Predictors of Healthcare Practitioners' Intention to Use AI-Enabled Clinical Decision Support Systems (AI-CDSSs): A Meta-Analysis Based on the Universal Theory of Acceptance and Use of Technology (UTAUT)

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Abstract

Background: Artificial Intelligence-enabled Clinical Decision Support Systems (AI-CDSSs) offer potential for improving healthcare outcomes, but their adoption among healthcare practitioners remains limited.

Objective: The meta-analysis identifies predictors influencing healthcare practitioners' intention to use AI-CDSSs based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and additional literature.

Methods: The literature search using electronic databases, forward searches, conference programs, and personal correspondence yielded 7,731 results, of which 17 studies met the inclusion criteria. Random-effects meta-analysis, relative weights analyses, and meta-analytic moderation and mediation analyses were used to examine the relationships of relevant predictor variables with the intention to use AI-CDSSs.

Results: The meta-analysis results supported the application of the UTAUT to the context of the intention to use AI-CDSSs. The results show that performance expectancy (rc = .66), effort expectancy (rc = .55), social influence (rc = .66), and facilitating conditions (rc = .66) were positively associated with the intention to use AI-CDSSs, in line with the predictions of the UTAUT. The meta-analysis further identified positive attitude (rc = .63), trust (rc = .73), anxiety (rc = -.41), perceived risk (rc = -.21), and innovativeness (rc = .54) as relevant additional predictors. Trust emerged as the most influential predictor overall. The results of moderation analyses show that the relationship between social influence and use intention becomes weaker with increasing age. In addition, the relationship between effort expectancy and use intention was stronger for diagnostic AI-CDSSs compared to devices that combined diagnostic and treatment recommendations. Finally, the relationships between facilitating conditions and use intention was mediated through performance and effort expectancy.

Conclusions: The meta-analysis contributes to the understanding of the predictors of the intention to use AI-CDSSs based on an extended UTAUT model. More research is needed to substantiate the identified relationships and to explain the observed variations in effect sizes by identifying relevant moderating factors. The research findings bear important implications for the design and implementation of training programs for healthcare practitioners to ease the adoption of AI-CDSSs into their practice. Clinical Trial: https://osf.io/b4j3t

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Keywords: UTAUT; AI-CDSSs; meta-analysis; healthcare practitioners

1. Introduction

The past decade has witnessed major advancements in the field of healthcare, particularly through the integration of artificial intelligence (AI). One area of progress involves the development of AI-enabled Clinical Decision Support Systems (AI-CDSS; [1–3]). AI-CDSSs use machine learning algorithms to process vast amounts of data and provide case-specific advice to healthcare practitioners to aid clinical decision-making [4–6]. AI-CDSSs use clinical data both from structured (e.g., lab results) and unstructured (e.g., clinician notes or imaging) sources. The interpretation of text-based data can be performed using Natural Language Processing (NLP) to transform text into usable data for clinical predictions [7]. Additionally, deep learning models, including neural networks, can be employed to generate recommendations based on image data, for example, in the detection of pneumonia from chest radiographs [8]. AI-CDSSs may improve the accuracy and efficiency of medical decision-making in several ways.

First, AI-CDSSs may offer structured rationales underpinning clinical decisions that can complement traditional care methods. This structured approach paves the way for clearer understanding, improved communication, and better tracking of the decision-making process in clinical settings [9,10]. Second, AI-CDSSs can integrate data from various sources to provide a comprehensive and personalized recommendation for every patient case [6]. Finally, AI-CDSSs promote the consistency of medical decisions. By leveraging AI algorithms, it may be ensured that the same set of facts will consistently produce the same recommendations, thus minimizing harmful consequences due to human error [8].

Despite these advantages, the implementation of AI-CDSSs into clinical practice must still overcome numerous barriers. A major challenge in the deployment of AI-CDSSs is the variability in performance. This can occur when the data used to develop the AI models does not adequately represent the population for which the tool is intended. Another issue is when AI-CDSSs are not used as designed, which can be due to a range of factors including user interface problems, lack of integration into clinical workflows, or insufficient training of healthcare professionals on the system's use [6,11–13]. The resulting low performance casts doubt on the value of AI-CDSSs in assisting with clinical decision-making [11,14]. Additionally, the lack of understanding how AI recommendations are derived heightens clinicians' reservations about using these systems [15–17]. There are also challenges relating to the alignment of AI-CDSSs with existing workflows that can cause additional workload when new AI systems are incorporated into clinical procedures [6,18–20].

As the development of high-performing AI-CDSSs proceeds, understanding the factors that influence healthcare practitioners' intention to use these systems becomes increasingly relevant. One of the most comprehensive theories to explain individual technology adoption is the Unified Theory of Acceptance and Use of Technology (UTAUT; [21]). The UTAUT proposes that a person’s intention to use a technology is determined by their beliefs and attitudes towards that technology, such as the perception of its performance or the perceived effort it would require to use it. The UTAUT's comprehensive nature and its ability to account for various determinants of technology acceptance make it an appropriate model for examining the predictors of healthcare practitioners’ intention to use AI-CDSSs.

Research to identify predictors of the intention to use AI-CDSSs has accumulated over the past years [3,22–24]. However, the existing literature remains scattered and in need of systematic synthesis. The overarching goal of this article, therefore, is to quantitatively integrate existing studies on the predictors of healthcare practitioners’ intention to use AI-CDSSs. The proposed hypotheses are based on the UTAUT model and existing empirical evidence. With the current meta-analysis, we make four major contributions to theory and practice. First, we use meta-analytic techniques to estimate the relationship between the predictors of the UTAUT and the intention to use AI-CDSSs, thus providing insight into the applicability of the UTAUT to the context of AI-CDSSs. Second, we identify additional predictors based on the existing literature and examine the relative contribution of the UTAUT and additional predictors in explaining the intention to use AI-CDSSs. With this approach, we contribute to a theoretical refinement and potential extension of the UTAUT model to the context of AI-CDSSs. Third, based on the UTAUT, we examine the role of contextual factors as moderators of the relationships between relevant predictors and use intention, thus shedding light on the conditions that influence the strength of these relationships. Finally, in line with the UTAUT model, this is the first meta-analysis that examines the role of mediators, thus allowing for a better understanding of the complex mechanisms through which use intention may be explained. The study protocol, including all hypotheses and research questions, has been pre-registered through the Open Science Framework (https://osf.io/b4j3t).

2. Theory and Hypothesis Development

2.1 The Unified Theory of Acceptance and Use of Technology (UTAUT) and the Intention to Use AI-CDSSs

The UTAUT integrates eight former technology use theories and has become one of the most prominent technology use models [21,25]. The UTAUT has been applied to investigate factors influencing the acceptance and use of technology in different contexts, including healthcare [26–28]. The primary outcome measure considered in the UTAUT alongside actual use is the intention to use a technology [21,29,30]. Intentions are indicators of motivation and reflect the level of determination individuals have to actually perform a certain behavior [31]. The successful deployment of any technology depends largely on the user intention to use it [32]. Accordingly, understanding the predictors of the intention to use AI-CDSSs may uncover potential levers to overcome individual-level impediments thwarting the adoption of AI-CDSSs in healthcare.

The UTAUT consists of four core predictors of individual use intention: Performance expectancy, effort expectancy, social influence, and facilitating conditions [21]. The relationships between these variables and use intention are proposed to be moderated by gender, age, experience, and voluntariness of use [21].

2.2 Predictors of the Intention to Use AI-CDSSs Based on the UTAUT

Performance expectancy refers to the extent to which individuals believe that using a technology will improve their job performance. AI-CDSSs have the potential to enhance job performance by aiding clinicians in deriving diagnoses or making treatment decisions [33]. If clinicians perceive their decisions to be improved by using AI-CDSSs, then performance expectancy will be high [34,35].

Hypothesis 1: Performance expectancy is positively related to the intention to use AI-CDSSs.

Effort expectancy concerns the perceived ease of use of a technology. It is suggested that a system that is perceived to be easy to use is more likely to be accepted than one that is perceived to be complicated to use [21]. If, for example, the perceived effort of using an AI-CDSS in one's existing clinical workflows is perceived to be high, healthcare practitioners may be less willing to use it [2,20,22].

