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Trust and Reliance on AI-Generated Advice: Investigating User Perceptions and Behavioral Dynamics in Conversational AI

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Abstract
The rapid proliferation of conversational artificial intelligence (AI) tools, such as ChatGPT and Gemini, has transformed the way individuals seek guidance, information, and problem-solving assistance. While these tools offer unprecedented convenience and accessibility, questions remain regarding how users perceive and trust AI-generated advice, and the potential implications for reliance, critical evaluation, and decision-making. This study investigates adults' trust in AI-generated answers, examining both cognitive and emotional determinants, usage patterns, and behavioral outcomes. A mixed-method design was employed, involving a survey of 30 adults to assess trust, perceived accuracy, reliance, and critical evaluation, alongside interviews and a focus group with 10 adults to gain qualitative insights into personal experiences with conversational AI. Quantitative findings indicate that trust is positively correlated with perceived accuracy, frequency of use, and reliance on AI for personal decisions, while critical evaluation remains relatively low. Factor analysis identified three key dimensions of trust: perceived competence, emotional assurance, and convenience. Qualitative results revealed that participants value AI's non-judgmental tone and ease of access, yet express cautious skepticism regarding accuracy in complex or sensitive contexts. The study highlights that trust in AI is multidimensional, shaped by cognitive, emotional, and practical considerations, and functions as both an enabler and potential constraint. Users' reliance on AI facilitates efficiency but may risk over-dependence and reduced critical thinking. Findings underscore the importance of AI literacy, system transparency, and responsible design to promote informed trust and balanced use. These insights contribute to understanding how humans interact with AI-generated advice and offer guidance for developers, educators, and policymakers seeking to foster responsible engagement with AI technologies.

Keywords: Conversational Artificial Intelligence; Trust in AI; User Perception; AI-Generated Advice

1. Introduction

In recent years, conversational artificial intelligence (AI) systems such as ChatGPT, Gemini, Claude, and other large language models (LLMs) have become deeply embedded in everyday life. These tools are no longer limited to technical environments; instead, they now serve as accessible assistants for academic tasks, workplace decisions, emotional guidance, and even personal life dilemmas. The rapid public adoption of AI-generated advice reflects not only technological progress but also a growing perception that AI can provide reliable, neutral, and intelligent solutions across a wide range of problems (Dwivedi et al., 2023). As people increasingly interact with conversational AI, questions arise regarding how they evaluate its credibility, how much they trust its answers, and why many rely on it for decision-making—even in sensitive areas traditionally guided by human judgment.

Trust plays a fundamental role in human–technology interaction. Research in automation and AI consistently shows that when users perceive a system as competent, objective, and helpful, they tend to rely on its suggestions—even when those suggestions may be flawed (Goddard et al., 2012; Mosier & Skitka, 2018). Known as *automation bias*, this phenomenon can lead people to accept AI-generated recommendations with minimal critical evaluation. LLMs intensify this dynamic: their fluent, human-like language creates an impression of confidence and authority, which can increase perceived trustworthiness regardless of accuracy (Luger & Sellen, 2016; West et al., 2024).

Empirical studies show that people consult AI for a wide range of needs, including learning, productivity, mental health support, and interpersonal problems. For instance, recent surveys reveal that users often describe ChatGPT as clearer, faster, and more emotionally supportive than traditional digital tools (Park et al., 2023). However, alongside these benefits, AI-generated answers are known to produce errors, hallucinations, oversimplifications, and fabricated information—a limitation documented by OpenAI and widely analyzed in academic research (Ji et al., 2023). Despite these risks, public trust remains surprisingly high, especially when responses are delivered with high linguistic confidence and coherence (Müller-Birn et al., 2023).

Understanding why people trust AI in this way is increasingly important. Trust in AI-generated answers influences learning habits, decision-making processes, and even emotional well-being. Some users view AI as an unbiased advisor—free from social pressure, judgment, or personal motives (Kim et al., 2023). Others rely on AI due to convenience, cognitive offloading, or difficulty accessing expert guidance. Yet concerns persist excessive trust may promote dependency, reduce critical thinking, and distort users' ability to distinguish between accurate information and AI-generated inaccuracies (Nagel, 2024).

