemiol. 62 (10), e1–e34. https://doi.org/10.1016/j.jclinepi.2009.06.006.
Lin, H., Chi, O.H., Gursoy, D., 2020. Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services. J. Hosp. Mark. Manag. 29 (5), 530–549. https://doi.org/10.1080/19368623.2020.1685053.

Lin, C.-Y., Xu, N., 2021. Extended TAM model to explore the factors that affect intention to use AI robotic architects for architectural design. Tech. Anal. Strat. Manag. 1–14 https://doi.org/10.1080/09537325.2021.1900808.
Lin, H.-C., Yun-Fang, T., Gwo-Jen, H., Hsin, H., 2021. From precision education to precision medicine: factors affecting medical staff's intention to learn to use AI applications in hospitals. J. Educ. Technol. Soc. 24 (1), 123–137. https://www.jstor.org/stable/26977862.
Liu, C., 2017. International competitiveness and the fourth industrial revolution. Entrepreneurial Bus. Econ. Rev. 5 (4), 111–133. https://doi.org/10.15678/EBER.2017.050405.
Liu, Z., Shan, J., Pigneur, Y., 2016. The role of personalized services and control: An empirical evaluation of privacy calculus and technology acceptance model in the mobile context. J. Inf. Privacy Security 12 (3), 123–144. https://doi.org/10.1080/15536548.2016.1206757.
Liu, K., Tao, D., 2022. The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services. Comput. Hum. Behav. 127, 107026 https://doi.org/10.1016/j.chb.2021.107026.
Lunney, A., Cunningham, N.R., Eastin, M.S., 2016. Wearable fitness technology: A structural investigation into acceptance and perceived fitness outcomes. Comput. Hum. Behav. 65, 114–120. https://doi.org/10.1016/j.chb.2016.08.007.
Luo, X., Li, H., Zhang, J., Shim, J.P., 2010. Examining multi-dimensional trust and multi-faceted risk in initial acceptance of emerging technologies: An empirical study of mobile banking services. Decis. Support Syst. 49 (2), 222–234. https://doi.org/10.1016/j.dss.2010.02.008.
McLean, G., Osei-Frimpong, K., 2019. Oct). Hey Alexa examine the variables influencing the use of artificial intelligent in-home voice assistants. Comput. Hum. Behav. 99, 28–37. https://doi.org/10.1016/j.chb.2019.05.009.
McLean, S., Read, G.J., Thompson, J., Baber, C., Stanton, N.A., Salmon, P.M., 2021. The risks associated with artificial general intelligence: A systematic review. J. Exp. Theor. Artif. Intell. 1–17.
Meidute-Kavaliauskiene, I., Cigdem, S., Yildiz, B., Davidavicius, S., 2021. The effect of perceptions on service robot usage intention: a survey study in the service sector. Article 9655 Sustainability 13 (17). https://doi.org/10.3390/su13179655.
Memon, A.M., Memon, A., 2021. Exploring acceptance of artificial intelligence amongst healthcare personnel: a case in a private medical centre. Int. Res. J. Modern. Eng. Technol. Sci. 3 (9).
Meyer-Waarden, B.L., Cloarec, J., 2021. "Baby, you can drive my car": Psychological antecedents that drive consumers' adoption of AI-powered autonomous vehicles. Technovation 102348. https://doi.org/10.1016/j.technovation.2021.102348.
Miltgen, C.L., Popovič, A., Oliveira, T., 2013. Determinants of end-user acceptance of biometrics: integrating the "big 3" of technology acceptance with privacy context. Decis. Support Syst. 56, 103–114. https://doi.org/10.1016/j.dss.2013.05.010.
Mitchell, M., 2019. Artificial Intelligence a Guide for Thinking Humans. Penguin Random House.
Mohr, S., Kühl, R., 2021. Acceptance of artificial intelligence in German agriculture: an application of the technology acceptance model and the theory of planned behavior. Precis. Agric. https://doi.org/10.1007/s11119-021-09814-x.
Mott, B., Lester, J., Branting, K., 2004. Conversational agents. *The Practical Handbook Of Internet Computing.* https://doi.org/10.1201/9780203507223.ch10.
Mun, Y.Y., Jackson, J.D., Park, J.S., Probst, J.C., 2006. Understanding information technology acceptance by individual professionals: toward an integrative view. Inf. Manag. 43 (3), 350–363. https://doi.org/10.1016/j.im.2005.08.006.
Murphy, K., Di Ruggiero, E., Upshur, R., Willison, D.J., Malhotra, N., Cai, J.C., Malhotra, N., Lui, V., Gibson, J., 2021. Artificial intelligence for good health: a scoping review of the ethics literature. BMC Med. Ethics 22 (1), 1–17. https://doi.org/10.1186/s12910-021-00577-8.
Ochmann, J., & Laumer, S., 2020. AI recruitment: Explaining job seekers' acceptance of automation in human resource management. Proceedings Of The 15th International Conference On Business Information Systems 2020 "Developments, Opportunities And Challenges Of Digitization." In Wirtschaftsinformatik (Zentrale Tracks).