Hypothesis 2: Effort expectancy is positively related to the intention to use AI-CDSSs.

Social influence refers to the impact of social factors, such as the expectations and influence of peers, on an individual's intention to use a technology. The positive relationship between social influence and the intention to use AI-CDSSs has consistently been supported in empirical studies [22,35]. For example, it was found that medical professionals holding the belief that their colleagues, top management, and professional bodies endorse the use of AI-CDSSs in clinical settings are more willing to adopt them [35].

Hypothesis 3: Social influence is positively related to the intention to use AI-CDSSs.

Facilitating conditions represent the organizational and technical infrastructure necessary for technology adoption [21]. It has been argued that if users believe that the resources and support are in place to facilitate the use of AI-CDSSs, they are more likely to intend to use them [3,21,36].

Hypothesis 4a: Facilitating conditions are positively related to the intention to use AI-CDSSs.

In addition, according to the UTAUT, there is a direct relationship between facilitating conditions and actual technology use [21]. Facilitating conditions refer to the resources and support available to use a technology, including the access to the necessary tools and knowledge. This practical aspect makes their influence on usage immediate, as users are more likely to use technology when they perceive a supportive environment and available resources. Unlike other predictors in the UTAUT, facilitating conditions are proposed as direct antecedents of actual use [21].

Hypothesis 4b: Facilitating conditions are positively related to actual use of AI-CDSSs.

2.3 Additional Predictors of the Intention to Use AI-CDSSs

The UTAUT has been modified and additional predictors have been added over time to account for various settings and technologies [29,37–39]. However, a meta-analytic review is limited to the relationships that have been studied in a literature. Following previous research and methodological best practices, we include additional predictors beyond the UTAUT in the meta-analysis that have been examined in at least three independent samples [40,41]. Following this criterion, we identified attitude, trust, perceived risk, AI anxiety, and personal innovativeness as additional predictors of the intention to use AI-CDSSs.

Individual behavior is driven by intention, which is in turn a function of an individual's attitude toward the behavior and subjective norms [29,42]. Indeed, a positive attitude towards AI-CDSSs has been identified as a relevant predictor of the intention to use AI-CDSSs [43–45].

Research Question 1: Is there a positive relationship between a positive attitude towards AI-CDSSs and the intention to use AI-CDSSs?

Trust in a technology generally refers to the confidence or belief users have in a technology to perform tasks reliably and safely [22,34,35]. In the context of AI-CDSSs, some studies refer to trust in terms of beliefs in the reliability and safety in AI-CDSSs before the potential user has been exposed to or actively used the system [2,35,46]. Others refer to trust in terms of the belief that AI-CDSSs have the ability, integrity, and benevolence needed to provide the service they claim to provide [47]. Trust has been argued to be a particularly relevant predictor of the intention to use AI-CDSSs due to the lack of transparency of how recommendations are derived and the high stakes of erroneous decisions in healthcare [22,35].

Research Question 2: Is there a positive relationship between trust and the intention to use AI-CDSSs?

In the context of AI-CDSSs, risk refers to the perceived potential negative consequences associated with their use, including performance failure and data insecurity [3]. Perceived risk has repeatedly been found to predict the intention to use AI-CDSSs [3,35,48,49]. For example, it has been found that performance and legal risk associated with an AI-CDSSs were positively related to resistance to change, which, in turn, decreased the intention to use AI-CDSSs [35].

Research Question 3: Is there a negative relationship between perceived risk and AI-CDSSs use intention?

AI anxiety encompasses fears and insecurities regarding AI technology. It represents an intuitive, negative affective reaction to specific AI technologies, for example, based on the fear of making mistakes [50,51]. If healthcare professionals experience anxiety in using AI-CDSSs, their intention to use them is presumably low. Indeed, AI anxiety has been identified as a negative predictor of the intention to use AI in healthcare [23].

Research Question 4: Is there a negative relationship between AI anxiety and the intention to use AI-CDSSs?

Personal innovativeness describes an individual's readiness to experiment with and embrace a new technology [52]. Those demonstrating a high degree of personal innovativeness have greater capabilities and, therefore, demonstrate greater readiness to use a new technology [53,54]. Indeed, there exists empirical evidence for a positive link between personal innovativeness and the intention to use AI-CDSSs [2,34].

Research Question 5: Is there a positive relationship between personal innovativeness and the intention to use AI-CDSSs?

2.4 The Relationship Between AI-CDSSs Use Intention and Actual Use

The UTAUT proposes that an individual's intention to use a technology is the main predictor of its actual use [21]. However, this relationship has not yet been extensively researched in the context of AI-CDSSs. The limited investigation of actual use may be attributed to the restricted number of AI-CDSSs implemented in clinical practice [55]. Nonetheless, some evidence indicates that use intention predicts the actual use of AI-CDSSs [3,45].

Research Question 6: What is the relationship between the intention to use AI-CDSSs and their actual use?

2.5 The Relative Contribution of the UTAUT Predictors and Additional Predictors in Explaining AI-CDSSs Use Intention

Existing empirical research has explored the extent to which the UTAUT predictors account for variance in technology use intention [56]. For example, performance expectancy has often emerged as the strongest predictor of use intention [57–59]. Other research has found that trust has a stronger effect on the intention to use AI-CDSSs than performance expectancy [35]. As the roles of UTAUT and additional predictors in explaining the intention to use AI-CDSSs remain unclear, we propose the following research question:

Research Question 7: What is the relative contribution of the UTAUT predictors and additional predictors in explaining the intention to use AI-CDSSs?

2.6 Moderators of the Relationships Between UTAUT Predictors and the Intention to Use AI-CDSSs

The relationships between UTAUT predictors and use intention are proposed to be moderated by age, gender, user experience with the system, and voluntariness of using the system [21]. First, it has been suggested that younger workers prioritize extrinsic rewards such as improved job performance, thus exhibiting a stronger relationship between performance expectancy and technology use intention [21]. In contrast, it is suggested that older workers generally face greater software challenges and are more likely to place increased relevance on social influences. Accordingly, they may rely more on effort expectancy and social influence when deciding to use a technology [21].

Hypothesis 5: The relationship of (a) performance expectancy with the intention to use AI-CDSSs becomes weaker and the relationships of (b) effort expectancy and (c) social influence with the intention to use AI-CDSSs become stronger with increasing age.

Second, the impact of performance expectancy on use intention is expected to be stronger among men, while the relationship of effort expectancy and social influence with use intention would be more pronounced among women [21].

Hypothesis 6: The relationship of (a) performance expectancy with the intention to use AI-CDSSs is stronger for men, and the relationships of (b) effort expectancy and (c) social influence with the intention to use AI-CDSSs is stronger for women.

Third, according to the UTAUT, limited experience increases the strength of the relationship between effort expectancy and social influence with use intention because individuals with limited experience tend to overestimate the challenges associated with using a new technology and their opinions are more susceptible to social influence [21]. In contrast, as experience increases, facilitating conditions have been proposed to exhibit a greater impact on actual technology use, as more experienced users know better how to take advantage of facilitating conditions when using the system [21].

Hypothesis 7: The relationships of (a) effort expectancy and (b) social influence with intention to use AI-CDSSs become weaker with increasing experience and the relationship of (c) facilitating conditions with actual use of AI-CDSSs becomes stronger with increasing experience.

Finally, the UTAUT distinguishes between voluntary (i.e., individuals decide themselves whether to use a technology) and mandatory (e.g., the use of a technology is mandated by the supervisor) adoption settings [21]. It has been suggested that social influence affects use intention in mandatory situations more because relevant others have the capacity to either incentivize desired actions or penalize noncompliance [21].

Hypothesis 8: The relationship of social influence with the intention to use AI-CDSSs is stronger in mandatory adoption settings.

In addition to the UTAUT moderators, we investigate the influence of additional contextual moderators, namely occupation, type of AI-CDSS, and culture. First, healthcare practitioners may work in different contexts requiring them to complete different tasks.

