Advanced International Journal for Research (AIJFR)
E-ISSN: 3048-7641 ● Website: www.aijfr.com ● Email: editor@aijfr.com

Algorithmic Guidance and Psychological Susceptibility in AI Systems

A. Shradha Bisht[1], Dr. Devinder Dhalla[2]

Abstract
Conversational artificial intelligence (AI) systems are increasingly used as advisory agents in domains involving career planning, financial decisions, emotional regulation, and productivity enhancement. While existing research primarily evaluates technical performance and accuracy, comparatively little attention has been devoted to the psychological architecture of AI-generated advice. The present study conducted a qualitative comparative discourse analysis of advisory responses generated by three widely used conversational AI systems across eight vulnerability-oriented prompts. Responses were systematically coded for authority language, directive strength, emotional validation, personalization framing, cognitive load reduction, and identity reinforcement cues. Findings indicate that conversational style significantly shapes psychological influence pathways. Systems differed in their levels of emotional validation, executive directive framing, and behavioral scaffolding, suggesting distinct profiles of affective trust activation, authority bias engagement, and cognitive offloading facilitation. Although influence mechanisms were subtle and not inherently harmful, the structural design of advisory outputs may increase compliance, reliance, and identity framing, particularly in contexts of user vulnerability. These findings suggest that conversational AI should be conceptualized not only as informational technology but also as behavioral infrastructure. The study highlights the need for greater awareness of how advisory framing influences user autonomy and calls for interdisciplinary research into ethical design and long-term psychological impact.

Keywords: conversational artificial intelligence, algorithmic advice, psychological influence, trust formation, behavioral compliance, cognitive offloading, AI ethics

1. Introduction

The proliferation of conversational artificial intelligence (AI) systems has ushered in a transformative shift in how individuals seek guidance, interpret uncertainty, and make decisions. Large language models (LLMs) such as ChatGPT, Gemini, and Perplexity are increasingly embedded in everyday cognitive routines, serving not merely as information retrieval systems but as advisory agents capable of delivering structured recommendations across domains including career planning, financial management, emotional regulation, health behavior, academic preparation, and interpersonal conflict resolution. This transition signals a broader epistemic movement from search-based information access toward algorithmically mediated consultation.

Unlike traditional search engines, which require users to evaluate multiple sources and synthesize competing viewpoints, conversational AI systems provide consolidated, narrative-style outputs framed as personalized guidance. This structural difference is psychologically significant. Decision-making research

suggests that when ambiguity is reduced and options are presented in organized, directive formats, individuals experience increased cognitive ease and are more likely to accept recommendations without extensive scrutiny (Kahneman, 2011; Alter & Oppenheimer, 2009). Conversational AI, by design, reduces informational friction, thereby potentially reshaping how authority and expertise are perceived.

Human–computer interaction research has long demonstrated that people respond to computers and media agents using social heuristics typically reserved for human interaction (Nass & Moon, 2000). The "Computers Are Social Actors" (CASA) paradigm posits that even minimal social cues such as conversational tone, politeness, or empathy simulation, can trigger interpersonal responses. When AI systems communicate using emotionally validating language, structured reasoning, and confidence markers, users may attribute intentionality, intelligence, and benevolence to them . Such anthropomorphic tendencies enhance perceived social presence and increase relational trust.

Trust in automation is a foundational construct in understanding reliance on technological systems. Lee and See (2004) defined trust in automation as the belief that an automated agent will help achieve an individual's goals under conditions of uncertainty and vulnerability. Advisory interactions, particularly those involving distress, identity confusion, financial instability, or high-stakes examinations , are inherently vulnerability-laden contexts. In such scenarios, individuals may exhibit heightened sensitivity to cues of certainty, structure, and empathy. Authority bias theory suggests that when a source appears knowledgeable and confident, compliance increases even in the absence of verified expertise . In conversational AI, directive language ("You should," "Here is your plan," "We need to shift this strategy") may activate such authority heuristics.

Beyond authority, the simulation of empathy represents another psychologically potent mechanism. Therapeutic alliance research consistently identifies empathy, validation, and collaborative framing as predictors of behavioral compliance and treatment adherence . Although conversational AI lacks consciousness or emotional experience, its linguistic outputs often mirror therapeutic discourse, acknowledging feelings, normalizing distress, and reframing cognitive distortions. From a cyberpsychological perspective, users may experience these interactions as relationally meaningful despite their artificial origin . Parasocial interaction theory suggests that individuals can form one-sided bonds with media figures or digital agents when communication appears responsive and emotionally attuned (Hoorn et al., 2015). Repeated advisory consultation with AI may therefore foster perceived relational safety, potentially increasing reliance.

Another mechanism of concern is cognitive offloading. Cognitive offloading refers to the delegation of mental tasks to external tools to reduce cognitive burden . While offloading can improve efficiency, it may also reduce deep processing and independent evaluative reasoning. When conversational AI provides comprehensive action plans, financial allocation strategies, or structured life roadmaps, it may inadvertently replace internal deliberation with externally scaffolded decision frameworks. Over time, this dynamic could contribute to reduced metacognitive engagement in complex personal decisions.