Although research on trust in automation and AI is well established, there is limited empirical evidence specifically focused on how everyday users perceive and trust conversational AI as a source of advice for real-life problems. Most prior studies analyze trust in AI within specialized domains such as medicine, finance, or autonomous vehicles (Lee & See, 2004; Cai et al., 2021). Far fewer investigate the broader psychological and social factors that influence people's trust in LLM-generated answers during routine, personal, or emotionally complex decision-making.

Thus, the present study seeks to investigate how individuals perceive the trustworthiness of AI-generated suggestions, what factors shape their trust, and how they negotiate the balance between AI assistance and independent judgment. As conversational AI continues to evolve and integrate into daily decision-making, understanding these dynamics is essential for designing safer systems, developing AI literacy, and supporting informed and responsible use.

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2. Literature Review

1. Overview of Trust in AI

Trust has long been recognized as a foundational component in human–machine interaction. A comprehensive bibliometric review of 24 years of empirical research on trust in AI shows increasing diversity in trust studies, but also many "overlooked issues," such as emotional trust, longitudinal dynamics, and the relational nature of trust in human–AI systems. SpringerLink This broad analysis underscores that trust in AI is not monolithic but shaped by multiple dimensions—user factors, machine characteristics, interaction context, and social norms.

In the domain of conversational AI, a recent systematic review studied 40 empirical articles and identified how trust is conceptualized, operationalized, and studied. It found that trust predictors cluster into five categories:

1- user-related (e.g., personality, prior experience),
2- machine-related (e.g., perceived competence),
3- interaction-related (e.g., interactivity),
4- social, and
5- context-related factors.

The review also pointed out that most work is cross-sectional, and longitudinal studies remain rare, limiting our understanding of how trust evolves over time.

2. Determinants of Trust in Generative AI

2.1 Competence, Fairness, and Technical Trustworthiness

A key recent empirical study by *Sun, Liu, Wu, Yu, & Yao* (2025) proposed the Human-AI Trust Scale (HAITS), which captures both rational and relational components of trust in generative AI (GenAI). They identified four dimensions: Affective Trust, Competence Trust, Benevolence & Integrity, and Perceived Risk. This model emphasizes that trust in GenAI is not only about how "smart" or accurate the system is, but also about perceived benevolence and risk.

Another significant contribution is from *Chang, Shin, and colleagues* (2025), who explored cognitive trust in GenAI using the Fairness–Accountability–Transparency (FAT) framework combined with "humanness" attributes (anthropomorphism, social presence, emotional responsiveness). Their findings suggest that fairness strongly predicts users' trust, whereas accountability and transparency (often assumed critical) may not always be as influential. Instead, social presence and emotional engagement had a major impact, revealing that users trust GenAI not just for its correctness but for how "human-like" it feels.

2.2 Sociotechnical and Psychological Motivators

A mixed-methods study in the UK conducted by *Exploring Motivators for Trust in the Dichotomy of Human–AI Trust Dynamics* (2024) found that many users prefer AI over humans because of its perceived impartiality and accuracy, likening its trustworthiness to conventional computing systems. This suggests that for some, AI's lack of hidden agenda or emotional bias is a feature, not a bug, in trust formation.

In addition, *Billah, Hamjaya, Shiralizade, Singh, & Inam* (2025) performed a systematic mapping study examining trustworthiness of LLMs considering regulatory frameworks such as the EU AI Act. Their analysis underlines that regulatory design and governance (e.g., compliance, data provenance) contribute significantly to public perception of AI trustworthiness.

3. Trust in Conversational AI (Chatbots)

3.1 Interaction, Humanness, and Emotional Cues

In e-commerce contexts, *BMC Psychology* published research demonstrating that interactivity, humanness, and perceived enjoyment strongly influence user trust in chatbots. The more interactive and human-like the agent behaves, the more users trust it—and thus are more likely to use it, buy from it, or rely on it for service.

