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Systematic Review

Patient Perception and Trust in Artificial Intelligence in Dental Care: A Systematic Review

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Abstract

Background: Patient trust may determine whether artificial intelligence (AI) is accepted in dental care, particularly when AI contributes to diagnosis or treatment planning. We aimed to synthesize patient-reported trust, confidence, acceptance, and preferences regarding dental AI and to identify factors associated with these outcomes. **Methods**: PubMed/MEDLINE, Scopus, and Web of Science were searched from database inception to 2 June 2026. Two reviewers independently screened records and extracted data. Risk of bias was assessed with the revised JBI tool for analytical cross-sectional studies. Because outcomes and metrics were heterogeneous, findings were synthesized narratively. The review was registered in PROSPERO (CRD420261439049). **Results**: The final synthesis included eight studies comprising 3171 participants from five countries. Attitudes were generally favourable when AI supported rather than replaced dentists. In one study, 47.7% accepted AI-assisted interpretation of diagnostic data, whereas 10.8% trusted an entirely AI-generated diagnosis. Another study found that 84.9% supported AI analysis of dental images followed by dentist review. A fixed-order vignette study improved lesion recognition but did not significantly change trust in the dentist. Interpretation was limited by non-probability sampling, heterogeneous and often non-validated measures, incomplete control of confounding, and reporting inconsistencies. **Conclusions**: Available evidence suggests conditional acceptance of dental AI, particularly when dentists retain oversight. Confidence in the prevalence estimates of trust and acceptance is low; these findings do not establish that AI improves trust. More representative studies using validated, conceptually distinct outcome measures are required.

Keywords: artificial intelligence; dentistry; patient trust; patient acceptance; clinical decision support; systematic review

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1. Introduction

Artificial intelligence (AI) is increasingly being investigated in dentistry for radiographic interpretation, early disease detection, treatment planning, workflow support, and patient communication [1,2]. Dental studies have evaluated caries detection and periodontal bone-loss detection [3,4], but technical performance does not establish patient trust. Patients may be concerned about reliability, privacy, accountability, costs, and loss of clinician–patient interaction [5–7]. Available dental studies suggest greater receptiveness

when AI supports rather than replaces the dentist, although populations, instruments, and proposed applications differ [6–8]. Previous systematic reviews have examined patient acceptance across healthcare and perceptions of AI in dentistry [5,9]. A focused assessment of trust-related outcomes must therefore consider both what patients were asked and the clinical responsibility assigned to AI.

Table 1 defines the outcome terms used to interpret the included studies. These distinctions guide interpretation; they do not retrospectively validate or reclassify the original questionnaires. The object of trust is specified wherever possible, because a dentist-trust instrument and an AI-attitude instrument assess different objects [10,11]. The reported outcomes are interpreted in relation to their question content, response format, denominator, clinical task, degree of autonomy, and exposure context [6–8,12–15]. Diagnostic performance remains a separate outcome: improved caries detection in a clinician trial did not establish a benefit for patient trust [16].

Table 1. Interpretive framework for patient-reported outcomes.

Term	Interpretation in This Review
Trust	Reliance on a specified object: the AI output, the dentist, or the care organisation.
Confidence	A patient's appraisal of reliability or diagnostic certainty, not an algorithm's confidence score.
Willingness/behavioural intention	A stated prospective choice or intention, not observed use or treatment uptake.
Acceptance	Endorsement of a specified application, procedure, or workflow.
Preference	A relative choice between stated options, such as dentist-led versus AI-only care.
Perceived usefulness/benefit	An expected advantage of AI, not itself trust, acceptance, or demonstrated clinical benefit.

Definitions are interpretive labels used for this synthesis, not a newly validated measurement instrument. Original study terminology is retained alongside the construct being interpreted.

A patient-centred account of dental AI must also consider the value and responsibilities of its use. Schwendicke et al. argued that dental AI should demonstrate tangible patient benefit while protecting privacy, autonomy, and human oversight [17]. Lee and See's framework for trust in automation similarly emphasizes appropriate reliance rather than indiscriminately high trust: reliance should correspond to the capabilities and limitations of the system in its intended context [18]. Applied to dental care, this perspective suggests that a higher trust score is not necessarily a desirable outcome unless patients also understand what the AI can and cannot do.

Technology-acceptance theory provides a complementary, but distinct, perspective. UTAUT2 was developed to explain behavioural intention and technology use, incorporating hedonic motivation, price value, and habit into the earlier acceptance framework [19]. It was not developed as a dental AI trust instrument. Its use in an included study [8] therefore offers a model of prospective adoption rather than evidence that intention, perceived usefulness, and trust are interchangeable constructs.

Building on the dentistry-specific review by da Cunha Lima et al. [9], this review provides a focused synthesis of trust-related outcomes, distinguishes assistive from autonomous AI, critically examines outcome measurement, and synthesizes eligible evidence within the search cutoff of 2 June 2026. The aim is to clarify what the available patient-reported evidence supports about AI in dental diagnosis and care.

2. Materials and Methods

2.1. Protocol and Registration

This systematic review was conducted and reported in accordance with PRISMA 2020 and was prospectively registered in PROSPERO before study screening (CRD420261439049) [20]. After registration, the planned methodological appraisal tool was changed to the revised JBI critical appraisal tool for analytical cross-sectional studies; the amendment was recorded in PROSPERO [21].

Our study is regarded as a systematic review with narrative synthesis, not a scoping review. The review addresses a defined patient-centered question, applies explicit eligibility criteria, appraises the included evidence, and interprets its findings; the absence of a meta-analysis does not change that classification. PRISMA 2020 is the reporting framework used for this manuscript [20].

2.2. Review Question and Eligibility Criteria

The review question was "What is known about dental patients' trust, confidence, and acceptance of AI used in dental diagnosis and care, and which factors are associated with these outcomes?" Eligibility was structured using PICo (Population, Phenomenon of Interest, and Context). Eligible studies included studies reported on adults receiving dental care or members of the public considered potential dental patients; evaluated AI used in dental diagnosis, treatment planning, or related clinical care; and reported patient-level trust, confidence, acceptance, willingness, preferences, or attitudes. Studies were excluded if they reported only clinician or student perspectives; assessed technical diagnostic accuracy without a patient-reported outcome; measured knowledge or awareness without a relevant attitudinal or acceptance outcome; were unrelated to dentistry; or were reviews, editorials, commentaries, or conference abstracts without extractable primary data. Only English-language reports were eligible; no geographical or care-setting restrictions were applied. In addition, other reviews, case reports, or book chapters were excluded.