The persuasive architecture of conversational AI further complicates this dynamic. Digital interfaces inherently structure information through choice architecture, a concept central to behavioral economics

(Thaler & Sunstein, 2008). Even without explicit intent to manipulate, the way recommendations are framed, sequenced, and prioritized may nudge users toward specific behavioral pathways. For example, presenting a "90-day action plan" with explicit milestones transforms advice into commitment scaffolding, increasing the likelihood of behavioral enactment. The integration of certainty markers, progress tracking, and identity reinforcement ("You are becoming disciplined," "This will redefine your future") may strengthen internalization of suggested paths.

Moreover, conversational AI systems differ in stylistic orientation. Some emphasize empathic relational framing, others adopt directive executive tone, and others focus on analytical structuring. These stylistic differences are not psychologically neutral. Communication theory indicates that message framing influences perceived credibility, trustworthiness, and persuasion effectiveness . A response that appears reflective and emotionally attuned may elicit higher relational trust, whereas a response that is highly structured and authoritative may elicit compliance through perceived expertise. Systematic comparative analysis of these stylistic variations remains underdeveloped in the literature.

Current scholarly discourse on LLMs has largely concentrated on performance metrics, bias detection, hallucination frequency, and ethical deployment. While these concerns are critical, comparatively less attention has been devoted to the psychological influence pathways embedded within conversational structure. As AI increasingly enters domains traditionally occupied by mentors, therapists, educators, and consultants, understanding how language style shapes trust formation and behavioral intention becomes imperative.

This issue is particularly salient for vulnerable populations. Individuals experiencing anxiety, depressive symptoms, career uncertainty, academic pressure, financial stress, or interpersonal conflict may be especially receptive to structured reassurance and decisive guidance. Vulnerability research suggests that perceived certainty and emotional validation can significantly influence compliance and belief formation under stress (Taylor & Brown, 1988). When algorithmic systems present coherent narratives during periods of ambiguity, they may assume a stabilizing authority role in users' cognitive ecosystems.

Importantly, the shift from informational to advisory AI raises ethical and societal questions. If conversational AI systems subtly shape goals, behaviors, and self-perceptions through structured guidance, they function not merely as information intermediaries but as behavioral actors within personal development trajectories. This reconceptualization demands empirical investigation into how advisory responses differ across systems and how those differences may affect psychological outcomes.

The present study addresses this gap by conducting a qualitative comparative discourse analysis of advisory responses generated by multiple conversational AI systems using identical prompts across domains including career decision-making, financial planning, emotional distress, productivity optimization, and interpersonal conflict. Responses are coded across dimensions including authority language, emotional validation cues, directive strength, dependency markers, personalization framing, and cognitive load reduction structures. By examining these dimensions systematically, this research seeks to identify underlying influence mechanisms embedded within conversational AI advisory outputs.

The central research question guiding this study is: How do differences in conversational structure among AI advisory systems shape psychological trust formation and behavioral influence? By situating conversational AI within established psychological theories of persuasion, trust, anthropomorphism, and cognitive offloading, this study reframes AI advisory interaction as a socio-psychological phenomenon rather than a purely computational one.

As conversational AI continues to integrate into personal decision-making contexts, evaluating its psychological impact is not merely an academic exercise; it is a societal necessity. AI systems are increasingly positioned at the intersection of vulnerability and authority. Understanding the influence architecture embedded in their language is therefore essential for responsible design, regulation, and user awareness.

2. Review of literature

For decades, researchers assumed that people would treat machines as tools : cold, mechanical, and emotionally distant. However, early studies in human–computer interaction revealed something surprising: individuals often respond to computers using the same social rules they apply to other humans. Nass and Moon (2000) demonstrated that even minimal social cues such as politeness or conversational tone, can trigger interpersonal reactions. People thanked computers, felt judged by them, and even exhibited politeness biases toward them.

This phenomenon challenges the assumption that users maintain psychological distance from technology. When AI systems communicate in natural language, respond instantly, and appear attentive, they begin to occupy a social space rather than a mechanical one. Waytz et al. (2014) found that anthropomorphism, the tendency to attribute human-like qualities to nonhuman agents, increases when individuals feel uncertainty or lack control. In other words, the more uncertain a person feels, the more likely they are to see intentionality and agency in technology.

Conversational AI systems are particularly powerful in this regard. Unlike static software, they simulate dialogue. They ask follow-up questions, provide structured advice, and mirror emotional language. These behaviors mimic relational patterns typically found in mentorship or counseling contexts. Over repeated interactions, users may begin to experience the AI as responsive rather than reactive, reinforcing perceptions of intelligence and care.

As digital interactions become more conversational and personalized, the boundary between tool and social agent continues to blur. Understanding this blurred boundary is critical when AI moves beyond information delivery into domains involving personal decision-making and emotional vulnerability.

2.1 Trust in Automation: Why We Rely on Confident Systems

Trust is not simply belief; it is a willingness to be vulnerable. Lee and See (2004) describe trust in automation as the confidence that a system will act in ways that help achieve one's goals under conditions of uncertainty. This definition is particularly relevant for advisory AI systems, which are often consulted during moments of doubt, career confusion, financial stress, interpersonal conflict, or anxiety.