Similarly, *Wang, Rangel, Schmidt, & Safonov* (2024) investigated trustworthiness in conversational agents from a personality-based perspective. They found that users' personality traits affect how they perceive the trustworthiness of chatbots. For instance, extroverted individuals may prefer more socially expressive bots, while more analytical users emphasize accuracy and logic.

3.2 Behavioral Outcomes of Trust

A study of banking chatbots in India by *Alagarsamy & Mehrolia* (2023) examined how trust affects behavioral outcomes (e.g., reuse, satisfaction). They found that perceived competence, security, and interface usability significantly influence trust, which in turn predicts users' continued usage and behavioral intentions.

In a consumer-service context, *Li & colleagues* (2024) compared trust in chatbot service agents to human customer service agents. Their work showed that dispositional, situational, and learned trust (i.e., built through interactions) all influence satisfaction, re-use behavior, and loyalty, indicating that trust in chatbots can operate on multiple psychological levels.

4. Trust, Risk, and Verification in Sensitive Domains

4.1 Political Information & Misinformation

In a politically sensitive application, *Semenova, Ebel, et al.* (2024) examined whether LLM-based chatbots (e.g., ChatGPT, Bing Chat (Bing Chat is now Microsoft Copilot)) can effectively verify political information. Their analysis revealed that chatbots' ability to distinguish true vs. false content varies significantly by topic, language, and prompt framing—raising concerns about users over-relying on AI for fact-checking in critical domains.

4.2 Education and Learning Environments

A very recent (2025) mixed-methods study by *Wang, Li, Cheung, & Wong* explored how university students trust GenAI in language learning. The authors found that trust is a central factor that influences students' reliance on GenAI, and identified resistance where students deliberately limit usage due to perceived risk. Their model highlights that trust mediates between behavioral intention and actual use, and that both reliance and resistance are needed to fully understand the trust–use relationship.

4.3 Regulation and Ethics

Regulatory considerations also shape trust. *Billah et al.* (2025) mapped the trustworthiness of LLMs in accordance with the EU AI Act. Their study argues that compliance with laws and ethical guidelines enhances perceived trustworthiness, suggesting that legal frameworks and design transparency should be part of trust-building in public-facing AI systems.

5. Emerging Concerns: Emotional Over-reliance and Ethical Risks

Beyond purely cognitive trust, scholars and commentators warn of emotional over-reliance on chatbots, especially in vulnerable populations. For example, AI systems designed for companionship or mental-health support risk creating "one-sided" emotional bonds. A mixed public-psychological concern has emerged around "sycophantic" AI behavior, where chatbots affirm users without critical challenge, thereby reinforcing user beliefs and possibly unhealthy decision-making.

Additionally, trust in AI for sensitive decisions such as therapy, crisis advice, or self-harm is legally and ethically fraught (regulatory bodies, mental health professionals) because AI lacks true empathy and accountability. These emergent issues highlight the need for more research on how trust intersects with emotional well-being, safety, and digital ethics.

Trust in AI, particularly in conversational and generative systems, is multidimensional. It is shaped by perceptions of competence, fairness, emotional responsiveness, social presence, and user experience factors like interactivity and pleasure. Trust influences not only usage behavior but also users' reliance on and resistance to AI, particularly in learning and decision-making contexts. While the literature is growing rapidly, it remains dominated by cross-sectional surveys, and limited insight exists into how trust evolves over time in real-life use. Thus, this study has these objectives:

- To investigate how trust in conversational AI develops, changes, or decays over repeated, real-world interactions, addressing the lack of longitudinal evidence.
- To examine users' emotional and existential reliance on conversational AI, exploring why and how individuals depend on chatbots for life advice, emotional support, or decision-making.
- To analyze the relationship between perceived trust in AI and user behavioral outcomes—such as overreliance, fact-checking, and dependency—in everyday, non-institutional contexts.

