Vol. 7, No. 1, 2026, pp. 568-575
DOI: https://doi.org/10.29210/992460

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Patient trust dynamics in ai-based telemedicine: a social psychological systematic review

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Article Info

Article history:
Received Jun 25th, 2026
Revised Jul 1st, 2026
Accepted Jul 8th, 2026

Keywords:
AI-based telemedicine,
Patient trust,
Human-AI interaction,
Social cognition,
Social acceptance

ABSTRACT

Background: Artificial intelligence (AI)-based telemedicine increasingly supports remote diagnosis, clinical decision support, and technology-mediated health communication. However, patient trust remains theoretically fragmented because prior studies often treat it as a general adoption variable rather than as a social psychological process. This review aimed to synthesize how patient trust in AI-based telemedicine is formed through social cognition, human-AI interaction, and institutional legitimacy. Method: A systematic literature review was conducted following PRISMA 2020. Scopus was the primary database, while PubMed and Google Scholar were used as complementary sources. Searches covered peer-reviewed literature published from 2015 to 2025 using Boolean combinations of trust, social acceptance, social psychology, human-AI interaction, artificial intelligence, telemedicine, telehealth, and virtual care. Two reviewers independently screened records, extracted data using a predefined matrix, and appraised empirical studies using the Mixed Methods Appraisal Tool, while conceptual papers were assessed for relevance, theoretical clarity, and contribution. Heterogeneity was handled through narrative thematic synthesis. Results: Eleven studies/reports were included. Three trust dimensions emerged: individual cognitive appraisal, including explainability, perceived risk, and prior experience; interactional attribution, including AI agency, role clarity, and communication quality; and socio-structural legitimation, including privacy, fairness, bias mitigation, and institutional governance. Human-AI interaction functioned as the experiential channel through which trust was calibrated, while social acceptance operated as a collective condition shaped by norms, professional identity, and legitimacy. Conclusion: Patient trust in AI-based telemedicine is a multilevel social psychological process. Sustainable implementation requires transparent design, privacy assurance, bias governance, and clear alignment between AI systems and clinical roles.

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Introduction

Telemedicine integrated with artificial intelligence (AI) has become an important transformation in contemporary health services. Telemedicine is no longer understood only as a technical solution for overcoming geographical distance or improving cost efficiency. With the inclusion of clinical decision support systems, diagnostic algorithms, health chatbots, predictive models, and large language model-based tools, AI-based telemedicine increasingly participates in clinical communication and decision processes (Holtz, 2021; Holtz et al., 2022; Li et al., 2024; Almutairi & Almatrodi, 2025). This transformation creates a new form of human-technology relationship in which the patient does not merely use a platform but interprets an AI-supported system as a source of advice, risk, uncertainty, and possible clinical authority.

The literature on digital health adoption commonly explains technology use through perceived usefulness, perceived ease of use, performance expectancy, and behavioral intention, as reflected in the Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology (Davis, 1989; Venkatesh et al., 2003). These frameworks remain useful for explaining why users may intend to use telemedicine. However, they do not fully explain why patients may still hesitate to rely on AI-mediated care even when the platform is accessible, technically functional, or clinically promising. Conversely, institutional, economic, and regulatory explanations also remain important, including reimbursement models, liability concerns, data governance, and organizational readiness. The puzzle addressed in this review is therefore not whether these explanations matter, but how patient trust operates between technical performance, institutional conditions, and actual willingness to engage with AI-based telemedicine.

Patient trust is especially important because AI-based telemedicine operates in a context of vulnerability, uncertainty, and asymmetry of knowledge. Foundational trust theory conceptualizes trust as willingness to accept vulnerability under conditions of uncertainty (Mayer et al., 1995), while automation trust research emphasizes calibrated reliance when system behavior is complex and difficult for users to fully verify (Lee & See, 2004; Hoff & Bashir, 2015). In medical AI, this problem is intensified because the patient must evaluate not only whether the technology is accurate, but also whether it is explainable, fair, accountable, and socially legitimate (Ferrario et al., 2020; Goisauf et al., 2025).