These differences may influence their perceptions, beliefs, and attitudes towards AI-CDSSs [23,49]. For instance, one study found differences in the relationship of social influence and perceived risk with use intention between clinicians (e.g., surgery, orthopedics) and non-clinicians (e.g., radiologists, pathologists). Specifically, for non-clinicians, social influence positively predicted the intention to use AI-CDSSs, while perceived risk did not emerge as a significant predictor. In contrast, among clinicians, the reverse pattern was observed [49]. Second, the type of AI-CDSS likely influences practitioners' use intention. Specifically, healthcare practitioners may place greater emphasis on the effectiveness and safety of treatment AI-CDSSs compared to diagnostic AI-CDSSs as an erroneous treatment decision is associated with more severe consequences [23]. Finally, cultural differences may influence the intention to use AI-CDSSs in healthcare [60,61]. For example, one study found perceived ease of use to be a more relevant predictor of the intention to use information technology among Taiwanese compared to US physicians [61]. Accordingly, we propose the following research question:

Research Question 8: Do (a) the practitioner's occupation, (b) the type of AI-CDSS, and (c) cultural background moderate the relationship between UTAUT predictors and the intention to use AI-CDSSs?

Finally, we investigate the influence of methodological moderators such as publication year and the scale used to measure AI-CDSSs use intention. In a meta-analysis based on the UTAUT, it was found that some effect sizes were stronger in more recent studies [56]. Moreover, while most studies use the intention to use scale introduced by Venkatesh et al. (2003), some studies employ self-developed scales to measure use intention [24,34].

Research Question 9: Do (a) publication year and (b) the use intention scale employed moderate the relationship between UTAUT predictors and the intention to use AI-

CDSSs?

2.7 Performance and Effort Expectancy as Mediators of the Relationship Between Facilitating Conditions and the Intention to Use AI-CDSSs

According to the UTAUT, the effect of facilitating conditions on use intention may be explained through performance and effort expectancy [21,62]. That is, if the required support infrastructure is provided, a person would perceive the system to be both high-performing and easy to use, which, in turn, positively influences their intention to use it. Indeed, effort expectancy has been found to fully mediate the relationship between facilitating conditions and use intention [62]. Accordingly, we propose the following research question to investigate the mediating role of performance and effort expectancy:

Research Question 10: Is the relationship between facilitating conditions and the intention to use AI-CDSSs mediated through (a) performance and (b) effort expectancy?

2.8 Overview of the Hypotheses and Research Questions

Figure 1 displays all hypotheses and research questions. We omitted the relationship between facilitating conditions and actual use if AI-CDSSs (Hypothesis 4b) as well as the moderators experience (Hypothesis 7), voluntaries (Hypothesis 8), and occupation (Research Question 8a) from the analyses due to the limited number of available independent samples (k < 3). All other deviations from the pre-registration are presented in Table S1 in the Online Appendix (https://osf.io/djwkz/?view_only=7d6046aac9424a3c8f2facab08ac1e16)

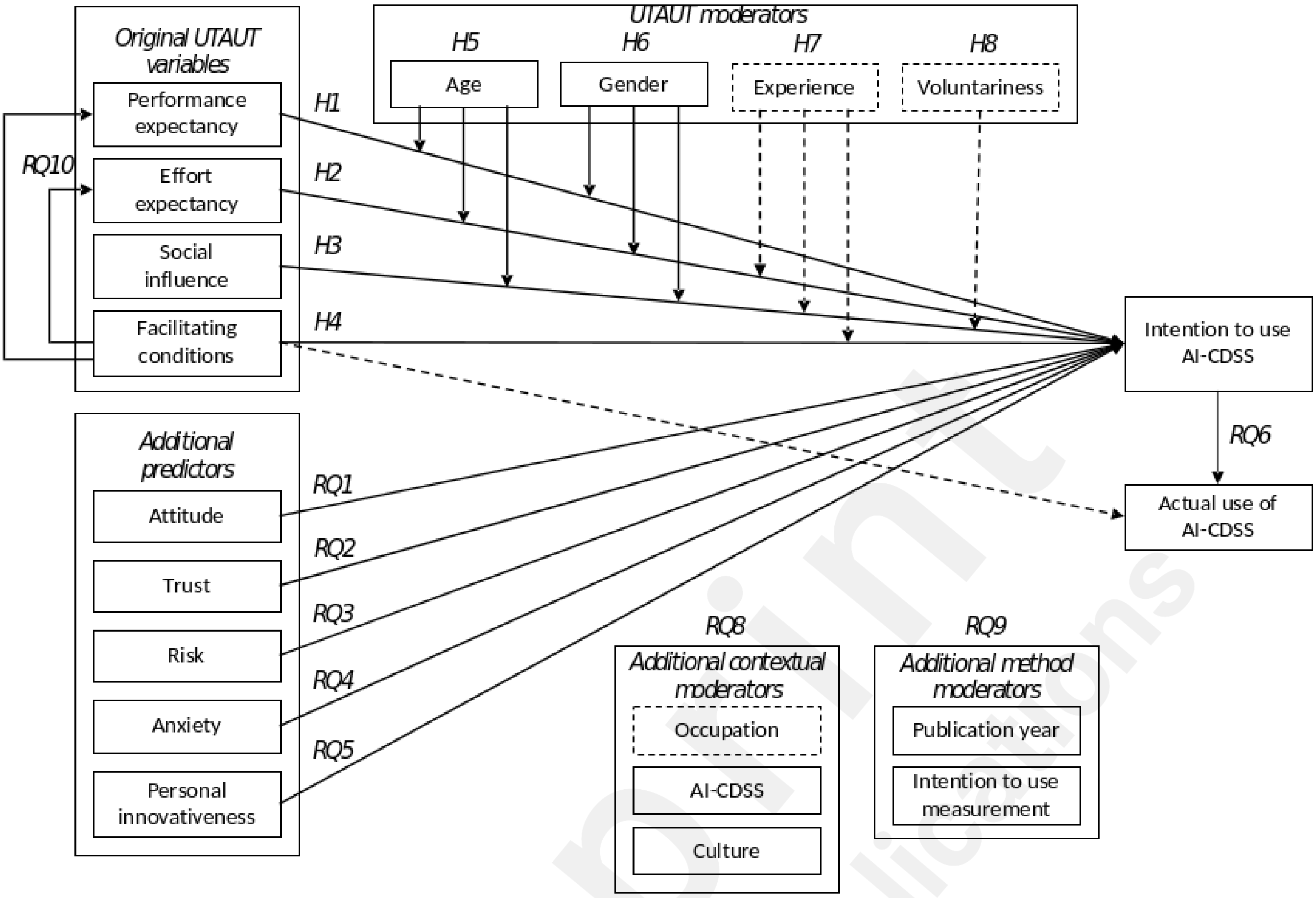

Figure 1. *The proposed research model.* Dashed lines represent pre-registered hypotheses and research questions that could not be investigated due to the limited number of available independent samples (*k* < 3). Research Question 7 is omitted from the Figure as it refers to the relative weights analysis.

3. Methods

3.1 Inclusion and Exclusion Criteria

To qualify for inclusion, the following criteria had to be met: First, studies had to be published in English. Second, studies had to include AI-CDSSs. The second inclusion criterion is fulfilled if a) one of the terms ‘artificial intelligence’, ‘AI’, ‘machine learning’, ‘deep learning’, or ‘deep neural networks’ was used to describe the technology [63] and b) the technology was referred to as a CDSS or it was described as providing recommendations regarding the diagnosis, treatment, or prognosis of health issues [5]. We included studies if AI-CDSSs were mentioned alongside other AI-enabled functionalities [64]. This led to the exclusion of studies that investigated the use intention of other healthcare technologies, such as telemedicine [65] or the medical internet of things [66]. Notably, one study examined the intention to use explainable and non-explainable AI-CDSSs in the same sample [36]. Because only one other study examined explainable AI [43], we included only the data for the non-explainable AI-CDSSs. Third, studies had to include a measure of the intention to use AI-CDSSs as defined in the UTAUT [21], including self-developed scales based on the UTAUT scale. This led to the exclusion of non-empirical studies, such as reviews or case studies [67]. Fourth, studies had to measure use intention among a sample of healthcare practitioners or medical students based on the list of health professionals by the World Health Organization [68]. Finally, studies had to measure at least one predictor variable from our theoretical model (Figure 1). For a detailed overview of the inclusion criteria per included study, please refer to Table S2 in the Online Appendix.