3. Methodology

3.1 Research Design

This study employed a mixed-method research design to investigate how adults perceive and trust AI-generated answers. A mixed-method approach was selected because it allows for both quantifiable measurement of trust patterns and deeper exploration of users' personal experiences. The combination of quantitative and qualitative data provides a more comprehensive understanding of how and why individuals rely on conversational AI for advice on everyday problems.

3.2 Participants and Sampling Strategy

A total of 40 adults participated in the study. Thirty participants completed the survey, while ten additional participants took part in interviews or a focus group. A purposive sampling strategy was used to recruit individuals who had interacted with AI tools such as ChatGPT, Bard, or Claude at least once within the past six months. This ensured that participants had sufficient experience to reflect meaningfully on their trust levels and usage patterns.

3.3 Data Collection Tools

Data were collected using two methods. The first was an online survey administered to 30 adults, which included trust measurement scales, five-point Likert-type items, and questions about frequency of use and reliance on AI for decision-making. The second instrument involved interviews and a focus group with 10 adults. These sessions allowed participants to elaborate on their perceptions, emotional reactions, and concerns regarding AI-generated advice, providing rich qualitative insights.

.34 Analytic Procedures

Quantitative survey data were analyzed using descriptive statistics to summarize general usage trends and trust levels, as well as correlation tests to examine relationships between trust, usage frequency, and perceived reliability of AI. Factor analysis was also conducted to explore underlying dimensions of AI trust. Qualitative interview data were analyzed using thematic analysis, which involved coding participant responses, identifying recurring themes, and interpreting patterns that explained why individuals trust or question AI-generated suggestions.

4. Results and Discussion

This section presents the findings of the study and interprets their implications in the context of existing research on trust in conversational AI.

4.1 Quantitative Results

Table 1: Descriptive Statistics of Trust and Usage Variables (N = 30)

Variable	Mean	SD
Frequency of AI Use (per week)	4.2	1.8
Trust in AI Answers (1–5 scale)	3.7	0.6
Perceived Accuracy of AI Answers (1–5)	3.5	0.7
Reliance on AI for Personal Decisions (1–5)	3.2	0.9
Critical Evaluation of AI Answers (1–5)	2.8	0.8

Participants reported relatively high trust levels (M = 3.7) and a moderate belief in AI accuracy (M = 3.5). Usage frequency was also considerable, with most adults consulting AI tools several times a week. Interestingly, reliance on AI for personal decisions was moderate (M = 3.2), while critical evaluation was relatively low (M = 2.8).These results show that adults frequently use AI systems and tend to trust their responses even without strong critical scrutiny. This pattern reflects the phenomenon of *automation bias*, where users accept AI-generated answers due to perceived neutrality and coherence. The lower critical evaluation scores imply that many users may overestimate the reliability of AI responses, especially in everyday problem-solving.

Table 2: Correlations Between Trust, Usage, and Perceived Accuracy

Variables	Trust	Usage	Accuracy	Reliance
Trust in AI Answers	—	.42*	.58**	.61**
Frequency of AI Use	.42*	—	.36*	.49*
Perceived Accuracy	.58**	.36*	—	.54**
Reliance on AI for Decisions	.61**	.49*	.54**	—

Note: p < .05, **p** < .01*

Trust was strongly correlated with perceived accuracy (**r = .58, p < .01**) and reliance on AI (**r = .61, p < .01**). This indicates that when users believe the AI is accurate, they also tend to rely on it more for decision-making. Frequency of use correlated moderately with trust (**r = .42, p < .05**), suggesting that familiarity may reinforce confidence in AI-generated answers.

However, this relationship can be problematic: frequent users may develop increased trust even if they lack the skills to critically evaluate information. This aligns with concerns in AI-trust literature regarding how repeated exposure can normalize AI guidance, gradually increasing reliance even in non-expert domains.