From a social psychology perspective, patient trust in AI-based telemedicine cannot be reduced to a simple cognitive belief that a system is reliable. Trust is formed through social cognition, attribution, perceived agency, learning from interaction, social norms, and institutional legitimacy. Human-AI interaction is therefore not only a usability issue; it is the interactional space in which patients infer competence, intention, responsibility, and trustworthiness from the behavior and communication style of AI systems (Oksanen et al., 2020; Pan et al., 2024; Glikson & Woolley, 2020). This lens differentiates the present review from conventional technology acceptance reviews by asking how patient trust is socially and psychologically constructed, rather than only whether trust predicts intention to use.

Trust also becomes more complex when AI systems are associated with bias, fairness, privacy, and inequality. AI models may reproduce structural biases embedded in health datasets, resulting in unequal performance for underserved populations (Celi et al., 2022; Seyyed-Kalantari et al., 2021). Standards for identifying and managing algorithmic bias show that fairness is not only a technical issue but also a condition for public trust and social acceptance (Schwartz et al., 2022). Privacy concerns, digital literacy, and system complexity may further reduce trust, particularly among non-users, older adults, and populations with limited digital access (Adams et al., 2021; Holtz et al., 2022; Lalot & Bertram, 2025).

Despite growing interest in AI, telemedicine, and trust, existing studies remain conceptually fragmented. Some studies treat trust as a dependent variable in adoption models, others examine human-AI interaction experimentally, and others focus on ethical or governance conditions of trustworthiness. Less attention has been given to integrating these strands into a social psychological explanation of patient trust in AI-based telemedicine. This review therefore aims to synthesize how patient trust is formed at individual, interactional, and socio-structural levels and how human-AI interaction mediates the relationship between trust and social acceptance. The guiding research question is: how is patient trust in AI-based telemedicine shaped through social cognition, human-AI interaction, and institutional legitimacy?

Method

This study employed a systematic literature review guided by the PRISMA 2020 statement to strengthen transparency, replicability, and methodological rigor (Page et al., 2021). The review was qualitative-synthetic because the included literature was methodologically heterogeneous, including surveys, experiments, conceptual papers, and governance-oriented reports. The purpose was not to estimate a pooled effect size, but to synthesize theoretical and empirical evidence concerning patient trust, social acceptance, and human-AI interaction in AI-based telemedicine.

Scopus was used as the primary database because it indexes multidisciplinary peer-reviewed literature across medicine, psychology, digital health, and information systems. PubMed and Google Scholar were used as complementary sources to identify additional relevant studies and theoretical references. The search covered literature published between 1 January 2015 and 31 December 2025. The Scopus syntax was: TITLE-ABS-KEY((trust OR "patient trust" OR "social acceptance" OR "technology acceptance") AND ("artificial intelligence" OR AI OR "machine learning" OR "human-AI interaction" OR "human computer interaction" OR chatbot OR "clinical decision support") AND (telemedicine OR telehealth OR "virtual care" OR "digital health")) AND PUBYEAR > 2014 AND PUBYEAR < 2026. The PubMed syntax was: ((trust[Title/Abstract] OR "social acceptance"[Title/Abstract] OR "technology acceptance"[Title/Abstract]) AND ("artificial intelligence"[Title/Abstract] OR "machine learning"[Title/Abstract] OR "human-AI"[Title/Abstract] OR chatbot[Title/Abstract]) AND (telemedicine[Title/Abstract] OR telehealth[Title/Abstract] OR "virtual care"[Title/Abstract] OR "digital health"[Title/Abstract])). Google Scholar was searched using equivalent keyword combinations, and the first 100 most relevant results were screened.