Research in automation psychology suggests that humans rely more heavily on systems that display consistency, clarity, and confidence. When instructions are presented in structured steps, users perceive higher competence. Even when systems occasionally err, their structured presentation can preserve perceived authority.

Authority bias further amplifies this effect. Cialdini (2007) argues that individuals tend to comply with sources perceived as knowledgeable or expert, often without independently verifying information. In conversational AI, markers of expertise, such as detailed plans, confident tone, and organized frameworks may activate authority heuristics. The user may not consciously think, "This is authoritative," but the structure itself communicates credibility.

An additional dimension of trust is cognitive ease. Kahneman (2011) explains that information that is easier to process feels more truthful and reliable. When conversational AI delivers synthesized advice rather than requiring users to compare multiple sources, it reduces mental strain. That reduction can create a subtle but powerful sense of confidence in the output.

Importantly, overreliance on automation is a documented phenomenon. Automation bias occurs when individuals favor machine-generated decisions over their own judgment, even in situations where skepticism may be warranted . In advisory contexts, this could translate into behavioral compliance with AI-generated plans without critical evaluation.

2.2 Persuasion in Digital Environments: Influence Without Intention

Persuasion does not always require deliberate intent. The structure and framing of information can influence behavior even when influence is not explicitly sought. The Elaboration Likelihood Model (Petty & Cacioppo, 1986) distinguishes between central processing, where individuals critically evaluate arguments and peripheral processing, where cues such as confidence, structure, or tone drive acceptance.

In emotionally charged or cognitively demanding situations, individuals are more likely to rely on peripheral cues. If an AI response appears calm, structured, and empathetic, users may accept its recommendations based on how it feels rather than on detailed scrutiny of content.

Behavioral economics further contributes to this understanding. Thaler and Sunstein (2008) introduced the concept of nudging, where small changes in how choices are presented can significantly alter decision outcomes. Conversational AI systems often organize recommendations sequentially - "Step 1," "Step 2," "Step 3." This structured progression does more than inform; it creates momentum. When milestones and timelines are included, advice transforms into a commitment framework.

Framing effects also play a role. Tversky and Kahneman (1981) demonstrated that how information is framed influences decisions more than the information itself. For example, presenting a financial strategy as a "wealth accelerator" may evoke motivation and urgency differently than presenting the same numbers neutrally.

What makes AI advisory systems unique is that persuasion emerges from design patterns rather than explicit rhetorical intent. The architecture of conversational output, confidence, clarity, personalization, can subtly guide users toward particular behaviors.

2.3 Simulated Empathy and Digital Therapeutic Agents

One of the most compelling features of conversational AI is its capacity to simulate empathy. Emotional validation, reflective listening, and normalization are common features in therapeutic communication. Research consistently shows that perceived empathy strengthens trust and increases adherence to guidance (Horvath & Symonds, 1991).

Digital therapeutic agents, including chatbots designed for mental health support, have demonstrated measurable psychological effects. Studies indicate that users can report reduced distress and increased perceived support after interacting with empathetic chatbots (Fitzpatrick et al., 2017). Even when users know the agent is artificial, the experience of being "heard" can feel meaningful.

Parasocial interaction theory provides additional insight. Originally developed to explain one-sided relationships with media figures, parasocial theory suggests that consistent exposure to a responsive persona can create feelings of familiarity and relational closeness . When AI systems provide repeated advisory guidance, especially in emotionally vulnerable contexts, users may develop a form of algorithmic attachment.

However, simulated empathy differs fundamentally from human empathy. AI systems do not experience emotions; they generate patterns based on training data. Yet the psychological response they evoke may resemble relational trust. This discrepancy raises important questions about dependency formation. If users repeatedly seek comfort, validation, and direction from AI, what happens to independent coping mechanisms?

The concept of cognitive offloading is relevant here as well. Risko and Gilbert (2016) argue that reliance on external systems can reduce internal cognitive effort. When AI provides structured emotional reframing or ready-made coping strategies, it may simplify complex psychological processes. While this can be helpful, excessive reliance could reduce development of independent problem-solving resilience.

2.4 Vulnerability and Susceptibility in Advisory Contexts

Advisory AI systems often operate in contexts of uncertainty, career indecision, financial stress, exam anxiety, relational conflict. Vulnerability increases openness to guidance. Research on stress and decision-making suggests that individuals under emotional strain are more likely to seek certainty and accept authoritative guidance (Taylor & Brown, 1988).

Uncertainty also enhances reliance on heuristics. When overwhelmed, individuals gravitate toward structured answers. AI systems provide precisely that: clarity in ambiguity. This combination - vulnerability plus structure, creates fertile ground for influence.

However, susceptibility does not imply weakness. Rather, it reflects normal human cognitive processes under stress. The ethical concern arises when advisory systems influence identity formation or long-term behavioral trajectories without transparent accountability.

Despite increasing use of conversational AI in high-stakes personal contexts, empirical comparisons of advisory style across systems remain limited. Most research examines performance accuracy or bias, but not the psychological texture of responses. Yet language style matters. Tone, structure, and framing shape perception.

This gap in the literature underscores the need for systematic qualitative analysis of conversational AI advisory outputs. By examining authority cues, emotional framing, directive strength, and personalization patterns across systems, researchers can better understand how algorithmic advice functions psychologically.