3.2 Search Strategy and Data Extraction

This meta-analysis was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure comprehensive and transparent reporting [69]. We used five steps to search for relevant data. First, relevant scientific articles, dissertations, and theses were searched using the electronic databases Embase, Medline, ProQuest, PsycINFO, and Web of Science between October 15th, 2022, and January 5th, 2023. Two follow-up searches were conducted on May 2nd, 2023 and November 7th, 2023. The search string was developed based on the participants, intervention, comparators, and outcome framework (PICO) [70]. The framework was adapted to fit the research purpose resulting in a three-tiered search term including the population (healthcare professionals), the technology (AI-CDSSs), and the outcome (use intention) of interest. An overview of the search terms is presented in Table S3 the Online Appendix. We used the search term to search in titles, abstracts, and keywords. We conducted follow-up searches in Google Scholar using the following search string:

[‘healthcare’], AND [‘Artificial Intelligence’] AND [‘UTAUT’]. Second, we conducted forward-searching of studies citing Venkatesh et al.’s (2003) seminal article via Google Scholar and backward searches in review articles [71–75]. Third, abstracts of relevant conference proceedings including the *Conference on Computer Supported Cooperative Work and Social Computing*, the *Conference on Human Factors in Computing Systems*, and the *Institute of Electrical and Electronics Engineers* were searched. Fourth, we sent requests for unpublished articles and data using the mailing list of the German Psychology Association (DGPs). Finally, authors of articles included in the meta-analysis were contacted and asked for unpublished data sets. No additional unpublished data was obtained.

We reached out to authors when critical information needed to decide the inclusion of a study, or details essential for the meta-analytic synthesis, such as a correlation table, were missing. From the 24 authors contacted to procure missing information, we successfully obtained six data sets. These data sets were used to derive the missing information, for instance, to calculate missing correlations between variables of interest.

Figure 2 shows the PRISMA diagram with the number of studies identified, included, and excluded, along with reasons for exclusion. The studies from the literature search were assessed following a three-stage approach. First, titles were screened to identify relevant articles. Second, the abstracts of the remaining articles were reviewed. Third, full article texts were reviewed. As a result of a review of 107 full texts, 17 studies met the inclusion criteria (K = 18 independent samples, N = 3,871).

Following the approach of previous meta-analyses, we only included relationships that were identified in a minimum of three separate samples [41,76]. We grouped overlapping variables into construct categories (see Table S4 in the Online Appendix). Studies from both the primary and the follow-up literature search were coded by two researchers each (AK and SG for the primary search; and JD and AK for the follow-up search). Any conflicts in the coding were resolved in weekly consensus meetings. Additionally, in line with approaches to ensure accuracy in coding established in previous meta-analyses [77], a random sample of ten of the 18 independent samples (56%) was re-coded by JC and AS. We included agreement on correlations, reliabilities, and moderator categories into the assessment of interrater agreement. Overall interrater agreement was high (94.7%). Notably, no disagreements were observed regarding correlations. Some mistakes in the coding of reliabilities occurred during the re-coding due to referencing an incorrect line from the source document. The final code sheet used for the analyses is published in the OSF Online Appendix (https://osf.io/djwkz/?view_only=7d6046aac9424a3c8f2facab08ac1e16).

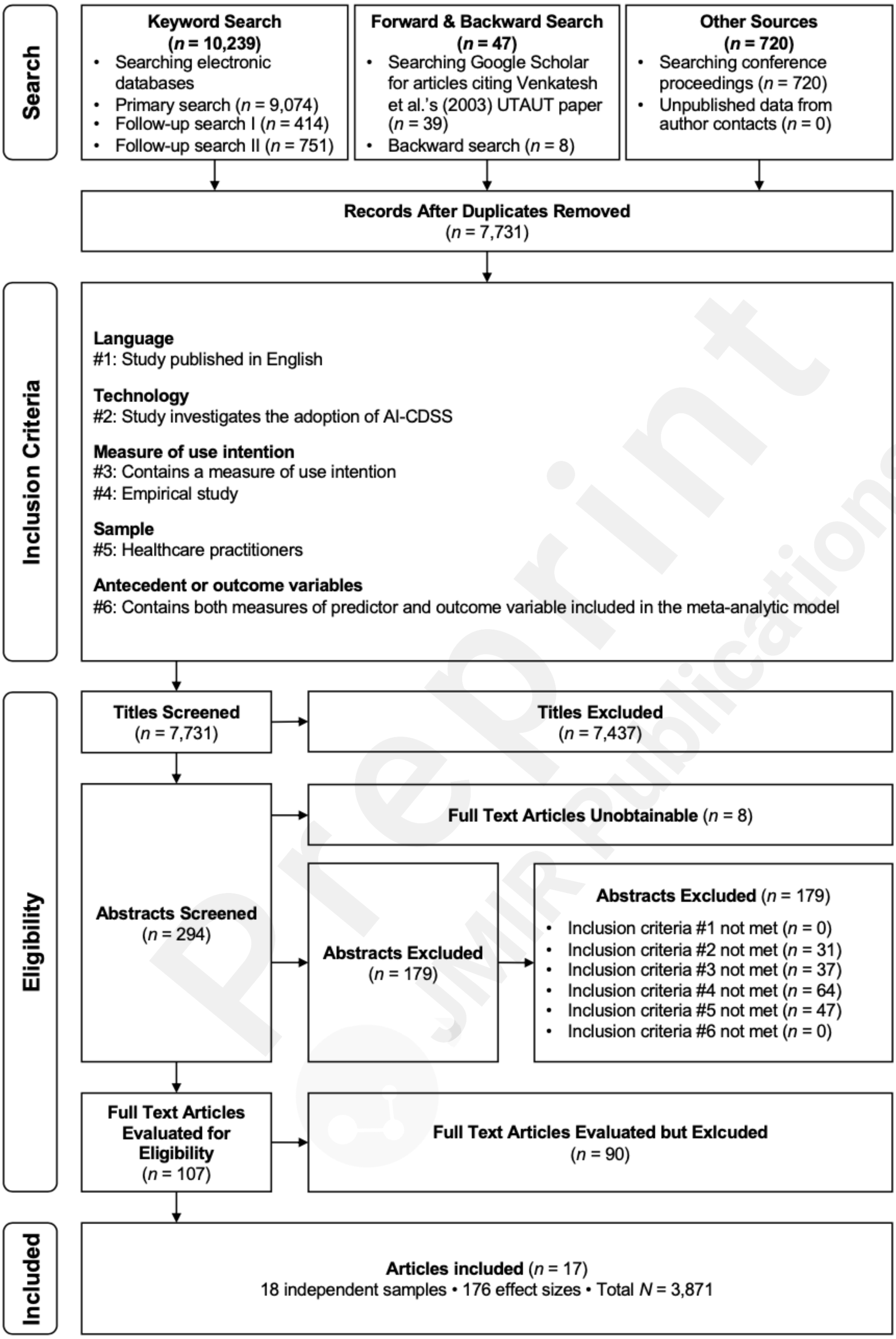

Figure 2. *PRISMA flow chart of the study selection process*

3.3 Meta-analytic procedures

All analyses were conducted with RStudio [78] using the R packages ‘psychmeta’ [79] and ‘metaSEM’ [80].