The mixed robotics/AI report by Al-Dabbagh et al. meets these criteria because it includes adult dental patients and reports acceptance of diagnosis and treatment planning as well as related clinical care [22]. Its procedural-robotics findings are interpreted separately from acceptance of software-based diagnostic assistance; a mixed technology label does not make the study a technical-accuracy or clinician-only investigation.

2.3. Sources and Search Strategy

PubMed/MEDLINE, Scopus, and Web of Science Core Collection were searched from database inception to 2 June 2026. The reported strategy combined controlled vocabulary and free-text terms for AI, dentistry, trust/acceptance/attitudes, and patient/public populations. Complete database-specific strategies, search dates, and limits are provided in Supplementary Table S1. Reference lists of included studies and relevant reviews were screened. ScienceDirect and Google Scholar were not part of the reported search strategy. PubMed/MEDLINE provides biomedical coverage, while Scopus and Web of Science broaden coverage across the clinical and technological literature relevant to dental AI. Reference-list screening supplemented these searches; it does not establish that all eligible studies were retrieved.

2.4. Study Selection

Records were imported into Rayyan and deduplicated using automated detection followed by manual verification [23]. Two reviewers independently screened titles and abstracts with decisions concealed and then assessed potentially eligible full texts. Disagreements were resolved by discussion, with consultation of a third reviewer when required.

Titles and abstracts were screened against the eligibility criteria in Section 2.2, including the population, dental AI application, patient-reported outcome, and primary-study design. Records that did not meet these criteria were excluded before full-text assessment.

During manuscript revision, the full text of Al-Dabbagh et al. was supplied for eligibility assessment and was added to the included-study set [22]. This assessment applied the existing criteria and retained the search cutoff of 2 June 2026; it was not a rerun of the database searches. Al-Dabbagh et al. is included in the final study-selection totals in Figure 1.

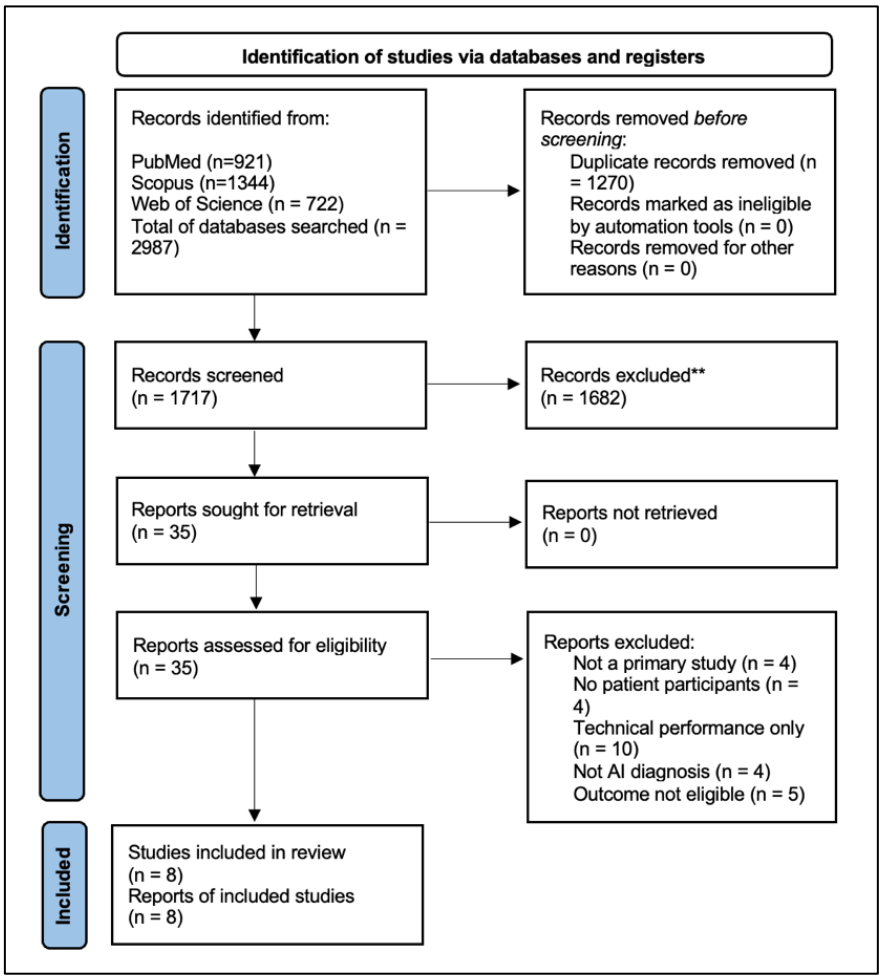


Figure 1. PRISMA 2020 flow diagram of study identification, screening, and inclusion. These are the final totals, including Al-Dabbagh et al. [22]. ** Records excluded following title and abstract screening against the predefined eligibility criteria.

2.5. Data Extraction

Two reviewers independently extracted data using a piloted form. Extracted variables included study identifiers, country and setting, design, sample size, participant characteristics, AI application, outcome instrument, trust/acceptance findings, associated factors, and reported concerns. Discrepancies were resolved by consensus. For studies reporting both patient and clinician data, only patient-level data were included in the synthesis. The revision presents sampling and response information in Table 2. Question content is distinguished from verbatim wording, and study sample sizes are distinguished from verified item-level denominators. Details not reported in the available source are identified explicitly; source labels and paraphrases are not presented as verbatim questionnaire items.

Table 2. Study characteristics, recruitment, and response information.