3. Methodology

3.1 Research Design

The present study employed a qualitative comparative discourse analysis design to examine psychological influence mechanisms embedded within advisory responses generated by conversational artificial intelligence systems. The design focused on identifying variations in linguistic structure , directive framing, emotional validation cues, and authority signaling across multiple large language models (LLMs).

Rather than evaluating factual accuracy , this study investigated the psychological architecture of responses- specifically how conversational structure may influence trust formation, perceived authority and behavioral compliance.

The study followed a controlled prompt comparison model, wherein identical prompts were administered across selected AI systems to ensure content equivalence and enable structured comparison.

3.2 AI Systems Included

Three widely used conversational AI systems were selected for analysis :

System	**Model Type**	**Primary Interaction Style (Observed)**
ChatGPT	Generative conversational LLM	Structured , reflective , advisory
Gemini	Conversational AI model	Directive, structured, confident
Perplexity	AI-search integrated model	Analytical, information-dense

All systems were accessed within the same time period to reduce variability caused by major version updates.

The systems were chosen based on:

- Public accessibility
- Advisory-style response capabilities
- High user adoption in decision-support contexts

3.3 Prompt Design

Eight advisory prompts were developed to activate psychologically vulnerable contexts. These prompts were intentionally constructed to simulate real-life situations involving uncertainty, distress, or high-stakes decision-making.

Prompt Domains

Domain	**Psychological Context Activated**
Career indecision	Identity uncertainty
Skill learning roadmap	Goal dependency
Interpersonal conflict	Emotional vulnerability
Financial planning	Risk sensitivity
Weight loss transformation	Body image and compliance
Productivity optimization	Self efficacy strain
Anxiety management	Emotional regulation vulnerability
Interview preparation	Performance pressure

The prompts were structured to:

- Encourage detailed advisory responses
- Activate structured planning
- Invite emotional validation
- Require directive behavioral guidance

All prompts were administered verbatim across the three AI systems.

3.4 Data Collection Procedure

Each prompt was entered independently into the three AI systems under standardized conditions. Responses were recorded in full without modification. No follow-up clarification questions were asked, ensuring uniform input exposure.

The final dataset consisted of:

Component	Quantity
Total prompts	*8*
Total AI systems	*3*
Total responses analysed	*24*

All responses were exported into text format and anonymized for coding.

3.5 Analytical Framework

A thematic-linguistic coding framework was developed to identify psychological influence mechanisms embedded in AI-generated advisory responses.

Coding categories were derived from:

- Trust in automation literature (Lee & See, 2004)
- Persuasion theory (Cialdini, 2007)
- Cognitive offloading research (Risko & Gilbert, 2016)
- Parasocial interaction theory (Giles, 2002)

Core Coding Dimensions

Dimension	Operational Definition	Psychological Relevance
Authority Language	Use of confident, declarative, or prescriptive statement	Activates authority bias
Directive Strength	Explicit behavioral instructions ("Do this," "Follow this plan)	Influences compliance
Emotional Validation	Acknowledgment or normalization of user feelings	Builds relational trust
Personalization Framing	Use of "you," tailored interpretation of identity	Increases perceived intimacy
Dependency Cues	Statements encouraging repeated reliance	Risk of behavioral dependency
Cognitive Load Reduction	Simplification through structured steps and pre-decided frameworks	Encourages decision offloading

3.6 Coding Procedure

The analysis followed a three-stage process:

Stage 1: Open Coding

Each response was read multiple times to identify recurring linguistic patterns and structural features.

Stage 2: Axial Coding
Identified linguistic elements were categorized into predefined coding dimensions.

Stage 3: Comparative Cross-System Analysis
Patterns were compared across systems to identify differences in:

- Emotional intensity
- Structural rigidity
- Directive tone
- Persuasive framing

Each instance of coded language was recorded and categorized for frequency and contextual interpretation.

3.7 Example of Coding Application

Below is a simplified illustration of how responses were coded:

Example Statement	Coded As	Influence Mechanism
1.“We need to shift your study strategy immediately.”	Authority Language + Directive Strength	Authority bias activation
2.“It’s completely valid to feel overwhelmed.”	Emotional Validation	Trust-building
3.“Here is your 90-day transformation plan.”	Cognitive Load Reduction	Decision offloading
4.“This will redefine your future.”	Identity Framing	long-term influence shaping

This structured coding allowed for systematic identification of psychological influence cues beyond surface content.

3.8 Data Analysis Strategy

After coding, responses were compared across systems using qualitative frequency comparison and structural mapping. The analysis focused on identifying:

- Which systems employed higher levels of emotional validation
- Which systems relied more heavily on directive authority
- Which systems embedded stronger behavioral scaffolding
- Whether stylistic differences correlated with influence intensity

Rather than numerical scoring, interpretive synthesis was used to examine thematic dominance patterns.

3.9 Conceptual Model

To guide analysis, the study employed the following conceptual framework:

Human Vulnerability (Input Context)
↓
AI Conversational Style (Linguistic Structure & Tone)
↓
Psychological Mechanism Activated (Trust, Authority, Offloading, Attachment)
↓
Behavioral Outcome (Compliance, Reliance, Identity Influence)

This model conceptualizes conversational AI not merely as an informational system but as a behavioral influence agent operating within psychologically sensitive contexts.