3.3.1 Bivariate Relationships

To examine the bivariate relationship of the four core constructs of the UTAUT (H1-H4) and the additional predictors (RQ1-RQ5) with the intention to use AI-CDSSs, random-effects meta-analysis was conducted [81]. Effect sizes were based on Pearson product-moment correlations. Composites were calculated if multiple measures of the same construct were reported for the same sample [81]. Specifically, a variance-weighted composite (across measures of the same construct) was calculated for each independent sample to combine multiple measures of the same construct into a single effect size per independent sample [81]. Sampling errors were corrected using sample size weighted correlations. Measurement errors were corrected based on Cronbach’s alpha [81]. In addition to the sample size-weighted correlation (r) and sample size-weighted and reliability-corrected correlation (r_c), the 95% confidence interval (95% CI) and 80% credibility interval (80% CR) for (r_c) are reported. Finally, we report the correlation between observed effects and the influence of the study design artifacts (cor(r, a)).

3.3.2 Relative Weights Analysis

We conducted relative weights analyses to capture the contribution of the correlated predictors [82]. Specifically, we calculated multivariate meta-analytic regression models based on the pooled correlation matrices to explore the incremental value of the UTAUT predictors and additional predictor variables in explaining the intention to use AI-CDSSs. We used the harmonic mean of the sample size across the correlations considered as the sample size for the estimated regression models [83]. In relative weights analysis, raw relative weights are calculated to reflect the proportion of variance explained in the outcome that is attributed to each of the predictors, while rescaled relative weights reflect the percentage of variance that is explained by each predictor variable [84,85].

3.3.3 Moderation Analyses

Moderator analyses were carried out for constructs that were represented in a minimum of k = 10 independent samples to ensure adequate coverage of moderator categories [86]. Five constructs met this minimum cutoff and were considered for the moderation analyses (i.e., performance expectancy, effort expectancy, social influence, trust, and perceived risk). We interpreted categorical moderator effects if each of the levels included $k \geq 3$ independent samples. Age was coded as the mean age of study participants, and gender as the percentage of females in the sample. For the type of AI-CDSS, three categories were initially identified: diagnostic decision support systems, treatment decision support systems, and systems that combined both diagnostic and treatment decision support. However, the category treatment decision support systems had to be excluded from the moderator analysis because of the low number of independent samples focusing on this kind of AI-CDSS ($k = 2$). Culture was operationalized based on the individualism versus collectivism dimension of the Hofstede country comparison tool [87,88]. A higher score denotes stronger individualism. The publication year was coded chronologically. Finally, the scale used to measure the intention to use AI-CDSSs was coded as a categorical moderator. We differentiated between studies using the Venkatesh scale and studies using self-developed scales. We conducted moderation analyses that were not pre-registered as part of exploratory analyses.

3.3.4 Mediation Analysis

To test Research Question 6, correlation-based meta-analytic structural equation modeling (MASEM) [89] based on the two-stage structural equation modeling approach (TSSEM) [90,91] was performed. In the first step, the sample-size weighted and reliability-corrected bivariate correlation matrices for each independent sample were pooled together.

In TSSEM, the total sample size is used for the estimation of the MASEM model [91]. In the second step, a path model was fitted to the pooled correlation matrix.

4. Results

4.1 Study Characteristics

The overall mean age was 36 years and 46% were female. Seven out of the 17 studies focused on diagnostic AI-CDSSs, two on treatment AI-CDSSs, four on treatment and diagnostic AI-CDSSs, and four on unspecific AI-CDSSs. Eleven studies were conducted in Asia (six in China), three in Europe, one in the U.S., and two globally in English-speaking countries.

4.2 Meta-Analytic Results

In the following, we report sample size-weighted and reliability-corrected correlations (r_c) for the relationships of relevant antecedent variables with AI-CDSSs use intention. In line with Cohen (1988), we classify our reported effects as weak (r_c = .1), moderate (r_c = .3), and strong (r_c = .5).

4.2.1 Bivariate Relationships

The results of bivariate meta-analytic analyses are shown in Table 1. The UTAUT predictors performance expectancy (r_c = .66, 95% CI [.59, .73]), effort expectancy (r_c = .55, 95% CI [.43, .67]), social influence (r_c = .66, 95% CI [.59, .72]), and facilitating conditions (r_c = .66, 95% CI [.42, .90]) exhibited a strong positive relationship with the intention to use AI-CDSSs. The findings support H1 through H4. Regarding the additional predictors beyond the UTAUT, attitude (r_c = .63, 95% CI [.52, .73]), trust (r_c = .73, 95% CI [.63, .82]) and innovativeness (r_c = .54, 95% CI [.43, .64]) exhibited strong positive relationships. Perceived risk (r_c = -.21, 95% CI [-.35, -.08]) was weakly negatively related to use intention. Although the estimate for AI anxiety was strong and negative (r_c = -.41), the 95% CI included zero (95% CI [-.98, .15]). Accordingly, we cannot conclude that AI anxiety is related to use intention. The 80% credibility interval for effort expectancy (.27 to .83), facilitating conditions (.33 to .99) and AI anxiety (-.81, -.01) were wide, suggesting the presence of moderators [81,92]. Finally, the intention to use AI-CDSSs was strongly positively related to the actual use of AI-CDSSs (k = 3, N = 478, r = .75, r_c = .85, SD_c = 0.09, 95% CI [.63, 1.00], 80% CR [.70, 1.00], $cor(r,a)$ = .44).

Table 1

Bivariate relationships between predictor variables and AI-CDSS use intention

Predictor Variable	*k*	*N*	*r*	r_c	SD_c	95% CI	80% CR	cor(*r*,a)
Performance expectancy	16	3,295	.59	.66	0.13	.59, .73	.50, .82	.39
Effort expectancy	15	3,058	.49	.55	0.22	.43, .67	.27, .83	.28
Social influence	15	3,058	.57	.66	0.12	.59, .72	.52, .80	.46
Facilitating conditions	6	1,048	.57	.66	0.23	.42, .90	.33, .99	.25
Attitude	9	2,048	.51	.63	0.14	.52, .73	.45, .80	.43
Trust	10	1,840	.66	.73	0.13	.63, .82	.55, .90	.35
Perceived risk	10	2,428	-.19	-.21	0.18	-.35, -.08	-.45, .02	.39
Anxiety	3	391	-.37	-.41	0.23	-.98, -.15	-.81, -.01	.38
Innovativeness	5	843	.47	.54	0.09	.43, .64	.46, .61	.81

Note. k = number of independent samples; *N* = cumulative sample size; *r* = sample size-weighted correlation; r_c = sample size-weighted and reliability-corrected correlation; SD_c = standard deviation of r_c; CI = confidence interval for r_c; CR = credibility interval; cor(*r*, *a*) = correlation between *r* and statistical artifacts (a).

4.2.2 Relative Weights Analysis

It was not possible to explore all nine predictors in a single relative weights analysis because they were not investigated together in a sufficient number of independent samples (see Table S5 in the Online Appendix, https://osf.io/djwkz/?view_only=7d6046aac9424a3c8f2facab08ac1e16). Accordingly, we analyzed one model with only the UTAUT predictors (Table 2) and four separate extension models, consisting of five to six predictors (Table 3). In the initial model with only the UTAUT predictors, the combined effects of performance expectancy, effort expectancy, social influence, and facilitating conditions explained 50% of the total variance in the intention to use AI-CDSSs. Performance expectancy was the dominant predictor accounting for 31% of the total variance explained, followed by social influence (28%), facilitating conditions (26%), and effort expectancy (15%). In the extension models, trust emerged as the most influential overall predictor of use intention (between 29% and 35% of the total variance explained). In all three models including trust, performance expectancy was the second most influential predictor (between 19% and 24% of the total variance explained). Facilitating conditions (between 20% and 25%) and social influence (between 14% and 21%) consistently explained additional variance in all extension models. In the extension models including trust and perceived risk, and trust and anxiety, the regression estimate of effort expectancy became negative. Finally, AI anxiety and perceived risk negatively predicted use intention and accounted for 10% (AI anxiety) and 2% (perceived risk) of the total variance explained.

Table 2

Multiple regression models and relative weights for the UTAUT predictors

Predictor	*B*	*SE*	*t*-value	*p*	Raw RW	RS RW
Performance expectancy	.31	0.02	13.97	<.001	.16	31.19%
Effort expectancy	.08	0.02	3.56	<.001	.08	15.20%
Social influence	.27	0.02	12.29	<.001	.14	27.91%
Facilitating conditions	.21	0.02	9.33	<.001	.13	25.70%

Note. *B* = regression estimate; *SE* = standard error of *B*; RW = relative weight; RS = rescaled. F = 429.28 (p < .001), R^2 = .498.