The inclusion criteria were: (1) peer-reviewed journal articles or authoritative scientific reports; (2) studies or conceptual papers discussing AI-based telemedicine, telehealth, virtual healthcare, or health-related human-AI interaction; (3) explicit discussion of patient trust, social acceptance, trustworthiness, human-AI interaction, explainability, privacy, bias, or related psychosocial determinants; and (4) relevance to social psychology, social cognition, human-computer interaction, or digital health adoption. Exclusion criteria were duplicate records, publications without abstracts, non-scholarly materials, studies focused purely on algorithm engineering without psychosocial or clinical interaction dimensions, and papers outside the publication period.

Two reviewers independently screened titles, abstracts, and full texts using the predefined criteria. Disagreements were resolved through discussion, and unresolved discrepancies were adjudicated by a third reviewer. Data were extracted using a structured matrix covering author, year, country or context, study design, population, AI or telemedicine technology, trust construct, human-AI interaction component, social acceptance determinant, quality appraisal result, and key contribution. Empirical studies were appraised using the Mixed Methods Appraisal Tool (MMAT) because the included empirical evidence involved qualitative, quantitative, and mixed designs (Hong et al., 2018). Conceptual and normative papers were assessed for theoretical relevance, clarity of argument, applicability to health AI, and contribution to the synthesis. Quality appraisal was used to weight interpretation rather than to exclude studies automatically, given the emerging and interdisciplinary nature of the field.

Synthesis was conducted using narrative thematic synthesis. First, extracted findings were coded deductively using three social psychological levels: individual cognitive appraisal, interactional attribution, and socio-structural legitimation. Second, inductive coding was used to identify recurring patterns, contradictions, and gaps across studies. Third, heterogeneous evidence was reconciled by comparing whether each study explained trust as system reliability, interpersonal-like relation, or institutional trustworthiness. This procedure allowed the review to distinguish patient trust from general technology acceptance and to identify the specific contribution of social psychology to AI-based telemedicine.

Results and Discussions

The PRISMA-based selection process identified 88 records from Scopus and 6 additional records from PubMed and Google Scholar. After automated and manual pre-screening, 37 records were screened by title and abstract, 24 were excluded as conceptually irrelevant, 13 reports were sought for full-text retrieval, and 5 full-text reports from the primary search met the eligibility criteria. Six additional eligible reports from complementary sources were included, resulting in 11 studies/reports in the qualitative synthesis.

Table 1 <Summary of Core Included Studies/Reports and Their Contribution to the Synthesis>

Study	Context	Design/source type	Contribution to synthesis
Adams et al. (2021)	Telemedicine non-users	Cross-sectional survey	Privacy, complexity, and low trust constrain adoption among non-users.
Holtz (2021)	Telemedicine patients	Survey	Patient perceptions of telemedicine changed after COVID-19 experience.
Holtz et al. (2022)	Rural telemedicine users	Survey and interviews	TAM constructs interact with privacy, access, and contextual barriers.

Study	Context	Design/source type	Contribution to synthesis
Li et al. (2024)	Video telemedicine follow-up	Cross-sectional study	Patient intention depends on perceived usefulness and social-cognitive expectations.
Oksanen et al. (2020)	AI/robot interaction	Online experiment	Initial human-technology interaction shapes trust toward AI and robots.
Pan et al. (2024)	Human-AI communication	Experimental study	Perceived AI agency affects trust, liking, and communication quality.
Ferrario et al. (2020)	Medical AI trust	Conceptual ethics paper	Trust in medical AI can be grounded in system reliability and governance.
Celi et al. (2022)	Health AI bias	Global review	Bias in health AI threatens fairness and trust for vulnerable groups.
Seyyed-Kalantari et al. (2021)	Diagnostic AI	Empirical bias study	AI underdiagnosis bias can harm underserved populations.
Schwartz et al. (2022)	AI bias governance	Technical standard/report	Bias identification and mitigation are prerequisites for trustworthy AI.
Goisauf et al. (2025)	Medical AI trustworthiness	Expert workshop	Trustworthiness requires interdisciplinary governance and professional consensus.