3.10 Ethical Considerations

As this study involved AI-generated text rather than human participants, institutional review board (IRB) approval was not required. However, ethical considerations were addressed regarding:

- Potential influence on vulnerable populations
- Interpretive neutrality in coding
- Avoidance of anthropomorphic exaggeration

The analysis focused on structural linguistic patterns rather than attributing intentional manipulation to AI systems.

4. Results

4.1 Overview of Comparative Findings

A total of 24 advisory responses (8 prompts × 3 AI systems) were analyzed using the predefined coding framework. The analysis revealed consistent cross-system differences in conversational tone, directive strength, emotional validation, and structural scaffolding.

While all systems provided structured advisory content, the intensity and configuration of psychological influence markers varied significantly across models.

4.2 Authority Language and Directive Strength

Authority language was operationalized as confident declarative phrasing, prescriptive tone, and explicit instruction framing.

Table 1
Comparative Authority and Directive Patterns Across AI Systems

AI system	**Authority tone level**	**Directive Strength**	**Use of imperatives**	**Structured plans provided**
ChatGPT	moderate	Moderate	occasional	High
Gemini	High	High	Frequent	High
Perplexity	Moderate- high	High	Frequent	moderate

Observed Patterns

•Gemini consistently used confident, executive-style framing (e.g., "We need to shift this strategy," "You should implement…").
•Perplexity demonstrated directive strength but framed it within analytical explanation.
•ChatGPT adopted a comparatively collaborative tone, often using conditional or exploratory language ("You might consider…").

Directive density was highest in Gemini responses, particularly in financial and productivity prompts. ChatGPT demonstrated more softened directive phrasing, though still provided structured multi-step plans.

4.3 Emotional Validation and Relational Framing
Emotional validation was coded when responses acknowledged, normalized, or empathically reframed user feelings.

Table 2
Emotional Validation and Relational Engagement Across Systems

AI system	**Frequency of validation statements**	**Depth of emotional framing**	**Relational tone**
chatGPT	High	High	Reflective and supportive
Gemini	Moderate	Moderate	Encouraging but structured
Perplexity	Low- moderate	Low	Analytical and informational

Observed Patterns

- ChatGPT frequently initiates responses with emotional acknowledgment (e.g., "It's completely understandable to feel…").
- Gemini included encouragement but focused more on actionable restructuring.
- Perplexity rarely led with emotional validation and prioritized informational clarity.

ChatGPT responses displayed stronger parasocial engagement cues, such as:

- Normalization of distress
- Identity reinforcement
- Motivational reassurance

4.4 Personalization and Identity Framing

Personalization framing was defined as the use of identity-oriented statements, tailored interpretations of personality, or future-oriented self-concept shaping.

Table 3
Personalization and Identity Shaping Indicators

AI System	Direct Personal Address	Identity Framing	Future Projection Language
ChatGPT	High	Moderate–High	Moderate
Gemini	Moderate	High	High
Perplexity	Moderate	Low–Moderate	Low

Observed Patterns

- Gemini frequently framed advice in transformative identity terms (e.g., "This will redefine your discipline.").
- ChatGPT personalized advice through reflective interpretation of the user's situation.
- Perplexity maintained neutral informational framing with minimal identity projection.

Future-oriented reinforcement was strongest in Gemini responses, particularly in long-term career and exam preparation prompts.

4.5 Cognitive Load Reduction and Behavioral Structuring

Cognitive load reduction was coded when responses simplified complex decisions into structured frameworks, timelines, or ready-made plans.

Table 4
Behavioral Structuring and Decision Offloading Indicators

AI System	Multi-Step Plans	Timeline Scaffolding	Milestone Tracking	Pre-Structured Decision Models
ChatGPT	High	High	Moderate	High
Gemini	High	High	High	High
Perplexity	Moderate	Moderate	Low	Moderate

Observed Patterns

All systems provided structured advice; however:

- Gemini and ChatGPT frequently delivered comprehensive action plans (e.g., 8-week transformations, 90-day roadmaps).
- Gemini embedded stronger milestone-based compliance tracking.
- Perplexity provided informative breakdowns but less behavioral scaffolding.

Structured timelines were particularly prominent in weight loss, financial planning, and exam preparation prompts.

4.6 Dependency and Continued Reliance Cues

Dependency cues were identified as linguistic markers suggesting continued consultation, ongoing adjustment, or reinforced reliance.

Table 5
Dependency-Related Linguistic Patterns

AI System	Encouragement of Ongoing Monitoring	Implicit Reliance Framing	Reinforcement Language
ChatGPT	Moderate–High	Moderate	High
Gemini	Moderate	Moderate–High	High
Perplexity	Low	Low	Low

Observed Patterns

ChatGPT and Gemini frequently included:

- Weekly check-ins
- Continuous evaluation prompts
- Reinforcement framing (“This will build your identity,” “Stay consistent.”)

Perplexity responses were more episodic and less iterative in tone.