Table 3

Multiple regression models and relative weights for UTAUT and additional predictors

Predictor	*B*	*SE*	*t*-value	*p*	Raw RW	RS RW
UTAUT Extension (attitude, perceived risk), F = 222.3053 (p < .001), R^2 = .509						
Performance expectancy	.25	0.03	9.355	<.001	.12	24.00%
Effort expectancy	.05	0.03	2.036	.042	.06	12.14%
Social influence	.17	0.03	6.404	<.001	.10	20.54%
Facilitating conditions	.28	0.03	10.821	<.001	.13	25.31%
Attitude	.13	0.03	5.023	<.001	.08	15.91%
Perceived risk	-.04	0.02	-2.204	.028	.01	2.09%
UTAUT Extension (trust, innovativeness), F = 308.50 (p < .001), R^2 = .542						
Performance expectancy	.22	0.03	8.774	<.001	.12	22.72%
Effort expectancy	.05	0.02	2.141	.032	.06	11.57%
Social influence	.19	0.03	7.622	<.001	.11	20.40%
Trust	.39	0.03	15.398	<.001	.19	35.04%
Innovativeness	.04	0.02	1.561	.119	.06	10.26%
UTAUT Extension (trust, perceived risk), F = 389.61 (p < .001), R^2 = .600						
Performance expectancy	.18	0.02	8.397	<.001	.11	18.76%
Effort expectancy	-.06	0.02	-2.654	.008	.05	8.81%
Social influence	.09	0.02	3.868	<.001	.09	15.66%
Facilitating conditions	.32	0.02	14.990	<.001	.13	22.03%
Trust	.42	0.02	19.786	<.001	.20	33.00%
Perceived risk	-.05	0.02	-2.804	.005	.01	1.74%
UTAUT Extension (trust, anxiety), F = 241.15 (p < .001), R^2 = .632						
Performance expectancy	.23	0.03	8.154	<.001	.12	19.25%
Effort expectancy	-.11	0.03	-3.922	<.001	.05	7.24%
Social influence	.07	0.03	2.440	.015	.09	14.13%
Facilitating conditions	.31	0.03	11.430	<.001	.13	20.44%
Trust	.38	0.03	13.483	<.001	.18	28.68%
Anxiety	-.20	0.02	-8.73	<.001	.06	10.26%

Note. *B* = regression estimate; *SE* = standard error of *B*; RW = relative weight; RS = rescaled.

4.2.3 Moderation Analyses

Table 4 shows the results of the meta-regression for continuous moderators. Regarding age, older participants revealed a weaker relationship between social influence and use intention (*B* = -.01, 95% CI [.-.01, -.00]). The effect is displayed in Figure S1 in the

Online Appendix. Gender, cultural individualism, and publication year did not impact any of the relationship between AI-CDSSs use intention and its predictors.

Table 4

Results of meta-regression

Predictor variable	Moderator	k_{mod}	*B*	*SE*	*p*	95% CI
Performance expectancy	Age	4	<.01	<0.01	.557	-.01, .01
	Gender	16	<.01	<0.01	.879	<-.01, <.01
	Individualism	14	<.01	<0.01	.660	<-.01, <.01
	Publication year	16	.02	0.03	.418	-.03, .07
Effort expectancy	Age	4	<.01	0.01	.970	-.02, <.01
	Gender	15	<.01	<0.01	.630	-.01, <.01
	Individualism	13	<.01	<0.01	.945	<-.01, <.01
	Publication year	15	.03	0.04	.679	-.06, .09
Social influence	Age	4	-.01	<0.01	.030	-.01, <-.01
	Gender	15	<.01	<0.01	.087	<-.01, .01
	Individualism	13	<.01	<0.01	.564	<-.01, <.01
	Publication year	15	.02	0.02	.214	-.02, .07
Trust	Age	3	<.01	0.01	.903	-.02, .02
	Gender	10	<.01	<0.01	.879	<-.01, <.01
	Individualism	9	<.01	<0.01	.912	<-.01, <.01
	Publication year	10	-.04	0.03	.244	-.10, .03
Perceived risk	Gender	10	<.01	<0.01	.639	-.01, .01
	Individualism	9	<.01	<0.01	.212	<-.01, <.01
	Publication year	8	-.02	0.04	.597	-.11, .06

Note. Moderator analysis for predictor variables with $k \geq 10$ independent samples. k_{mod} = number of independent samples per moderator; *B* = regression estimate; *SE* = standard error; CI = confidence interval; Age = chronological age in years; Gender = Percentage female.

The Wald-type pairwise comparisons for each level of categorical moderators are presented in Table 5. Regarding the intention to use scale, no differences between studies using the Venkatesh et al. (2003) scale and those employing other measures were observed. Additionally, there were no differences for the type of AI-CDSS (diagnostic AI-CDSSs vs. diagnostic and treatment AI-CDSSs) on the relationships of performance expectancy and social influence. However, the positive relationship of effort expectancy on use intention was stronger for diagnostic AI-CDSSs compared to AI-CDSSs that combined diagnostic and treatment recommendations (Diff = -.31, 95% CI [-.58, -.04]).

Table 5
Wald-type pairwise comparisons of categorical moderators

Predictor variable	k_1	k_2	F	r_{c1}	r_{c2}	Diff.	95% CI
AI-CDSSs type: *Diagnostic and treatment AI-CDSSs* (level 1) compared to *diagnostic AI-CDSSs* (level 2)							
Performance expectancy	4	7	1.48	.62	.71	-.09	-.31, .13
Effort expectancy	4	6	7.15	.41	.72	-.31	-.58, -.04
Social influence	4	6	6.97	.59	.72	-.14	-.28, <.01
Trust	3	4	0.09	.70	.72	-.02	-.28, .24
Use intention scale: *Other scales* (level 1) compared to *Venkatesh et al. (2003)* (level 2)							
Performance expectancy	10	6	0.07	.66	.68	-.02	-.18, .15
Effort expectancy	9	6	0.48	.59	.51	.08	-.18, .35
Social influence	9	6	0.82	.64	.70	-.06	-.21, .09
Trust	5	5	0.01	.73	.72	.01	-.19, .20
Perceived risk	7	3	2.41	-.16	-.37	.21	-.10, .53

Note. Moderator analysis for constructs with at least k = 10 independent samples. k_1 and k_2 = number of independent samples for moderator level 1 and 2; r_{c1} and r_{c2} = sample size-weighted and reliability-corrected correlation for moderator level 1 and 2; Diff. = Mean difference, CI = confidence interval.

4.2.4 The Mediating Role of Performance and Effort Expectancy in the Relationship Between Facilitating Conditions and AI-CDSSs Use Intention

The role of performance and effort expectancy as mediators of the relationship between facilitating conditions and the intention to use AI-CDSSs were analyzed by fitting two separate mediation models. The results are displayed in Table 6. Performance expectancy mediated the relationship between facilitating conditions and the intention to use AI-CDSSs (indirect effect: B = .20, 95% CI [.12, .34]). In the second mediation model with effort expectancy as mediator, the direct path from facilitating conditions to use intention did not reach statistical significance, while the indirect effect was positive (B = .21, 95% CI [.09, .37]). Accordingly, the relationship between facilitating conditions and use intention was fully mediated through effort expectancy.

Table 6

Mediation models with performance and effort expectancy as mediators

Path	*B*	95% CI
Mediator: Performance expectancy		
Direct effects		
Facilitating conditions → Performance expectancy	.38	NA, .54
Performance expectancy → Use intention	.53	.36, .70
Facilitating conditions → Use intention	.29	-.01, .57
Indirect effect		
Facilitating conditions → Performance expectancy → Use intention	.20	.12, .34
Mediator: Effort expectancy		
Direct effects		
Facilitating conditions → Effort expectancy	.48	.35, .62
Effort expectancy → Use intention	.43	.17, .68
Facilitating conditions → Use intention	.29	-.04, .61
Indirect effect		
Facilitating conditions → Effort expectancy → Use intention	.21	.09, .37

Note. B = regression estimate; CI = confidence interval.