The included literature covered empirical telemedicine studies, human-AI interaction experiments, medical AI ethics papers, bias and fairness studies, and digital health acceptance studies. This distribution indicates that patient trust in AI-based telemedicine is not located in a single disciplinary tradition, but at the intersection of technology acceptance, automation trust, social cognition, and health system legitimacy.

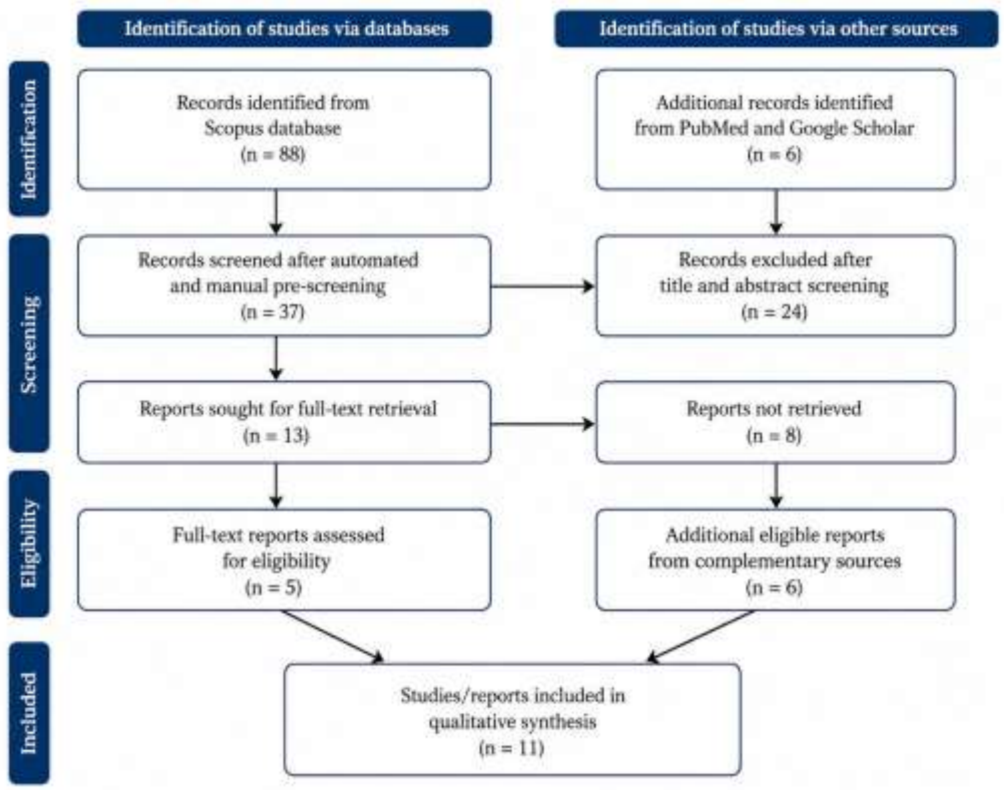

Figure 1 <PRISMA 2020 Study Selection Flow Diagram. Source: Author Synthesis based on PRISMA 2020. Characteristics of Included Studies>

Thematic Synthesis

Three dominant thematic results emerged from the synthesis. First, patient trust was consistently conceptualized as a multidimensional construct. Across studies, trust involved reliability, explainability, transparency, fairness, privacy assurance, and accountability. At the individual level, trust was linked to cognitive appraisal of risk, prior experience, and understanding of AI output. Explainability was particularly important because patients need to understand why an AI-supported recommendation is made before they can rely on it (Ferrario et al., 2020; Li et al., 2024).

Second, human-AI interaction functioned as the interactional mechanism through which trust was tested and calibrated. Experimental studies showed that users respond to AI systems not only as tools but as interaction partners with perceived agency, competence, and communicative style (Oksanen et al., 2020; Pan et al., 2024). This pattern supports a social cognition interpretation: patients infer trustworthiness from cues such as response clarity, role explanation, feedback, and the degree to which AI supports rather than replaces human judgment.