Study/Design	Setting and Sampling	Sample and Response	Questionnaire/Measurement Instrument	Principal Finding
Naik (2025) [8] Cross-sectional survey; SEM	Saudi Arabia, Riyadh; King Saud University Dental Hospital. Consecutively identified eligible clinic patients; electronic invitation.	N = 505; 505/1000 invited completed (50.5%).	Adapted UTAUT2; 7-point Likert; CFA/SEM.	SI and FC associated with behavioural intention at $p < 0.01$; $R^2 = 0.681$. Other path claims were inconsistent.
Sharka (2025) [12] Cross-sectional survey; hierarchical regression	Saudi Arabia, Makkah; Umm Al-Qura University Dental Teaching Hospital and Dental Centre. Convenience recruitment.	N = 511; 511/586 invited; reported response 87%.	28-item literature-informed questionnaire; 5-point Likert.	Experience (beta = 0.471), personalised care (0.222), and cost efficiency (0.153) associated with willingness.
Imran (2026) [13] Cross-sectional survey	India, Patna; dental OPD, Patna Medical College & Hospital. Consecutive eligible clinic attendees.	N = 420; 420/450 approached completed; reported response 93.3%.	35-item study-developed survey; expert review and pilot.	41.0% high/moderate trust (172/420); 57.6% definite/conditional willingness; 63.8% human-only preference.
Kostov (2025) [14] Cross-sectional survey; patient subgroup	Bulgaria; patient setting and recruitment procedure not adequately reported. Voluntary participation.	N = 251 patients; invitation denominator and response rate not reported.	Study-developed single-choice items.	47.7% accepted AI-assisted interpretation; 10.8% trusted AI-only diagnosis; 67.7% preferred dentist diagnosis.
Ayad (2023) [7] Cross-sectional survey	Germany, Münster; university cranio-maxillofacial outpatient clinic and private dental clinic. Convenience sample.	N = 265 analysed; 330/348 responded (94.8%); 265/348 complete (76.1%). Percentages calculated.	18-item literature-informed, pilot-tested questionnaire.	60.8% selected diagnostic confidence as a benefit; 84.9% supported AI-first, dentist-review workflow.
Bahadir (2025) [6] Survey; fixed-order clinical scenarios	Türkiye; restorative dentistry clinic. Volunteers aged >18 years with advanced occlusal caries; April 2023–January 2024.	N = 272 completed; approached denominator and response rate not reported.	Dentist Trust Scale; separate non-validated AI/vignette items.	AI usefulness 3.86/5; radiograph support 4.05/5; education-group difference $p = 0.026$.
Kosan (2022) [15] Survey; fixed-order vignettes	Germany, Berlin; Charité dental emergency service and student clinics. Clinic-attender recruitment described as random, without a specified random mechanism.	N = 140 analysed; 148/165 initially agreed (89.7%); 140/165 analysed (84.8%). Percentages calculated.	Pilot-tested AI/vignette items; BFI-10 and PHQ-4 covariates.	Lesion recognition increased from 2.8 to 3.5 ($p < 0.0005$); trust change was not significant ($p = 0.44$).
Al-Dabbagh (2024) [22] Cross-sectional survey	Saudi Arabia, Jeddah; King Abdulaziz University Dental Hospital. Invited adult clinic patients; random selection not specified.	N = 807; 807/858 invited; reported response 94%.	Adapted questionnaire; pilot n = 30; mixed robotics/AI content.	Diagnosis/planning 62.7%; dentist + robot 61.5%; robot-only 15.6%. Agreement calculated from counts.

Response percentages retain their reported definitions. For Ayad and Kosan, the analysed-sample yield is calculated from the completed/analysed and approached counts and is not presented as the initial participation rate. An unreported approached denominator is not assumed to equal the analysed sample. Instruments and principal findings are retained.

For Al-Dabbagh et al., combined agreement was calculated as (agree + strongly agree)/807 and rounded once to one decimal place, rather than by adding rounded percentages [22]. Source-report inconsistencies are documented in the risk-of-bias assessment (Section 3.3).

2.6. Risk-of-Bias Assessment

The risk of bias of included studies was independently assessed by two reviewers using the revised JBI critical appraisal tool for analytical cross-sectional studies [21]. The eight items were rated yes, no, unclear, or not applicable. Accordingly, the condition-measurement item was rated not applicable when eligibility was not based on a defined health condition. Domain-level judgments were reported without a numerical score or quality threshold; disagreements were resolved by consensus. Therefore, no study was excluded solely on the basis of the appraisal. The revised framework distinguishes study-level information (Q1, Q3, Q5, and Q8), outcome-level judgments (Q2, Q4, and Q6), and result-level judgments (Q7) [21]. Q8 concerns completeness of reporting rather than internal validity. Table 3 separates study-level items from outcome- and result-specific judgments and explanations; no overall concern category is assigned. For descriptive proportions, interpretation considers recruitment, non-response, question validity, and denominator integrity; lack of covariate adjustment is not itself a defect in an unadjusted descriptive proportion. Confounding is considered when interpreting associations. Fixed-

order vignette comparisons are additionally examined for order, learning, and carryover effects that cannot be isolated by the JBI item ratings alone.

Table 3. JBI critical appraisal of the included studies: study-level and outcome- and result-specific judgments, supporting explanations, and source locations.

Study-Level Judgments				
Study and Year	**Q1**	**Q3**	**Q5**	**Q8**
Naik (2025) [8]	Y	U	Y	Y
Sharka (2025) [12]	Y	U	Y	Y
Imran (2026) [13]	Y	U	Y	Y
Kostov and Yordanova (2025) [14]	N	Y	N	N
Ayad (2023) [7]	Y	Y	N	Y
Bahadir (2025) [6]	Y	Y	Y	Y
Kosan (2022) [15]	Y	Y	Y	Y
Al-Dabbagh (2024) [22]	Y	U	Y	Y