Omohundro, S., 2014. Autonomous technology and the greater human good. J. Exp. Theor. Artif. Intell. 26 (3), 303–315. https://doi.org/10.1080/0952813X.2014.895111.
Parasuraman, R., Riley, V., 1997. Humans and automation: Use, misuse, disuse, abuse. Hum. Factors 39 (2), 230–253. https://doi.org/10.1518/001872097778543886.
Park, J., Hong, E., Le, H.T., 2021. Adopting autonomous vehicles: The moderating effects of demographic variables. J. Retail. Consum. Serv. 63, 102687 https://doi.org/10.1016/j.jretconser.2021.102687.
Pelau, C., Dabija, D.C., Ene, I., 2021. What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. Comput. Hum. Behav. 122, 106855 https://doi.org/10.1016/j.chb.2021.106855.
Pillai, R., Sivathanu, B., Dwivedi, Y.K., 2020. Shopping intention at AI-powered automated retail stores (AIPARS). J. Retail. Consum. Serv. 57, 102207 https://doi.org/10.1016/j.jretconser.2020.102207.
Prakash, A.V., Das, S., 2021. Medical practitioner's adoption of intelligent clinical diagnostic decision support systems: a mixed-methods study. Inf. Manag. 58 (7), 103524 https://doi.org/10.1016/j.im.2021.103524.
Rafique, H., Almagrabi, A.O., Shamim, A., Anwar, F., Bashir, A.K., 2020. Investigating the acceptance of mobile library applications with an extended technology acceptance model (tam). Comput. Educ. 145, 103732 https://doi.org/10.1016/j.compedu.2019.103732.
Rambsy, K., 2016. Text-mining short fiction by Zora Neale Hurston and richard wright using voyant tools. CLA Journal 59 (3), 251–258. http://www.jstor.org/stable/44325917.
Ramu, M.M., Shaik, N., Arulprakash, P., Jha, S.K., Nagesh, M.P., 2022. Study on potential AI applications in childhood education. Int. J. Early Childhood 14 (03), 2022. https://doi.org/10.9756/INT-JECSE/V14I3.1215.
Roy, P., Ramaprasad, B.S., Chakraborty, M., Prabhu, N., Rao, S., 2020. Customer acceptance of use of artificial intelligence in hospitality services: an Indian hospitality sector perspective. Glob. Bus. Rev. https://doi.org/10.1177/0972150920939753.
Salmon, P.M., Carden, T., Hancock, P.A., 2021. Putting the humanity into inhuman systems: How human factors and ergonomics can be used to manage the risks associated with artificial general intelligence. Hum. Factors Ergon. Manuf. Serv. Ind. 31 (2), 223–236. https://doi.org/10.1002/hfm.20883.
Savela, N., Turja, T., Latikka, R., Oksanen, A., 2021. Media effects on the perceptions of robots. Hum. Behav. Emerg. Technol. 3 (5), 989–1003. https://doi.org/10.1002/hbe2.296.
Schmidt, A., Giannotti, F., Mackay, W., Shneiderman, B., & Väänänen, K. (2021). Artificial intelligence for humankind: a panel on how to create truly interactive and human-centered AI for the benefit of individuals and society. IFIP Conference on Human-Computer Interaction.
Schwab, K., 2017. The Fourth Industrial Revolution. World Economic Forum.
Seo, K.H., Lee, J.H., 2021. The emergence of service robots at restaurants: Integrating trust, perceived risk, and satisfaction. Article 4431 Sustainability (Switzerland) 13 (8). https://doi.org/10.3390/su13084431.
Sheng, H., Nah, F.-F.-H., Siau, K., 2008. An experimental study on ubiquitous commerce adoption: impact of personalization and privacy concerns. J. Assoc. Inf. Syst. 9 (6), 15. https://doi.org/10.17705/1jais.00161.
Sohn, K., Kwon, O., 2020a. Technology acceptance theories and factors influencing artificial intelligence-based intelligent products. Telematics Inform. 47, 101324 https://doi.org/10.1016/j.tele.2019.101324.
Sohn, K., Kwon, O., 2020b. Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products. Telematics Inform. 47, 101324 https://doi.org/10.1016/j.tele.2019.101324.
Song, S.Y., Kim, Y.K., 2020. Factors influencing consumers' intention to adopt fashion robot advisors: psychological network analysis. Cloth. Text. Res. J. https://doi.org/10.1177/0887302X20941261.
Song, Y. W., 2019. *User acceptance of an artificial intelligence (AI) virtual assistant : an extension of the technology acceptance model* [Thesis; text, ddu. https://search.ebscohost.com/login.aspx?direct=true&db=ddu&AN=194F628A9A233EB6&site=ehost-live&scope=site.
Taddeo, M., Floridi, L., 2018. How AI can be a force for good. Science 361 (6404), 751–752. https://doi.org/10.1126/science.aat5991.
Thomas, T., Singh, L., Gaffar, K., 2013. The utility of the UTAUT model in explaining mobile learning adoption in higher education in Guyana. Int. J. Educ. Develop. ICT 9 (3). https://www.learntechlib.org/p/130274/.