Third, social acceptance appeared as a collective and institutional process rather than merely an individual intention to use technology. Acceptance was shaped by social norms, privacy concerns, professional identity, and legitimacy of institutions implementing AI. Concerns about algorithmic bias and unequal performance were especially important because they linked patient trust with social justice and governance (Celi et al., 2022; Seyyed-Kalantari et al., 2021; Schwartz et al., 2022; Goisauf et al., 2025).

Table 2. Thematic Synthesis of Patient Trust Dynamics in AI-based Telemedicine

Level of trust formation	Key determinants	Synthesized interpretation
Individual cognitive appraisal	Explainability, perceived risk, prior experience, perceived usefulness, privacy concern	Patients evaluate whether AI output is understandable, safe, and personally relevant.
Interactional attribution	AI agency, role clarity, feedback quality, communication style, perceived competence	Human-AI interaction becomes the setting where trust is formed, weakened, or recalibrated.
Socio-structural legitimation	Institutional trust, fairness, bias mitigation, ethical governance, professional consensus	Trust depends on whether AI is perceived as legitimate, accountable, and aligned with healthcare values.

Discussion

This review shows that patient trust in AI-based telemedicine cannot be adequately explained by general technology acceptance alone. TAM and UTAUT explain important adoption antecedents such as usefulness, ease of use, performance expectancy, and social influence (Davis, 1989; Venkatesh et al., 2003). However, these models primarily explain intention to use technology and do not fully address why patients may hesitate to rely on AI-generated or AI-mediated clinical recommendations. The evidence synthesized here suggests that trust becomes central when patients must accept vulnerability in a clinical interaction involving limited transparency, probabilistic outputs, and uncertain accountability.

The social psychology lens contributes by explaining patient trust as a multilevel process. At the individual level, patients appraise risk, uncertainty, explainability, and previous experience. At the interactional level, patients infer competence and intention from AI behavior, response style, and role clarity. At the socio-structural level, patients evaluate whether institutions, developers, clinicians, and regulators can guarantee privacy, fairness, accountability, and professional oversight. This three-level interpretation draws from interpersonal trust theory, automation trust, and social cognition, but it does not simply anthropomorphize AI (Mayer et al., 1995; Lee & See, 2004; Hoff & Bashir, 2015). Rather, it argues that patients use social psychological cues to evaluate non-human systems when the system participates in consequential health decisions.

This directly addresses an important theoretical tension in the field. One position treats trust in AI as a form of system-reliability assessment: users trust AI when it is accurate, predictable, and technically dependable. Another position argues that AI trust resembles interpersonal trust because users attribute agency, intention, and responsibility to intelligent systems. The findings of this review support an integrative position. Trust in AI-based telemedicine is not identical to interpersonal trust, but it is also not purely technical reliability. It is a hybrid form of socio-technical trust: patients evaluate system performance through social cues and institutional safeguards, especially when they cannot independently verify clinical algorithms (Ferrario et al., 2020; Glikson & Woolley, 2020; Goisauf et al., 2025).

Alternative explanations for low AI-telemedicine adoption remain important. Regulatory uncertainty, reimbursement models, liability concerns, digital infrastructure, and organizational readiness can all constrain implementation. However, these factors do not replace the need to examine patient trust. Instead, they shape the social context in which trust is formed. For example, privacy regulation affects whether patients feel safe sharing data; reimbursement and institutional endorsement affect whether telemedicine appears legitimate; and clinical workflow integration affects whether AI is perceived as supporting or threatening professional care. Therefore, the social psychology perspective complements rather than excludes institutional and economic explanations.

The review also clarifies the role of human-AI interaction. Human-AI interaction is not only a technical interface issue, but a relational mechanism through which trust is formed. When AI clearly communicates its role, explains recommendations, and preserves human clinical authority, patients are more likely to perceive the system as supportive. Conversely, opaque recommendations, ambiguous responsibility, or excessive autonomy may weaken trust. This finding is consistent with human-AI communication evidence showing that perceived AI agency affects trust, liking, and evaluation of interaction quality (Pan et al., 2024), and with broader AI trust literature emphasizing representation, machine intelligence, and interaction context (Glikson & Woolley, 2020).