Outcome- and Result-Specific Judgments		
Study/Outcome or Result	**Judgments and Supporting Explanation**	**Primary-Report Location**
Naik [8] Behavioural intention/SEM paths	Q2 NA; Q4 U: BI composite reliability 0.651 and AVE 0.482 are below the study's stated thresholds. Q6 N: demographic factors and prior AI experience were not included in the primary SEM. Q7 U for path claims: some significance statements conflict with the prespecified $p < 0.01$ threshold.	Methods and source Tables 2 and 3 (items/measurement); Results, structural model; PDF pp. 3–6.
Sharka [12] Willingness/adjusted benefit coefficients	Q2 NA; Q4 Y for the three-item willingness scale: adopted, reviewed and piloted items; alpha = 0.91. This is not validation of observed uptake. Q6 Y: age, sex and education entered in hierarchical regression; residual confounding remains possible. Q7 Y for the tabulated regression coefficients; narrative beta formatting is not used.	Sections 2.3–2.5, pp. 5–6; source Table 1, p. 7; source Tables 2 and 3, p. 8. Item labels are reported in the main article.
Imran [13] Trust and willingness/knowledge associations	Q2 NA; Q4 U: expert review and pilot testing, but no reported reliability estimates for these items. Q6 N for trust/willingness associations: regression adjusted knowledge, not these outcomes. Q7 U for trust/willingness estimates: source text uses an aware subgroup ($n = 304$), while source Table 3 uses $n = 420$ and different categories. Source Table 3 counts are retained explicitly, not silently reconciled with the text.	Study instrument and statistical analysis, p. 819; Results, p. 820; source Table 3, p. 821.
Kostov and Yordanova [14] Assistance/AI-only trust and preference	Q2 NA; Q4 N: study-developed questions without reported validation. Q6 N for associations; no adjustment reported. Q7 N for group-comparison inference because tests are insufficiently described. Tabulated patient proportions remain descriptive; the 47.4% text versus 47.7% table discrepancy limits precision.	Materials and methods; Results; source Tables 2 and 3. Patient subgroup, not the dentist sample.
Ayad [7] Workflow endorsement/perceived benefit	Q2 NA; Q4 U: literature review and pilot testing without reliability estimates. Q6 NA for simple proportions, N for age-group associations without adjustment. Q7 Y for tabulated frequencies and named categorical tests. Convenience sampling and incomplete responses restrict representativeness.	Materials and methods, p. 2; questionnaire, source Table 1, pp. 3–4; Results and participant flow, pp. 2 and 5–7.
Bahadir [6] Dentist Trust Scale	Q2 U: advanced-caries eligibility lacks explicit diagnostic criteria. Q4 U for this sample: an established 11-item dentist-trust scale was used, but local measurement properties were not reported. Q6 NA for descriptive scale scores; Q7 Y for descriptive item summaries. This judgment does not extend to the separate AI items.	Materials and methods, pp. 53–54; source Table 2, p. 55; Discussion limitations, p. 58.
Bahadir [6] AI items/vignette associations	Q2 U; Q4 N: AI and vignette items were acknowledged as not necessarily validated. Q6 Y for demographic associations: ordinal regression included age, sex and education. Q7 U: inconsistent intervals in source Table 6 and incomplete paired scenario reporting. Fixed control-then-AI presentation does not isolate order or carryover effects.	Methods, pp. 53–54; source Tables 3 and 4, pp. 55–56; source Table 6, p. 57; limitations, p. 58.
Kosan [15] Recognition/dentist-trust vignette items	Q2 NA; Q4 N: pilot-tested, not established validated outcome items. Q6 Y for covariate analyses; Q7 Y for paired analyses. These ratings do not remove the fixed-order design limitation: learning, repeat presentation and carryover cannot be separated from AI. Validated psychological covariates do not validate the outcome items.	Section 2.1, pp. 2–3; source Table 1, p. 4; Sections 2.2–2.5, pp. 4–5; Discussion, p. 8.
Al-Dabbagh [22] Task-specific preferences	Q2 NA; Q4 U: adapted/piloted items, without current-sample reliability, combine robotics and AI. Q6 NA for simple descriptive proportions. Q7 Y for the coherent tabulated counts used in extraction; these are not a validated global trust score.	Sections 2.2–2.4; source Tables 3 and 4; Limitations.
Al-Dabbagh [22] Exposure/composite-score associations	Q2 NA; Q4 U for the composite outcomes; Q6 N: no multivariable confounding control. Q7 U for exposure-related and composite-score inference because the reporting inconsistencies detailed in Section 3.3 remain unresolved. These results are not interpreted as effects of prior AI use.	Original report [22], Results. The specific reporting discrepancies are described once in Section 3.3.

Q1, inclusion criteria; Q3, exposure measurement; Q5, identification of confounders; Q8, description of participants and setting. Y, yes; N, no; U, unclear; NA, not applicable. The original study-level ratings are retained in the study-level section. Outcome-level Q2, Q4, and Q6 and result-level Q7 are presented in the outcome- and result-specific section. Overall "Mild", "Moderate", and "Major" concern categories have been removed because no reproducible derivation was specified. This table does not provide a formal certainty rating. Q2 concerns measurement of the eligibility condition; Q4, outcome validity/reliability; Q6, confounding strategies; Q7, appropriateness of the stated result analysis. Y, yes; N, no; U, unclear; NA, not applicable. For a simple proportion, Q6 is not an adjustment requirement. Sampling and response limitations are reported separately in Table 2. The outcome- and result-specific section distinguishes judgments for the outcomes and results used in this synthesis. Source page numbers refer to printed article pages where available and otherwise to PDF pages.

2.7. Data Synthesis

Due to differences in the constructs, instruments, and effect metrics across studies, the results were synthesised narratively. Findings were grouped by (1) trust and acceptance of AI-supported care, (2) preference for human oversight, and (3) factors associated with trust and reported concerns. A proportion meta-analysis was considered only if at least four studies reported sufficiently comparable definitions, denominators, and measurement methods. This criterion was not met; therefore, no pooled estimate was calculated. The synthesis was reported in accordance with SWiM guidance where applicable [24].

A post hoc narrative sensitivity assessment was added during revision. Findings were reconsidered after setting aside the mixed robotics/AI study and, in a more restrictive assessment, reports with unresolved outcome-reporting inconsistencies or inadequately documented patient recruitment. The omitted reports and the outcomes remaining in each assessment are specified in Section 3.8. This assessment did not change eligibility or produce a pooled estimate; the remaining studies were not considered free of bias.

2.8. Assessment of Confidence in the Evidence

Since the synthesis comprised heterogeneous quantitative survey and vignette findings rather than qualitative evidence, GRADE-CERQual was not applicable. No formal certainty-rating framework was used. Confidence in each synthesis finding was considered narratively in relation to risk of bias, consistency, directness, precision, and adequacy of the contributing evidence.

3. Results

3.1. Study Selection

Database searches yielded 2987 records (PubMed/MEDLINE, $n = 921$; Scopus, $n = 1344$; Web of Science, $n = 722$). After 1270 duplicates were removed, 1717 records underwent title and abstract screening, and 1682 were excluded using the eligibility criteria described in Section 2.2. All 35 reports sought for retrieval were obtained and assessed for eligibility. Of these, 27 were excluded: not a primary study ($n = 4$), no patient participants ($n = 4$), technical performance only ($n = 10$), not AI diagnosis ($n = 4$), and outcome not eligible ($n = 5$) (Figure 1).

The final synthesis included eight studies comprising 3171 participants. This total includes Al-Dabbagh et al. (807 participants), incorporated after eligibility assessment during revision [22]. Figure 1 presents the final study-selection flow, with this report already counted among the 35 assessed reports and eight included studies.