4.3 Sensitivity Analysis

To assess the robustness of the meta-analytic findings, we employed cumulative meta-analysis. This approach involves conducting a sequence of iterative meta-analyses, with each analysis adding an additional effect size for a specific relationship. Effect sizes are added in the order of decreasing precision, meaning the initial effect sizes added represent the most accurate population effect size estimates. If less precise studies tend to skew the meta-analytic estimates, this will be observable as a shift in cumulative results when these studies are included [86]. The results of the cumulative meta-analyses are depicted in Figure S2 in the Online Appendix. Five "drifts" were identified and all relationships drifted towards stronger effects as less precise studies were added, indicating an overestimation of the true effect. However, for none of the relationships, meaningful differences were observed after half the studies were added compared to after all studies were added (Table S6 in the Online Appendix). Accordingly, we conclude that none of the drifts influenced the meta-analytic conclusions.

5. Discussion

5.1 Summary of Findings and Implications for Future Research

The primary goal of the meta-analysis was to gain a better understanding of the predictors of the intention to use AI-CDSSs among healthcare practitioners based on the UTAUT and its extensions. The results of the meta-analysis provide empirical support for the applicability of the UTAUT to the context of AI-CDSSs. As predicted, performance expectancy, effort expectancy, social influence, and facilitating conditions were positively related to the intention to use AI-CDSSs. These findings are largely in line with the findings of UTAUT meta-analyses in other fields [25,30,38,56].

The results of relative weights analyses showed that all four UTAUT predictors together explain 50% of the variance in use intention among healthcare practitioners, reaffirming the relevance of the UTAUT predictors in the context of AI-CDSSs. Among the UTAUT predictors, performance expectancy emerged as the most relevant predictor, accounting for 31% of the total explained variance, followed by social influence (28%), facilitating conditions (26%), and effort expectancy (15%). In most UTAUT research, performance expectancy is more relevant than effort expectancy, possibly because performance expectancy is inherently connected to the primary motives behind technology use [30,38]. That is, it directly relates to the perceived benefits that users expect to gain from using a technology [30,38]. Effort expectancy refers to the expected ease of using a technology [21]. While important, the ease of use may become a secondary consideration if the technology does not meet the primary performance-related objectives. In other words, users might be willing to overcome a steeper learning curve if they believe the payoff in performance is worthwhile. This could explain why performance expectancy accounts for a higher percentage of the variance in technology acceptance and use intentions compared to effort expectancy. Overall, the findings of the current meta-analysis reflect a common trend in technology acceptance where the anticipated improvement in performance is a stronger driver of user acceptance than the anticipated effort to learn and use the technology [30,38,56].

Among the UTAUT predictors, effort expectancy and facilitating conditions had the widest credibility intervals (.56 and .66, respectively), suggesting the presence of moderating influences [81,92]. For example, previous research suggests that radiologists, accustomed to complex machines and heavy workloads, may be willing to invest effort into learning how to use new technology if it reduced their workload, indicating a moderating influence of occupation on the relationship between effort expectancy and use intention [3,35]. In addition, the strength of the relationship between effort expectancy and use intention has been shown to differ between AI-CDSS for feedback versus decision support [23].

In addition to the core UTAUT variables, we identified attitude, trust, perceived risk, AI anxiety, and personal innovativeness as predictors of the intention to use AI-CDSSs. Although all included studies reported a negative relationship between AI anxiety and use intention, the confidence interval for AI anxiety included zero. This lack of an observed relationship may be due to the low sample sizes (total sample size was n = 391) and the resulting high uncertainty in the true effect. Interestingly, in the relative weights analyses, trust proved to be a more relevant factor than performance expectancy in explaining variance in the intention to use AI-CDSSs. The relevance of trust may be explained by the lack of transparency in how AI recommendations are generated, coupled with the high stakes associated with clinical decision-making [93]. Indeed, research has suggested that even highly efficient AI-CDSSs may face resistance in clinical applications if healthcare practitioners do not trust in the system's safety [94–96]. The findings of the current meta-analysis align with research advocating for the inclusion of trust into the UTAUT model [94].

Furthermore, the current meta-analysis emphasizes the need to consider both drivers and inhibitors of the intention to use AI-CDSSs for a more comprehensive understanding of the adoption process [97]. The relative weights analyses demonstrate that AI anxiety explained about ten percent in the intention to use AI-CDSSs, after trust (29%), facilitating conditions (20%), performance expectancy (19%), social influence (14%), and before effort expectancy (7%). The relevance of perceived risk as a predictor of use intention was small (about 2% after all other predictors). Risk perception is a cognitive assessment of the potential losses and gains from using AI-CDSSs, which is based on logical evaluation and can be mitigated by providing relevant information [98]. In contrast, AI anxiety is an emotional response that encompasses fears and insecurities about AI technology [99]. Accordingly, AI anxiety is less rational and more difficult to alleviate because it can be deeply rooted in concerns about AI's impact on job security, professional autonomy, and the quality of patient care [23,100,101].

Even for relationships with a substantial number of independent samples, such as performance expectancy, effort expectancy, attitude, trust and perceived risk, the credibility intervals are wide (> .34), suggesting the presence of moderators [81,92]. This observation is supported by the modest amount of variance accounted for by statistical artifacts, indicating that there may be other reasons for substantial variance between individual studies [81,92]. While we considered multiple moderators suggested by the UTAUT and additional contextual and methodological moderators, we only found two moderation effects:

First, age moderated the relationship between social influence and use intention, with older healthcare practitioners experiencing a weaker relationship between social influence and use intention. This finding does not align with the UTAUT proposing that older individuals place more relevance on the opinion of relevant others when intending to use a new technology [21]. One explanation for this discrepancy may be that, especially in the healthcare context, practitioners value their professional independence increasingly more with age, thus devaluing the opinion of others regarding technology use as they get older. It has to be noted that the observed moderation effect is based on only four independent samples, underscoring the need to systematically study the influence of age on the relationship between social influence and use intention.

Second, the relationship between effort expectancy and use intention was stronger for diagnostic AI-CDSSs compared to devices that combined diagnostic and treatment recommendations. When clinicians assess a tool solely for diagnostic purposes, they may find it easier to anticipate the required effort to use it, as the task is more singular and the outcome more direct. This clear understanding may strengthen the relationship between effort expectancy and use intention. The multifaceted nature of combined tools likely makes it more challenging for clinicians to evaluate the effort needed to understand and utilize them. This uncertainty can lead to a weaker relationship between effort expectancy and use intention, as clinicians may not be able to adequately assess the effort required, thus not being able to use it as a source of information when it comes to indicating their intention to use it.

The results of the mediation analyses indicate that the relationship between facilitating conditions and use intention is fully explained through effort expectancy and partially explained through performance expectancy. This finding aligns with the

UTAUT proposing that when performance and effort expectancy are considered, facilitating conditions lose their importance in predicting use intention [21]. One explanation for the relevance of effort expectancy as a mediator may be that issues related to the support infrastructure, a critical aspect of facilitating conditions, are also conceptually addressed by effort expectancy [21]. That is, if healthcare organizations establish the appropriate support infrastructure, the effort required to use AI-CDSSs becomes lower [21,48]. Similarly, if a user perceives that the technology is supported by adequate facilitating conditions, they may be more likely to believe in the performance benefits when using the system, explaining the mediating role of performance expectancy.

5.2 Practical Implications

Performance expectancy and trust emerged as the two most relevant predictors of AI-CDSSs use intention, suggesting that measures targeted towards healthcare practitioners' beliefs in the performance and trustworthiness of AI-CDSSs may be effective in enhancing their intention to use them. However, the consistently positive link between performance expectancy and use intention also suggests that healthcare institutions need to take measures to deter the perception of low-performing systems as high-performing, which could potentially cause more harm than benefit [102]. Healthcare practitioners require transparent communication regarding the performance and limitations of AI-CDSSs, alongside adequate training to ensure their correct use. In addition, regulatory bodies like the FDA need to ensure that available AI-CDSSs meet certain safety and performance standards [63,103,104]. Adequate policies and oversight in these contexts may ensure a balance between the adoption and safe application of AI-CDSSs in healthcare decision-making.