Social acceptance should therefore be understood as a collective condition surrounding patient trust. In AI-based telemedicine, acceptance is shaped not only by individual intention but by shared norms about what counts as legitimate care, what roles clinicians should retain, how privacy is protected, and whether AI distributes benefits and risks fairly. Bias studies demonstrate that algorithmic underdiagnosis and dataset imbalance can undermine trust among underserved groups (Celi et al., 2022; Seyyed-Kalantari et al., 2021). This means that social acceptance depends on ethical governance and fairness, not only on user education or interface design.

The main theoretical proposition generated by this synthesis is a three-level social-psychological trust pathway. Patient trust begins with individual cognitive appraisal, is tested through interactional attribution in human-AI encounters, and is stabilized or weakened by socio-structural legitimation. This proposition advances prior literature by connecting adoption theory, automation trust, and health AI governance into a single explanatory framework. It also specifies why a social psychology perspective is necessary: patient trust is not merely a variable predicting acceptance, but a process through which patients interpret AI as a clinical, communicative, and institutionally embedded actor.

Practically, the findings suggest that AI-based telemedicine should be designed and implemented as a human-centered, explainable, and socially accountable service. Developers should prioritize explainability, transparency, privacy protection, and role clarity. Health professionals should communicate that AI functions as decision support rather than a replacement for clinical judgment. Policymakers and institutions should implement bias monitoring, privacy safeguards, and accountability standards to strengthen legitimacy. Patient groups with limited digital literacy, older adults, rural communities, and non-users may require differentiated trust-building strategies, including simple explanations, risk communication, and accessible support.

This review has limitations. First, the number of included studies was limited because AI-based telemedicine trust remains an emerging field and many studies still focus on technical performance rather than psychosocial mechanisms. Second, the included evidence was heterogeneous, which prevented meta-analysis and required narrative synthesis. Third, several studies were conducted in Global North contexts, limiting generalizability to low- and middle-income countries. Fourth, most empirical studies used cross-sectional or experimental designs, so the longitudinal development of trust remains underexamined.

Future research should test the proposed three-level trust pathway using longitudinal and cross-cultural designs. Studies should distinguish patient trust from clinician trust, system reliability, general technology acceptance, and institutional trust. Future work should also examine how trust changes after repeated AI-telemedicine encounters and how trust is affected by algorithmic errors, explanations, privacy breaches, or clinician endorsement. More empirical studies are needed in digitally underserved populations to evaluate whether AI-based telemedicine strengthens access or reinforces inequity.

Conclusions

This systematic review demonstrates that patient trust in AI-based telemedicine is a multilevel social psychological process. The synthesis identified three interrelated levels of trust formation: individual cognitive appraisal, interactional attribution in human-AI encounters, and socio-structural legitimation through governance, fairness, and institutional accountability. These findings move beyond conventional technology acceptance explanations by showing that patients do not only evaluate whether AI-based telemedicine is useful or easy to use; they also interpret whether AI is understandable, safe, fair, professionally appropriate, and institutionally trustworthy.

The theoretical contribution of this review is the formulation of a three-level social-psychological trust pathway linking patient cognition, human-AI interaction, and institutional legitimacy. This framework challenges approaches that treat trust merely as a static adoption variable or as a direct proxy for system reliability. Instead, trust is positioned as a dynamic process through which patients negotiate vulnerability, interpret AI agency, and evaluate the legitimacy of AI-supported healthcare. Human-AI interaction functions as the central mechanism through which trust is calibrated, while social acceptance represents the broader collective condition that can sustain or constrain trust.

AI-based telemedicine should therefore be implemented as a socio-technical healthcare system. Sustainable adoption requires not only accurate algorithms and functional platforms, but also explainable communication, privacy assurance, bias mitigation, role clarity, clinician involvement, and accountable governance. Future studies should empirically test this framework across patient groups, healthcare settings, and cultural contexts.

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