3.2. Characteristics of Included Studies

The eight included studies were published from 2022 to 2026 and conducted in Saudi Arabia, Germany, Bulgaria, India, and Türkiye. Sample sizes ranged from 140 to 807, with 3171 participants in total. All used cross-sectional questionnaires; Kosan et al. and Bahadir et al. also included fixed-order vignette comparisons. The studies assessed heterogeneous constructs and used instruments ranging from the UTAUT2 framework and Dentist Trust Scale to literature-informed or study-developed questionnaires. Table 2 summarizes study characteristics.

Al-Dabbagh et al. recruited adult patients at King Abdulaziz University Dental Hospital, Jeddah, between July and December 2023 [22]. Of 858 invited patients, 807 completed the survey (reported response rate, 94%). The reported institution, city, and sample size differ from the other included Saudi studies [8,12]; these report-level distinctions support separate inclusion but do not establish person-level non-overlap.

3.3. Risk-of-Bias Assessment

Risk-of-bias concerns differed by study and outcome (Table 3). Recruitment and setting were inadequately described by Kostov and Yordanova [14]. The condition-measurement item was not applicable when no disease was required for entry; the criteria for the advanced-caries population in Bahadir et al. remained unclear [6]. Sharka et al. reported high internal consistency for willingness, whereas Naik et al. reported subthreshold composite reliability and average variance extracted for several constructs [8,12]. Ayad et al. and Imran et al. described content review or pilot testing without reliability estimates [7,13]. The Dentist Trust Scale used by Bahadir et al. must be distinguished from that study's non-validated AI and vignette items; Kosan et al. and Kostov and Yordanova also used study-specific or non-validated items [6,14,15]. Association estimates were limited by incomplete adjustment in Naik, Imran, Ayad, and Kostov; Imran's adjusted model concerned knowledge rather than trust or willingness [7,8,13,14]. Reporting inconsistencies affected Naik's path-significance claims, Imran's denominators, and several confidence intervals in Bahadir [6,8,13]. In the fixed-order vignette studies, sequential presentation leaves order and carryover effects unresolved [6,15].

Al-Dabbagh et al. added concerns about measurement validity and reporting consistency [22]. Although eligibility, setting and demographic characteristics were described, AI and robotics were not clearly separated and current patient-instrument reliability was not established. Demographic comparisons and correlations did not provide multivariable control of confounding. The text incorrectly pairs 52.8% refusal of a free robot trial with $n = 381$; Table 1 of the original report by Al-Dabbagh et al. [22] instead reports 426 refusals (52.8%) and 381 acceptances (47.2%). AI-awareness counts are reversed within the original report by Al-Dabbagh et al. [22], and 258 respondents supplied an applicable satisfaction answer despite only 65 reporting prior AI treatment. These inconsistencies limit interpretation of exposure and composite-score associations, but the directly tabulated preference counts remain extractable. The condition-measurement item is also not applicable to this study because no specific disease was required for entry. Table 4 presents the operationalization of the principal patient-reported outcomes.

Table 4. Operationalization of the principal patient-reported outcomes.

Study/Question Content and Construct	Response Format/Denominator	Clinical Task/Autonomy	Exposure Context/Source Location
Naik [8] "I intend to use AI-powered dental diagnosis in the future". Behavioural intention; other BI items concern reliance and clinic preference (paraphrased).	7-point agreement scale; 1 = strongly disagree, 7 = strongly agree. Analysed sample 505. SEM paths are not acceptance proportions.	Dental diagnosis; AI-powered care, without a single defined autonomy level for all items.	Prospective intention, not observed adoption. Source Table 2 (BI items); Methods.
Sharka [12] Willingness scale: "Acceptance of AI technology", "Acceptance of AI diagnosis", and "Acceptance of AI treatment plans" are source item labels, not complete questions.	Three items, 5-point Likert; analysed $N = 511$; alpha = 0.91. Full wording and response anchors are not reproduced in the main report. Coefficients concern scores, not proportions.	Dental treatment; diagnosis and planning appear among item labels. A single autonomy level is not defined.	Self-reported prior/current AI treatment in 9%; no verified longitudinal uptake outcome. Sections 2.3–2.5 and 3.1, pp. 5–6; source Table 1, p. 7.
Imran [13] Source Table 3 labels: trust in AI diagnostic accuracy; willingness to accept AI-assisted diagnosis; practitioner preference. These are outcome labels, not complete questionnaire wording.	Trust: high, moderate, neutral, low, none. Willingness: definitely; if dentist recommends; unsure; no. Preference: human only, AI-assisted human, none, AI only. Source Table 3 denominator = 420. High + moderate trust = (48 + 124)/420 = 41.0%; willingness = (86 + 156)/420 = 57.6%.	Diagnostic accuracy perceptions and care preferences; assisted versus human-only and AI-only care are distinct options.	Cross-sectional attitudes, not verified clinical AI use. Source Table 3, p. 821. Source Results, p. 820, describes $n = 304$ inconsistently; see Table 3, outcome- and result-specific judgments.

Table 4. *Cont.*

Study/Question Content and Construct	Response Format/Denominator	Clinical Task/Autonomy	Exposure Context/Source Location
Kostov and Yordanova [14] AI-assisted data interpretation (paraphrased); "Would you trust a diagnosis made by AI to form your treatment?" Trust/preference.	Single-choice categories. Autonomous item contrasts trusting AI, preferring medical work, and uncertainty. Patient subgroup 251; separate items, not a common scale.	Assisted interpretation versus entirely AI-made diagnosis.	Proposed use, not observed treatment. Source Methods and source Tables 2 and 3.
Ayad [7] Workflow to endorse: "Dental X-rays will be analyzed by an artificial intelligence and the findings will be assessed by the dentist afterwards". Acceptance; diagnostic benefit is separate.	Yes/no/unsure; $N = 265$. Workflow: 225/265 yes (84.9%). Perceived advantages allow for multiple responses; the diagnostic-confidence result is not a trust score.	Image analysis followed explicitly by dentist review; assistive workflow.	Hypothetical workflow after an information sheet, not observed uptake. Methods, p. 2; source Table 1, p. 4; Results, Hypothetical workflow.
Bahadir [6] "AI is useful"; "AI can help dentists evaluate radiographs." Perceived usefulness, separate from the 11-item Dentist Trust Scale and preference for humans over AI (paraphrased).	5-point agreement: strongly disagree, disagree, neither agree nor disagree, agree, strongly agree. $N = 272$ completed. Dentist-trust items and AI/vignette ratings are separate scores.	Caries radiograph interpretation and dentist-provided care; usefulness does not measure acceptance of autonomous treatment.	Own radiographs shown conventionally then with an AI overlay in fixed order; clinical demonstration, not longitudinal implementation. Methods, pp. 53–54; source Tables 2–4, pp. 55–56.
Kosan [15] "I can see the disease (caries) on the radiograph." "I trust the decision my dentist has made based on the radiograph."	5-point agreement scale (1 = strongly disagree to 5 = strongly agree); 140 analysed participants; paired vignette responses.	Caries recognition and trust in the dentist's decision; dentist explanation with versus without an AI overlay.	Hypothetical control followed by AI scenario in fixed order. Source Section 2.1, pp. 2–3; source Table 1, p. 4.
Al-Dabbagh [22] "A dentist performs your treatment assisted by a robot"; robot-only treatment and diagnosis/planning are separate items (paraphrased). Acceptance/preference.	Dentist/robot items: 5-point agreement from strongly disagree to strongly agree. Dentist + robot: 496/807 (61.5%); robot-only: 126/807 (15.6%), combining agree + strongly agree. Procedure items: yes/no; diagnosis/planning: 506/807 yes (62.7%).	Mixed robotics/AI. Dentist assistance versus robot-only treatment; diagnosis/planning and image acquisition are separate tasks.	Stated preferences, not verified post-exposure outcomes. Source Table 3 (treatment statements), source Table 4 (procedure acceptance).