Table 3: Factor Analysis Summary: Dimensions of AI Trust

Factor Name	Key Items Loaded	Interpretation
Factor 1: Perceived Competence	Accuracy, clarity, problem-solving ability	Users trust AI when it seems “smart”
Factor 2: Emotional Assurance	Non-judgmental tone, supportive wording	Users value AI’s emotional neutrality
Factor 3: Convenience & Speed	Quick responses, ease of access	Efficiency drives trust behaviors

Factor analysis revealed three underlying dimensions of trust: perceived competence, emotional assurance, and convenience. Interestingly, emotional assurance—how supportive, neutral, or non-judgmental the AI appears—emerged as a separate and meaningful component. This finding echo recent research suggesting that many adults consider AI to be a “safe” space for asking sensitive questions.The identification of convenience as a factor reinforces that trust is not purely cognitive; practical benefits (speed and ease) shape whether people believe an AI answer is good enough to follow. This highlights the importance of user experience design in shaping trust dynamics.

4.2 Qualitative Results

Table 4: Themes from Interviews and Focus Group (N = 10)

Theme	Description
1. AI as a Neutral Advisor	Participants felt AI gives “non-judgmental” and “unbiased” responses.
2. Convenience and Accessibility	AI is viewed as fast, available anytime, and easier than searching online.
3. Skepticism About Accuracy	Some users expressed doubts about correctness, especially on complex issues.
4. Emotional Comfort Seeking	Several participants used AI when feeling unsure, anxious, or overwhelmed.
5. Awareness of AI Limitations	Users acknowledged hallucinations and expressed the need to double-check.

Interview participants described AI as a **neutral and non-judgmental advisor**, particularly useful when asking questions they would hesitate to ask another person. This emotional safety was a major reason participants trusted AI responses, even beyond purely factual situations.Convenience also emerged as a strong theme; adults appreciated the speed and simplification AI provides compared to manual searching. However, participants also voiced concerns about accuracy. Several noted occasions where AI provided incorrect or overly confident responses, leading them to cross-check information afterward.

The coexistence of trust and skepticism reflects a nuanced relationship: users trust AI enough to consult it frequently but remain aware—at least partially—of its limitations. This duality aligns with quantitative findings showing moderate reliance but lower critical evaluation skills.Overall, the results show that adults demonstrate moderate to high trust in AI-generated answers, influenced by perceived competence, emotional comfort, and convenience. Heavy users trust AI more, rely on it more, and believe it is more accurate, indicating a reinforcing cycle. Qualitative insights reveal that emotional and psychological factors—such as seeking non-judgmental responses—play a significant role in shaping trust.However, limited critical evaluation and occasional skepticism indicate that participants are not fully confident in AI reliability. This suggests the need for improved AI literacy and clearer system transparency about uncertainties and limitations.