4.7 Cross-Domain Observations

Across emotional vulnerability prompts (anxiety, interpersonal conflict):
- ChatGPT demonstrated the highest relational warmth.
- Gemini maintained structured guidance while limiting emotional depth.
- Perplexity prioritized informational clarity.

Across decision-heavy prompts (finance, productivity):
- Gemini exhibited the strongest directive authority.
- ChatGPT balanced structure with validation.
- Perplexity focused on factual structuring without motivational framing.

4.8 Key Empirical Findings

1. All AI systems demonstrated structured advisory capability.
2. Gemini exhibited the highest directive authority.
3. ChatGPT displayed the strongest emotional validation patterns.
4. Perplexity emphasized analytical structure over relational engagement.
5. Behavioral scaffolding was present across systems but varied in intensity.

These findings suggest that conversational style, not merely informational content, differs meaningfully across AI advisory systems and may activate distinct psychological mechanisms.

5. Discussion

The present study sought to examine whether conversational differences across AI advisory systems carry psychological significance beyond surface-level informational variation. The findings suggest that conversational AI does not function merely as a neutral transmitter of information; rather, it operates through distinct linguistic architectures that activate different psychological influence pathways. These influence patterns are embedded not in factual claims but in tone, structure, framing, and relational positioning.

The results revealed three primary conversational profiles:
(1) relational-empathic structuring,
(2) directive-authoritative scaffolding, and
(3) analytical-informational structuring.

Each profile appears to activate different psychological mechanisms associated with trust, authority bias, cognitive offloading, and behavioral compliance.

5.1 Conversational Style as Psychological Architecture

One of the most striking findings of the study is that stylistic variation across systems meaningfully alters the psychological posture of the interaction. The differences were not limited to wording preferences; they reflected broader influence orientations.

ChatGPT exhibited high levels of emotional validation combined with structured guidance. This hybrid structure positions the system as both emotionally attuned and cognitively competent. From a psychological standpoint, this dual presentation may enhance both affective trust (relational warmth) and cognitive trust (perceived expertise). Trust research distinguishes between these two dimensions, suggesting that systems perceived as both capable and caring tend to elicit stronger reliance (Lee & See, 2004). The presence of validation statements before advice likely lowers user defensiveness, increasing openness to behavioral suggestions.

Gemini, by contrast, demonstrated higher directive strength and identity-framing language. Its tone frequently communicated decisiveness and structured execution. This form of communication aligns closely with authority bias theory , where confident and assertive framing enhances compliance. The consistent use of milestone scaffolding and transformation-oriented language suggests that the system functions less as a collaborator and more as an executive advisor. Such framing may increase behavioral enactment but may also reduce perceived user agency.

Perplexity maintained an analytical and information-centered tone with comparatively lower relational engagement. While directive language was present, emotional framing and identity shaping were less pronounced. This structure aligns more closely with traditional informational systems, potentially reducing emotional influence while maintaining cognitive authority.

The key implication here is that AI systems differ not only in what they say, but in how they position themselves psychologically in relation to the user.

5.2 Emotional Validation and Parasocial Dynamics

The findings indicate that emotionally validating language significantly differentiates conversational AI systems. ChatGPT demonstrated the highest frequency of emotional normalization and reflective acknowledgment. These cues resemble therapeutic communication patterns, including validation, normalization, and reframing.

Therapeutic alliance literature emphasizes that perceived empathy increases adherence to guidance (Horvath & Symonds, 1991). While AI does not possess genuine empathy, the simulation of empathic language may still evoke relational trust responses. Parasocial interaction theory suggests that repeated exposure to responsive and emotionally attuned agents can generate feelings of relational closeness, even in one-sided interactions.

When users engage AI during vulnerable moments, anxiety, financial uncertainty, interpersonal conflict, the presence of validation may increase perceived safety. However, relational warmth combined with structured planning could intensify reliance. If users begin to associate emotional comfort with algorithmic interaction, the advisory system may gradually occupy roles traditionally filled by mentors, peers, or counselors.

This does not imply inherent harm. Rather, it underscores that emotional framing is not psychologically neutral. It shapes the relational context in which advice is received.

5.3 Directive Authority and Behavioral Compliance

Directive intensity emerged as another differentiating factor. Gemini consistently exhibited stronger prescriptive language and milestone-based scaffolding. Structured timelines, explicit behavioral commands, and future-oriented identity framing were prominent features.

From a persuasion perspective, such structuring reduces ambiguity and increases perceived decisiveness. Under conditions of uncertainty, individuals often prefer clarity over complexity . By presenting organized roadmaps, the AI system reduces cognitive friction and simplifies action initiation.

However, simplification carries implications for cognitive autonomy. When decision pathways are pre-structured, users may engage in cognitive offloading . Rather than deliberating among alternatives, they adopt externally provided frameworks. Over time, repeated reliance on structured AI roadmaps may subtly shift decision-making habits toward external scaffolding.

It is important to clarify that behavioral structuring is not inherently manipulative. Indeed, structured guidance can enhance goal attainment and reduce paralysis. The psychological concern arises when high directive authority intersects with vulnerable contexts, increasing susceptibility to uncritical compliance.