Quotation marks identify verified source wording; labels are identified as labels, and other descriptions are paraphrases rather than invented questionnaire questions. Sharka's main report provides willingness-item labels but does not reproduce the full questionnaire wording or response anchors; the reported labels are retained here. Imran's source Table 3 supplies outcome labels and response categories rather than full question stems. Denominators and exposure contexts are retained separately. Percentages calculated from counts are rounded once to one decimal place; thus Imran's high/moderate trust is 172/420 = 41.0%, rather than the sum of rounded category percentages (40.9%).

3.4. Synthesis of Findings

Regarding patients' trust and acceptance of AI-assisted diagnosis, across the eight included studies, attitudes toward dental AI were generally favorable but conditional, and the findings should not be interpreted as evidence that AI itself increases trust. In Kostov and Yordanova, 47.7% of patients accepted AI-assisted reading or interpretation of diagnostic data, whereas 10.8% trusted a diagnosis made entirely by AI; 67.7% preferred a dentist-made diagnosis, and 13.5% would trust treatment delivered by an AI-controlled dental machine [14]. The study reported 47.4% for AI-assisted data interpretation, whereas source Table 2 reports 47.7%; the table value is used here, and the inconsistency is noted. In Imran et al., 41.0% (172/420; calculated from the source Table 3 counts) reported high or moderate trust in AI diagnostic accuracy, 57.6% expressed definite or dentist-conditional willingness to accept AI-assisted diagnosis, and 63.8% preferred a human dentist only [13]. In Ayad et al., 60.8% selected improved diagnostic confidence as a perceived advantage of AI, and 84.9% endorsed a workflow in which AI analysed dental images before dentist review [7].

In Al-Dabbagh et al., 506/807 participants (62.7%) accepted diagnosis and treatment planning performed by robotics/AI alone [22]. Acceptance of taking radiographs was 695/807 (86.1%); this item concerns image acquisition, not AI interpretation of radiographs

or diagnostic accuracy. Acceptance varied across procedures, including 121/807 (15.0%) for root canal treatment and 92/807 (11.4%) for periodontal or implant surgery. The mixed robotics/AI label is retained for these task-specific outcomes (Table 4).

Model-based studies identified potential determinants but were not directly comparable. In Naik et al., social influence (beta = 0.56, $p = 0.002$) and facilitating conditions (beta = 0.34, $p < 0.001$) met the study's prespecified $p < 0.01$ threshold, and the model explained 68.1% of behavioural-intention variance; reported effects for performance expectancy, effort expectancy, and habit were internally inconsistent with the stated significance threshold and with other sections of the paper [8]. In Sharka et al., patient-enhanced experience (standardized beta = 0.471), personalised dental care (beta = 0.222), and cost efficiency (beta = 0.153) were independently associated with willingness to accept AI, whereas the four perceived-risk domains were not significant [12]. Bahadir et al. reported favourable mean scores for the usefulness of AI (3.86/5) and its ability to assist radiograph evaluation (4.05/5), alongside a preference for humans over AI (3.79/5) [6]. In the fixed-order vignette study by Kosan et al., AI-coloured overlays improved participants' ability to identify the caries lesion (mean 2.8 to 3.5, $p < 0.0005$), but trust in the dentist's diagnosis did not change significantly (4.4 to 4.5, $p = 0.44$) [15].

3.5. Preference for Human Oversight

Evidence for human oversight was clearest in studies that explicitly contrasted assistive and autonomous AI. Kostov and Yordanova reported substantially greater preference for dentist-made than fully AI-made diagnoses, and Imran et al. found no participants who preferred AI-only care [13,14]. Ayad et al.'s high endorsement of AI-first image analysis followed by dentist review likewise supports a human-in-the-loop model [7]. However, the studies used different questions and denominators, so no pooled estimate of preference for oversight is warranted.

Al-Dabbagh et al.'s mixed robotics/AI survey provides a further within-survey contrast: 496/807 participants (61.5%; 232 agree plus 264 strongly agree) endorsed a dentist performing treatment with robot assistance, compared with 126/807 (15.6%; 74 plus 52) endorsing robot-only treatment [22]. Combined agreement for robot-only simple procedures was 290/807 (35.9%), versus 78/807 (9.7%) for complex procedures. The comparison is descriptive: there was no randomized allocation of oversight, and paired response data were not reported. It therefore supports a preference pattern, not a causal effect of supervision.

3.6. Factors Associated with Trust and Reported Concerns

Associations with trust and acceptance were heterogeneous. Sharka et al.'s adjusted model identified perceived patient experience, personalised care, and cost efficiency as independent correlates of willingness [12]. Bahadir et al. found an overall difference in AI-attitude scores by education ($p = 0.026$), driven by the small master's-degree subgroup; this cross-sectional association should not be interpreted as an educational effect [6]. Ayad et al. found that participants older than 35 years required higher AI performance standards than younger participants [7]. Naik et al. reported differences in selected UTAUT2 construct scores by age, education, sex, nationality, and prior AI experience, but these variables were not incorporated into the primary structural model [8]. Imran et al.'s multivariable model predicted AI knowledge rather than trust or willingness; associations between knowledge and trust or willingness were unadjusted correlations [13]. Kosan et al. reported exploratory effect modification by age, education, anxiety, and personality [15].