Trust in technology is a multifaceted construct including users' perceptions of a system's benevolence, integrity, and competence [46,105]. Consequently, actions taken to enhance performance expectancy may not be sufficient for building trust in a system [94]. If organizations aim to improve healthcare practitioners’ trust in AI-CDSSs, they need to address the various facets relevant to trust in technology. This includes dealing with ethical issues related to data privacy and the potential misuse of AI-CDSS as well as addressing the lack of transparency and explainability in AI-generated recommendations [106,107]. For example, trust has been associated with the system's capability to explain its decision-making process, emphasizing the role of explainable AI as a path to building trust in AI-CDSSs [94,108].

Social influence has been demonstrated to be a relevant predictor of healthcare practitioners’ intentions to use AI-CDSSs, particularly among younger professionals. Institutions aiming to adopt AI-CDSSs can leverage the important role of social influence by establishing a culture that values technological advancements and by engaging key opinion leaders to advocate and exemplify the use of these systems. Additionally, trainings can be structured not only to educate but also to establish a shared understanding and a community of practice that positively reinforces the application of AI-CDSSs [109,110]. By addressing the social aspects of technology acceptance, healthcare institutions can ensure that their investment in AI is met with a user base that is both competent and willing to integrate these tools into their daily practice.

The importance of facilitating conditions underscores the need for healthcare organizations to provide a supportive infrastructure that simplifies the integration of AI-CDSSs into existing workflows. For instance, the provision of training programs, allowing healthcare practitioners to gain first-hand experience, and setting up accessible support teams ready to address system-related issues can considerably boost healthcare practitioners' intention to use such systems [22,111].

AI anxiety has emerged as a barrier to the intention to use AI-CDSSs in the relative weights analysis. Therefore, hospitals and other healthcare institutions should consider measures to counteract any irrational negative emotional reactions to AI before and during the integration of AI-CDSSs into clinical workflows. One potential method to mitigate AI anxiety involves increasing medical staff involvement in the development process [101] or providing more training opportunities to increase their exposure to AI-enabled devices, thus reducing irrational fears [109]

5.3 Limitations and Implications for Future Research

The current meta-analysis is not without limitations. First, the present study offers insight into the predictors of use intention as the key determining factor of actual use. However, some healthcare practitioners may express intentions to use AI-CDSSs but are hesitant when it comes to their actual implementation. Few studies included in the meta-analysis examined the predictors of actual use, underscoring the need for additional research on predictors of the actual use of AI-CDSSs [3,45].

Second, we were unable to explain the considerable variation in some of the effects based on moderator analyses. We could not evaluate three UTAUT moderators—experience with AI-CDSSs, voluntariness of use, and occupation—owing to insufficient samples incorporating these variables. Additionally, although all studies including AI anxiety reported negative relationships with use intention, the confidence interval of the meta-analytic estimate included zero due to the low sample size and the associated high uncertainty in the estimate. More studies on the relationship of AI anxiety with the intention to use AI-CDSSs are needed. The large credibility intervals and the low correlations between estimates and statistical artifacts suggest the existence of moderating factors not included in the meta-analysis [81,92]. Future research should put a stronger emphasis on exploring moderating effects to better understand the boundary conditions that affect the relationships between predictors and the intention to use AI-CDSSs.

Third, the nine relevant predictors could not be examined in a single relative weight analysis. The use of multiple models with subsets of predictors is a pragmatic approach to addressing data sparsity. However, the selected approach hinders definitive conclusions regarding the importance of all considered predictors. Furthermore, innovativeness could not be assessed in the relative weights analysis due to a lack of available samples assessing this predictor. The compromises that had to be made in the relative weights analyses highlight the need for an updated meta-analysis that includes complete predictor sets.

Fourth, the insight derived from the meta-analysis are primarily confined to unspecific AI-CDSSs. Given that AI-CDSS adoption is still limited, only a handful of studies have delved into exploring predictors of specific AI-CDSSs with distinctive features [3,23,36]. The results of these studies show that the attitude towards AI-CDSSs may vary depending on use cases and system features. Future research should examine the adoption of individual systems and variations in effects across different types of AI-CDSSs.

Fifth, the existing body of research on AI-CDSS adoption primarily relies on cross-sectional observational studies, with questionnaires as the main method of data collection, cf. [36]. These studies inherently limit the establishment of causal relationships, thus underscoring the need for future research to include longitudinal or experimental designs for more robust evidence of causality. Longitudinal studies may also be used to shed light on the development of use intention and the relevance of relevant predictors over time. For example, it is possible that initial trust plays a crucial role during the implementation phase, but becomes less relevant once a system has been successfully implemented.

Sixth, we selected the UTAUT as a general theoretical framework to examine the predictors of the intention to use AI-CDSSs. However, there has been some criticism of the UTAUT [59,112]. For example, the UTAUT may not answer questions related to the determinants and processes involved in *value-adding* technology use [59,113,114]. We found support for the prediction that beliefs about the performance and ease of use of AI-CDSSs lead to a higher intention to use these systems. However, based on the UTAUT, it may not be resolved whether these beliefs are well-founded, i.e., whether positive expectations actually lead to beneficial use because the system is indeed high-performing and easily implementable. Another criticism pertains to the UTAUT's narrow viewpoint on individual use. Other models, such as the non-adoption, abandonment, scale-up, spread, and sustainability (NASSS) framework [115] adopt a system perspective. This approach enables the examination of predictors on micro (individual technology users), meso (organizational processes and systems), and macro (national policy and wider context) levels, thereby more accurately representing the complex processes involved in technology adoption [115,116]. Additionally, the UTAUT focuses on an individual's intention to use a technology and does not fundamentally consider how well the technology fits the task it is being utilized for. Theories such as the task-technology fit (TTF) model examine the interconnectedness between task and technological characteristics. The model delves into how features of both the assigned task and the technology at hand shape the task-technology fit, thereby influencing the overall performance and use intentions [117].

Finally, some of the predictors included in the current meta-analysis, particularly the additional predictors beyond the UTAUT, may not be adequately represented using standard measurement instruments. For instance, AI anxiety has a multitude of dimensions, such as privacy violation anxiety, bias behavior anxiety, job replacement anxiety, learning anxiety, or ethics violation anxiety [118]. The current meta-analysis does not distinguish between these different aspects of AI anxiety as separate predictors of AI-CDSS use intentions. Similarly, trust in AI is a multifaceted construct that includes perceptions of the system's perceived benevolence, competence, and integrity [46,105]. Finally, risk perception may refer to different facets of AI-CDSSs, such as the risk of malfunction [3] or the risk of losing control over the output or the privacy of the data [45]. Although these variables have been demonstrated to predict the intention to use AI-CDSSs, additional research is needed to further distinguish between different aspects of broader constructs to better understand their value as additional predictors of the intention to use AI-CDSSs.

6. Conclusion

The meta-analysis underscores the relevance of the UTAUT to examine the predictors of the intention to use AI-CDSSs in healthcare. The results indicate that performance expectancy, effort expectancy, social influence, and facilitating conditions are all positively related to the intention to use AI-CDSSs among healthcare practitioners. The analyses further reveal the relevance of the additional predictors attitude, trust, personal innovativeness, AI anxiety, and perceived risk. The results of mediation analyses show that expectancy and performance expectancy mediate the relationship between facilitating conditions and use intention, thereby highlighting strategies to enhance use intention. Despite identifying age and AI-CDSSs type as moderating influences, there is a scope for future research to delve into other possible moderator variables to explain the variability in the observed effects. Finally, the meta-analysis recommendations pave the way for implementing strategies that could elevate healthcare practitioners' readiness to adopt AI-CDSSs.

Conflicts of Interest

The authors have no conflicts of interest to declare.

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