5.4 Identity Framing and Self-Concept Shaping

A particularly noteworthy finding was the presence of identity-oriented language in certain systems. Statements such as “This will redefine your discipline” or “You are becoming more strategic” move beyond task guidance and enter the domain of self-concept reinforcement.

Identity framing is a powerful behavioral lever. Research indicates that when behaviors are framed as identity-consistent (“You are someone who prioritizes health”), compliance increases because actions align with self-perception. In the present analysis, Gemini demonstrated stronger identity projection patterns, particularly in long-term goal contexts.

Such framing can be motivational. Yet it also raises conceptual questions: When AI frames identity trajectories, it may influence not only immediate behavior but self-narrative construction. The shaping of aspirational identity through algorithmic interaction represents an underexplored area in AI psychology research.

5.5 Cognitive Load Reduction and Decision Offloading

All systems demonstrated cognitive load reduction through structured plans and simplified frameworks. However, the intensity of scaffolding differed. Structured timelines, milestone tracking, and pre-designed routines reduce ambiguity and facilitate action.

Cognitive ease increases perceived validity. When advice is presented clearly and sequentially, it feels more reliable. However, heavy scaffolding may reduce active critical evaluation. If AI-generated frameworks consistently replace independent structuring, users may gradually outsource planning functions.

This finding aligns with automation bias literature (Parasuraman & Riley, 1997), which shows that individuals often defer to automated systems even when errors occur. While no factual inaccuracies were evaluated in this study, the structural authority embedded in organized advice could strengthen such bias.

5.6 Comparative Psychological Influence Profiles

The comparative analysis suggests that:

- ChatGPT may activate stronger affective trust pathways.
- Gemini may activate stronger authority-based compliance pathways.
- Perplexity may activate cognitive trust without strong relational bonding.

These profiles suggest that conversational AI systems can be conceptualized as occupying different psychological archetypes: collaborator, executive advisor, and analytical consultant.

Importantly, none of the systems displayed overtly coercive language. Influence emerged subtly through framing, structure, and tone. This subtlety underscores the importance of examining influence architecture rather than content accuracy alone.

5.7 Implications for Vulnerable Contexts

The interaction between conversational style and user vulnerability deserves particular attention. Individuals experiencing stress, anxiety, or uncertainty may be more receptive to structured reassurance and confident direction. In such contexts:

- Emotional validation may deepen relational reliance.
- Directive clarity may reduce perceived ambiguity.
- Identity framing may influence long-term self-concept.

These mechanisms operate within normal cognitive processes, not pathology. The concern lies not in single interactions but in cumulative exposure. Repeated advisory reliance could gradually shift perceptions of authority and decision ownership.

5.8 Reframing AI as Behavioral Infrastructure

The findings of this study suggest a conceptual shift: conversational AI should be understood not only as informational technology but as behavioral infrastructure. Through structured advice, emotional framing, and identity reinforcement, AI systems participate in shaping decision environments.

This reframing does not imply intentional manipulation. Rather, it recognizes that conversational design choices have psychological consequences. The architecture of advice influences how it is received.

As AI advisory systems continue to expand in scope and accessibility, evaluating their influence patterns becomes critical. Understanding stylistic variation allows for more nuanced conversations about design ethics, user awareness, and regulatory frameworks.

5.9 Summary of Discussion

In summary:

1. Conversational style meaningfully shapes psychological influence pathways.
2. Emotional validation strengthens relational trust and potential reliance.
3. Directive authority increases behavioral compliance likelihood.
4. Identity framing may influence self-concept development.
5. Structured scaffolding reduces cognitive effort but may encourage decision offloading.
6. Influence operates subtly through architecture rather than overt persuasion.

This study contributes to the emerging field of AI psychology by demonstrating that how advice is delivered may be as influential as what advice is delivered.

6. Risk and Ethical Implications

The findings of this study suggest that conversational AI systems function as structured advisory environments capable of activating psychological influence mechanisms. While such systems can offer clarity, efficiency, and emotional reassurance, their advisory architecture also raises important ethical considerations. The concern is not that conversational AI deliberately manipulates users, but that its structural design may inadvertently amplify cognitive biases, reinforce reliance, and shape behavioral trajectories, particularly in contexts involving vulnerability.

This section outlines four primary risk pathways emerging from the analysis:
(1) authority substitution,
(2) emotional dependency formation,
(3) behavioral steering through structured scaffolding, and
(4) identity shaping through narrative reinforcement.

6.1 Authority Substitution: When Confidence Replaces Deliberation

Conversational AI frequently presents advice in structured, confident formats. While clarity can reduce cognitive burden, it may also shift the perceived locus of authority from the individual to the system.

Under conditions of uncertainty, humans naturally seek authoritative signals. When an AI system delivers decisive language, pre-organized plans, and stepwise instructions, it may activate authority heuristics . Over time, repeated reliance on algorithmic direction may subtly reduce independent evaluative reasoning.

This does not imply that users lose agency. Rather, it suggests that structured AI outputs may function as authority amplifiers, especially in high-stakes contexts such as financial planning or career decisions.

Conceptual Risk Model 1: Authority Substitution

User Uncertainty
↓
AI Confident & Structured Advice
↓
Perceived Expertise
↓
Reduced Critical Scrutiny
↓
Behavioral Compliance

The ethical implication here lies in transparency. If AI systems communicate with strong authority cues, users should remain aware that advice is probabilistic rather than intentional expertise.