Al-Dabbagh et al.'s mixed robotics/AI survey reported higher mean perception scores in men than women (14.16 versus 12.36; $p < 0.001$) and a correlation between perception

and procedure-acceptance scores ($r = 0.599$; $p < 0.001$) [22]. These were unadjusted cross-sectional associations, not causal determinants.

Reported concerns included privacy and security, diagnostic accuracy, accountability, costs, job displacement, and reduced human interaction. Their prevalence varied markedly by study and question. Imran et al. reported privacy concerns in 68.2%, fear of replacing dentists in 54.8%, and accuracy or error concerns in 47.6% [13]. Ayad et al. most often identified workforce effects (37.7%), challenges to the dentist–patient relationship (36.2%), and increased costs (31.7%); only 12.8% identified data privacy as a disadvantage [7]. Naik et al.'s figure reported concern about diagnostic accuracy in 75%, job displacement in 47%, privacy in 35%, and loss of human interaction in 6%, although these values are not fully consistent with the abstract [8].

In Al-Dabbagh et al.'s mixed robotics/AI survey, distrust of a machine providing treatment was selected by 156/807 participants (19.3%), safety by 128/807 (15.9%), and lack of understanding or compassion by 124/807 (15.4%) [22]. These are proportions of the entire sample selecting concern options, not estimates among only those refusing treatment. At a stated reduced cost, 184/807 (22.8%) agreed or strongly agreed to robot-only treatment. A separate free-trial question had 381 acceptances (47.2%) and 426 refusals (52.8%). Different questions about price and a trial experience do not establish a price effect or actual uptake.

3.7. Assessment of Confidence in the Evidence

Confidence in the prevalence estimates of trust and acceptance is low. Non-probability recruitment and incomplete response information limit representativeness; non-validated or differently worded measures limit comparability; and hypothetical responses do not establish actual uptake. Incomplete control of confounding and reporting inconsistencies further limit interpretation of associations. The descriptive pattern of conditional acceptance should therefore be distinguished from a population prevalence or a causal benefit of AI. No formal certainty-rating framework was applied.

Table 5 links each principal finding to its contributing outcomes and methodological concerns. The aggregate sample of 3171 is not a common denominator for trust or acceptance.

Table 5. Principal findings, contributing evidence, and interpretive limitations.

Synthesis Finding	Contributing Outcomes	Methodological Consequence/Sensitivity
Conditional acceptance of clinician involvement	Ayad's dentist-review workflow [7]; human versus AI preferences in Imran and Kostov [13,14]; dentist-assisted versus robot-only treatment in Al-Dabbagh [22].	Questions differ. Removing mixed robotics/AI retains the descriptive pattern; the restrictive assessment leaves support for a supervised workflow, not a general comparative preference.
Understanding and trust are distinct	Kosan's lesion-recognition and dentist-trust vignette responses [15]; Bahadir's separate dentist-trust and AI items [6].	Fixed order and measurement differences prevent attribution of a trust effect to AI. Kosan's non-significant trust change is not proof of equivalence.
Perceived benefits correlate with willingness	Adjusted willingness model in Sharka [12]; behavioural-intention paths in Naik [8]; unadjusted or differently targeted models in other surveys [6,7,13,22].	Sharka's adjusted associations remain in the restrictive assessment. Associations do not establish causal determinants or observed adoption.
No common prevalence estimate is justified	Trust, willingness, preference, usefulness, and task-specific acceptance across all eight studies [6–8,12–15,22].	Non-probability sampling, differing instruments/denominators, and inconsistent reporting limit confidence. This conclusion is unchanged across the assessed evidence sets.

3.8. Outcome-Specific Synthesis and Narrative Sensitivity Assessment

Setting aside Al-Dabbagh et al. leaves the descriptive preference for clinician involvement supported by Ayad, Imran, and Kostov and Yordanova [7,13,14]. A more restrictive assessment also sets aside Naik, Imran, Kostov and Yordanova, and Bahadir because of unre-

solved outcome-reporting inconsistencies or inadequately documented patient recruitment, as detailed in Table 3. Ayad's endorsement of a dentist-reviewed workflow remains [7]. That narrower evidence supports acceptability of supervised use but does not establish a general comparative preference for supervised over autonomous care across populations.

In this restrictive assessment, Sharka's adjusted associations between perceived benefits and willingness remain, as does Kosan's finding of improved lesion recognition without a statistically significant change in dentist trust [12,15]. These findings concern different outcomes; neither establishes actual uptake or a causal trust benefit. Across the full and restricted evidence sets, a common prevalence estimate and causal claims about determinants remain unsupported. This post hoc sensitivity assessment changes the breadth of the conclusion rather than removing studies from the review. The remaining studies still have sampling and measurement limitations.

4. Discussion

4.1. Principal Findings

Across eight studies, acceptance of dental AI was conditional on the task and the dentist's role. The clearest descriptive support for clinician involvement came from Ayad's dentist-reviewed imaging workflow and the assistive-versus-autonomous questions in Imran and Kostov and Yordanova [7,13,14]. The mixed robotics/AI survey by Al-Dabbagh also showed greater endorsement of dentist-assisted than robot-only treatment, but these procedural findings are not interchangeable with acceptance of software-based diagnosis [22].

These findings are consistent with the earlier dentistry-specific review by da Cunha Lima et al. [9]. The present review adds a focused examination of trust-related outcomes, assistive versus autonomous applications, and measurement limitations using evidence within the 2 June 2026 search cutoff. The outcome framework in Table 1 and the outcome-level extraction in Table 4 clarify why willingness, perceived usefulness, and trust cannot be treated as a common endpoint. The sensitivity assessment supports a narrower conclusion about acceptability of clinician-supervised use when studies with the greatest relevant concerns are set aside.

Evidence from other healthcare settings provides context for these findings but was not included in the dental-study synthesis. In a US survey of 926 respondents, 66.0% considered it very important to be told when AI had played a major role in their diagnosis or treatment [25]. Yakar et al.'s general-population survey in the Netherlands found that views differed across radiology, robotic surgery, and dermatology, with slightly greater trust in dermatological applications [26]. In Saudi Arabia, a single-centre convenience survey of 382 radiology patients found a preference for personal interaction with physicians alongside neutral aggregate attitudes towards efficiency and distrust/accountability [27]. These studies place the dental findings within a broader pattern of task- and outcome-dependent attitudes, without establishing that acceptance levels can be transferred between specialties or populations.