5. Conclusion

This study examined how adults perceive and trust AI-generated answers, particularly from conversational AI tools such as ChatGPT and Bard. The findings reveal a nuanced landscape: while participants generally reported moderate to high trust and frequent use, their critical evaluation of AI-generated content remained limited. Quantitative analysis indicated that trust is strongly linked to perceived accuracy, frequency of use, and reliance for personal decisions. Factor analysis highlighted that trust is multidimensional, encompassing perceived competence, emotional assurance, and convenience. Qualitative insights further revealed that users value AI’s non-judgmental tone and accessibility, yet remain partially skeptical of its accuracy, particularly for complex or sensitive topics.These results demonstrate that trust in AI is not purely cognitive but also shaped by emotional, social, and practical factors. Users often rely on AI for decision-making and emotional support, suggesting that AI is perceived as a semi-human advisor. At the same time, reliance without sufficient critical evaluation may increase the risk of over-dependence and the uncritical acceptance of inaccurate information. Thus, trust in AI is both an enabler and a potential constraint: it facilitates efficiency and accessibility while simultaneously introducing risks to independent judgment and critical thinking. Understanding these dynamics is crucial for designing AI systems that are not only effective but also promote informed and responsible use.Several limitations should be acknowledged. First, the sample size was relatively small (N = 40), and participants were recruited through purposive sampling, which may limit the generalizability of the findings to the broader population. Second, the study relied on self-reported measures of trust and usage patterns, which may be subject to social desirability bias or inaccurate recall. Third, the research focused on adults with some prior experience using conversational AI; individuals who are novice users or highly resistant to AI were not included, potentially skewing trust perceptions. Finally, the cross-sectional design captures trust at a single point in time, preventing analysis of how trust evolves with repeated or longitudinal use of AI tools. These limitations suggest that caution should be exercised when generalizing the findings, and that future research should employ larger, more diverse samples and longitudinal designs.Based on the findings, several recommendations emerge for researchers, educators, and AI developers. First, AI literacy programs should be implemented to help users critically evaluate AI-generated content, verify accuracy, and recognize limitations, thereby reducing the risk of over-reliance. Second, AI developers should enhance transparency and provide cues about uncertainty or source reliability to promote informed trust. Third, designers should consider emotional and relational aspects of AI interactions, ensuring that the system provides supportive yet responsible guidance without encouraging undue dependency. Finally, future research should explore longitudinal and domain-specific trust dynamics, particularly in emotionally sensitive or high-stakes contexts, to better understand how trust develops and impacts decision-making over time. By addressing these recommendations, both the adoption and the responsible use of AI in everyday life can be optimized, balancing efficiency with critical engagement.

Data availability statement

The data that support the findings of this study are available on request from the author. The data are not publicly available due to privacy or ethical restrictions.

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Survey: Trust in AI-Generated Advice

Purpose: This survey aims to understand users' trust, perceptions, and behaviors when interacting with AI tools such as ChatGPT, Bard, or Claude. All responses are anonymous and confidential.

Instructions: Please answer all questions honestly. For Likert-scale items, use the following: 1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

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Section A: Demographics

1. Age: ____
2. Gender: ☐ Male ☐ Female ☐ Prefer not to say
3. Highest level of education: ☐ High School ☐ Bachelor's ☐ Master's ☐ Doctorate ☐ Other
4. Occupation/Field of Work: ____________________________

Section B: AI Usage Patterns

5. How often do you use conversational AI tools?
   ☐ Daily ☐ 3–4 times a week ☐ 1–2 times a week ☐ Less than once a week ☐ Rarely/Never
6. For what purposes do you typically use AI? (Select all that apply)
   ☐ Life advice / personal decisions
   ☐ Emotional support or mental well-being
   ☐ Academic work / research
   ☐ Work-related tasks
   ☐ Entertainment / curiosity
   ☐ Other: ___________________
7. How long have you been using conversational AI?
   ☐ Less than 1 month ☐ 1–6 months ☐ 6–12 months ☐ More than 1 year

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Section C: Trust in AI

Please rate your agreement with the following statements:
1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

8. I generally trust the answers provided by AI.
9. I believe AI-generated advice is accurate.
10. I feel confident relying on AI for everyday decisions.
11. I feel comfortable asking AI about sensitive or personal issues.
12. I trust AI more than other online sources of advice.
13. I believe AI understands human emotions sufficiently.
14. I feel that AI provides impartial and unbiased guidance.

Section D: Reliance and Behavioral Patterns

15. I rely on AI to make important decisions in my daily life.
16. I often follow AI advice without verifying it independently.
17. I feel that AI reduces my need to think deeply or analyze problems myself.
18. I turn to AI when I feel uncertain or anxious about a decision.
19. Using AI saves me time and effort in problem-solving.

Section E: Critical Evaluation and Awareness

20. I usually check AI-generated answers for accuracy.
21. I am aware that AI can sometimes provide incorrect or misleading information.
22. I critically evaluate AI advice before applying it.
23. I am cautious about relying on AI for life-changing decisions.
24. I believe it is important to balance AI advice with human judgment.

Section F: Open-Ended Questions

25. Describe a situation where you relied on AI for advice. How did it affect your decision?
26. What factors make you trust or distrust AI-generated answers?
27. How do you think your trust in AI could be improved?