Tran, K., Nguyen, T., Kimura, T., 2021. Preliminary research on the social attitudes toward AI's involvement in Christian education in Vietnam: promoting AI technology for religious education. Religions 12 (3), 208. https://doi.org/10.3390/rel12030208.

Turner, M., Kitchenham, B., Brereton, P., Charters, S., Budgen, D., 2010. Does the technology acceptance model predict actual use? A systematic literature review. Inf. Softw. Technol. 52 (5), 463–479. https://doi.org/10.1016/j.infsof.2009.11.005.

Upadhyay, N., Upadhyay, S., Dwivedi, Y.K., 2021. Theorizing artificial intelligence acceptance and digital entrepreneurship model. Int. J. Entrepreneurial Behav. Res. https://doi.org/10.1108/IJEBR-01-2021-0052.

van Eeuwen, M., 2017. *Mobile conversational commerce: Messenger chatbots as the next interface between businesses and consumers* University of Twente]. http://purl.utwente.nl/essays/71706.

Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: toward a unified view. MIS Q. 425–478 https://doi.org/10.2307/30036540.

Vu, H.T., Lim, J., 2021. Effects of country and individual factors on public acceptance of artificial intelligence and robotics technologies: a multilevel SEM analysis of 28-country survey data. Behav. Inform. Technol. https://doi.org/10.1080/0144929X.2021.1884288.

Wallace, B. C., Small, K., Brodley, C. E., Lau, J., & Trikalinos, T. A. (2012). Deploying an interactive machine learning system in an evidence-based practice center. Proceedings Of The 2nd Acm Sighit International Health Informatics Symposium.

Wang, G., Liu, X., Wang, Z., Yang, X., 2020a. Research on the influence of interpretability of artificial intelligence recommendation system on users' behavior intention. Acm International Conference Proceeding Series.

Wang, S.M., Huang, Y.K., Wang, C.C., 2020b. A model of consumer perception and behavioral intention for AI service. Proceedings Of The 2020 2nd International Conference On Management Science And Industrial Engineering.

Wang, Y., Liu, C., Tu, Y.F., 2021. Factors affecting the adoption of AI based applications in higher education: an analysis of teachers perspectives using structural equation modeling. Educ. Technol. Soc. 24 (3), 116–129. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85110454980&partnerID=40&md5=c59227a37550a07ad8a4695ad30dcc82.

Wu, K., Zhao, Y., Zhu, Q., Tan, X., Zheng, H., 2011. A meta-analysis of the impact of trust on technology acceptance model: Investigation of moderating influence of subject and context type. Int. J. Inf. Manag. 31 (6), 572–581.

Xian, X., 2021. Psychological factors in consumer acceptance of artificial intelligence in leisure economy: A structural equation model. J. Internet Technol. 22 (3), 697–705. https://doi.org/10.3966/160792642021052203018.

Xia, W., Zhou, D., Xia, Q.Y., Zhang, L.R., 2020. Design and implementation path of intelligent transportation information system based on artificial intelligence technology. J. Eng. 2020 (13), 482–485. https://doi.org/10.1049/joe.2019.1196.

Xu, N., Wang, K.J., 2019. Adopting robot lawyer? the extending artificial intelligence robot lawyer technology acceptance model for legal industry by an exploratory study. J. Manag. Organ. 1–19 https://doi.org/10.1017/jmo.2018.81.

Ye, T.T., Xue, J.L., He, M.G., Gu, J., Lin, H.T., Xu, B., Cheng, Y., 2019. Psychosocial factors affecting artificial intelligence adoption in health care in China: cross-sectional study. Article e14316 J. Med. Internet Res. 21 (10). https://doi.org/10.2196/14316.

Zarifis, A., Kawalek, P., & Azadegan, A., 2021. Evaluating if trust and personal information privacy concerns are barriers to using health insurance that explicitly utilizes AI. *J. Internet Commerce, 20*(1), 66-83. https://doi.org/10.1080/15332861.2020.1832817.

Zerilli, J., Bhatt, U., Weller, A., 2022. How transparency modulates trust in artificial intelligence. Patterns 100455. https://doi.org/10.1016/j.patter.2022.100455.

Zhang, S., Meng, Z.X., Chen, B.B., Yang, X., Zhao, X.R., 2021. Motivation, social emotion, and the acceptance of artificial intelligence virtual assistants-trust-based mediating effects. Front. Psychol. 12, 728495 https://doi.org/10.3389/fpsyg.2021.728495.

## *Further reading*

Donia, J., Shaw, J.A., 2021. Co-design and ethical artificial intelligence for health: An agenda for critical research and practice, 205395172110652 Big Data Soc. 8 (2). https://doi.org/10.1177/20539517211065248.

Walsh, T., 2018. 2062: The World that AI Made. La Trobe University Press.