Experimental research offers a possible explanation for reluctance to replace clinicians. Longoni et al. linked resistance to medical AI to the perception that it would overlook individual characteristics; resistance was attenuated when AI supported rather than replaced a human provider [28]. This suggests a hypothesis for the importance of retaining the dentist's role, not an established explanation for the cross-sectional preferences in this review.

4.2. Methodological Limitations

Confidence in prevalence estimates of trust and acceptance is low. Convenience or clinic-attender recruitment, incomplete response information, a geographically limited

evidence base, and predominantly hypothetical outcomes restrict generalisability. Different instruments and denominators prevent a defensible pooled estimate. Non-validated AI items cannot inherit validity from a separate dentist-trust scale, and internal consistency alone does not resolve the construct differences in Table 1. Cross-sectional associations do not establish that education, familiarity, or perceived benefits cause acceptance [6–8,12–15].

The COSMIN content-validity methodology, developed for patient-reported outcome measures, emphasizes whether items are relevant, comprehensive, and comprehensible for the intended population and context [29]. These principles offer a useful starting point for dental AI questionnaire development. Patient input and cognitive interviews could establish whether respondents distinguish trust in the dentist from trust in an algorithmic finding and understand the proposed degree of autonomy. Validation of a radiology-specific questionnaire [11] is informative but does not by itself validate adaptation to a different dental task or population. These are recommendations for future measurement development, not an additional appraisal conducted in this review.

The fixed-order vignette studies cannot isolate the effect of AI from learning, repeated presentation, or additional explanation [6,15]. Kosan's improved lesion recognition without a significant trust change therefore supports separating understanding from trust, not a causal conclusion about either outcome [15]. For Al-Dabbagh, the mixed technology definition and reporting inconsistencies documented in Section 3.3 limit interpretation of exposure-related and composite-score associations; the tabulated task-specific preferences remain descriptive [22].

The review itself is vulnerable to selection bias. Restriction to English-language reports and three databases may have missed eligible evidence, particularly reports indexed under willingness, preference, perception, or robotics. Independent screening and reference-list checks reduce some selection errors but cannot demonstrate complete retrieval. The revision-stage addition was a targeted eligibility reassessment, not an updated comprehensive search. No formal certainty framework was applied, and the sensitivity assessment was post hoc rather than prespecified.

4.3. Implications for Dental AI Implementation

The findings support discussing the specific task performed by AI and the dentist's continuing role in reviewing findings and making care decisions. Patient concerns about accuracy, privacy, accountability, costs, and human interaction should be addressed in that discussion [7,8,13]. These are implications of the reported preferences, not evidence that a particular communication strategy increases trust. Acceptance of a proposed workflow should not be presented as demonstrated treatment uptake, consent to autonomous procedures, or improved clinical outcomes. The procedural robotics findings should remain identified separately when applying the review to diagnostic software.

The effect of explanation also requires careful interpretation. In preregistered experiments outside dentistry, Cadario et al. found that brief explanatory interventions increased subjective understanding of medical algorithms and willingness to use algorithmic providers [30]. These outcomes do not establish an improvement in dental trust or informed decision-making. Considered alongside Kosan et al.'s non-significant dentist-trust result [15], this evidence supports testing communication strategies while measuring understanding, willingness, and trust separately, rather than assuming that making an AI output more understandable will improve all three.

Ethical and implementation guidance adds a complementary perspective. WHO guidance emphasizes human autonomy, transparency, privacy, accountability, and equity in healthcare AI [31]. The FUTURE-AI consensus guideline organizes trustworthy development and deployment around fairness, universality, traceability, usability, robustness, and

explainability [32]. For dental services, these principles suggest explaining the AI's task and limitations, identifying who reviews its output, providing an opportunity for patient questions, and establishing data-protection and performance-monitoring processes. They are normative and consensus-based recommendations, not evidence that a particular governance arrangement increases patient trust. Their purpose is to support justified reliance, not simply to persuade patients to accept AI.

4.4. Priorities for Future Research

Future studies should use representative, multicentre recruitment and report approached, responding, and analysed participants. They should specify the clinical task, autonomy level, exposure context, item wording, response options, and denominator for each outcome. Measures of trust in the dentist and trust in an AI-supported finding should be validated separately from willingness and perceived usefulness. Randomized or counterbalanced comparisons are needed to test oversight and explanation without fixed-order effects. Longitudinal studies involving actual clinical exposure should assess whether stated acceptance translates into informed choices and sustained experience. These priorities follow from the sampling, measurement, and design limitations of the included evidence rather than from untested governance frameworks.

Clinical evaluations that also collect patient perceptions should describe the AI system and care workflow. The dentistry-specific AI research checklist supports reporting of system evaluations [33], DECIDE-AI addresses early-stage clinical evaluation [34], and CONSORT-AI specifies AI-related reporting for randomized trials [35]. Relevant details include the system version, intended users, input/output handling, human–AI interaction, and errors or safety concerns [34,35]. These design-specific guidelines complement validation of patient-reported outcomes; they were not used to appraise this review's cross-sectional surveys.

5. Conclusions

Available evidence suggests that dental patients accept some AI-supported workflows when dentists retain oversight. Confidence in the prevalence estimates of trust and acceptance is low, and the evidence does not establish a causal improvement in trust. The mixed robotics/AI study supports task-dependent preferences for dentist-assisted procedures but should not be treated as evidence about software-based diagnosis alone [22]. More representative research with validated, distinct outcomes and explicit comparisons of clinician-supervised and autonomous care is needed.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app162110482/s1, Table S1. Complete database-specific search strategies, search dates, and search limits.

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Abbreviations

AI, artificial intelligence; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; PROSPERO, International Prospective Register of Systematic Reviews; PICo, Population, Phenomenon of interest, Context; JBI, Joanna Briggs Institute; SWiM, Synthesis Without Meta-analysis; GRADE-CERQual, Confidence in the Evidence from Reviews of Qualitative research; UTAUT2, Unified Theory of Acceptance and Use of Technology 2; SEM, structural equation modelling; CFA, confirmatory factor analysis; PE, performance expectancy; EE, effort expectancy; SI, social influence; FC, facilitating conditions; BFI-10, 10-item Big Five Inventory; PHQ-4, 4-item Patient Health Questionnaire.

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