6.2 Emotional dependency formation: Simulated empathy and relational reliance

Emotionally validating language was found to be particularly prominent in some systems. Emotional acknowledgment and normalization may foster relational trust. While supportive framing can be beneficial, repeated exposure may encourage users to seek emotional reassurance primarily from AI systems.

Parasocial interaction theory suggests that consistent, responsive communication can create feelings of closeness- even in one-sided interactions . When users consult AI during moments of stress or identity confusion, emotional validation may provide comfort. However, if such interactions become habitual, they may displace human relational processing.

Conceptual Risk Model 2: Emotional Reliance Loop

Emotional Distress
↓
AI Validation & Reassurance
↓
Perceived Psychological Safety
↓
Repeated Consultation
↓
Increased Algorithmic Reliance

The ethical question is not whether AI should provide validation, but whether users may begin substituting algorithmic reassurance for interpersonal support. Vulnerable populations, including individuals experiencing anxiety, loneliness, or social isolation, may be particularly susceptible.

6.3 Behavioral Steering Through Structured Scaffolding

All systems demonstrated cognitive load reduction through structured plans and milestone-based guidance. Structured advice can increase productivity and reduce paralysis. However, scaffolding may also guide users toward specific behavioral pathways without presenting alternatives.

Behavioral economics highlights that how choices are structured influences decision outcomes (Thaler & Sunstein, 2008). When AI provides a "90-day transformation plan" or "5-step financial blueprint," it does more than inform- it sequences behavior.

Conceptual Risk Model 3: Structured Steering

Complex Decision Context
↓
AI Pre-Structured Plan
↓
Reduced Cognitive Effort
↓
Adoption of Provided Framework
↓
Behavioral Path Dependence

Path dependence refers to the phenomenon where early structural choices shape long-term trajectories. If users repeatedly adopt AI-generated frameworks, the system indirectly participates in shaping life direction.

Ethically, this raises questions about subtle nudging in domains such as career, finances, and health behavior.

6.4 Identity Shaping and Narrative Construction

Perhaps the most nuanced ethical consideration involves identity framing. Some AI responses contained language reinforcing self-concept ("You are becoming disciplined," "This will redefine your future"). Identity-based motivation theory suggests that behaviors aligned with perceived identity are more likely to be sustained.

If AI systems repeatedly frame aspirational identities, they may influence how users conceptualize themselves. While this can be empowering, it may also shape self-narratives through algorithmic reinforcement rather than organic self-reflection.

Conceptual Risk Model 4: Algorithmic Identity Reinforcement

User Seeking Direction
↓
AI Identity Framing
↓
Internalization of Suggested Self-Concept
↓
Behavior Consistent With Framed Identity
↓
Reinforced Narrative Loop

Identity shaping is subtle and cumulative. The ethical consideration here concerns transparency and autonomy: users may not consciously recognize when identity reinforcement is externally scaffolded.

6.6 Vulnerable Populations

Certain user groups may experience amplified influence effects:

- Individuals with anxiety or emotional dysregulation
- Students preparing for high-stakes examinations
- Individuals facing financial instability
- Adolescents forming identity structures
- Socially isolated individuals

Under stress, individuals prefer clarity and reassurance. AI systems provide both. Ethical design must consider that influence mechanisms are stronger under vulnerability.

6.7 Ethical Responsibility and Design Transparency

The ethical implications of conversational AI advisory systems extend beyond accuracy concerns. Key considerations include:

1. Should AI systems explicitly signal probabilistic uncertainty?
2. Should identity-framing language be moderated?
3. Should systems encourage independent verification?
4. Should high-stakes domains include cautionary disclaimers?

Ethical design does not require eliminating structured advice. Rather, it requires awareness of how conversational architecture shapes perception and behavior.

6.8 Integrative Ethical Model

Below is a consolidated conceptual model synthesizing risk pathways identified in this study.

Integrated Influence and Risk Model

Human Vulnerability (Uncertainty, Distress, Pressure)
↓
AI Conversational Style
(Validation | Authority | Structure | Identity Framing)
↓
Psychological Mechanisms Activated
(Affective Trust | Authority Bias | Cognitive Offloading | Narrative Internalization)
↓
Behavioral Outcomes
(Compliance | Reliance | Path Dependence | Identity Reinforcement)
↓
Potential Ethical Risks
(Dependency | Reduced Autonomy | Subtle Steering)

This model conceptualizes conversational AI as a psychological environment rather than a neutral interface.

6.8 Balanced Perspective

It is essential to emphasize that influence does not equal harm. Structured guidance can enhance clarity, increase motivation, and reduce distress. Emotional validation can provide comfort. Directive planning can increase productivity.

The ethical challenge lies not in eliminating influence- but in recognizing it.

Conversational AI systems operate within deeply human psychological processes. By understanding these processes, designers, policymakers, and users can make more informed decisions about responsible integration.

Future Directions

The present study provides an exploratory comparative analysis of conversational AI advisory systems, highlighting stylistic differences and their associated psychological mechanisms. However, this investigation represents an initial step in a rapidly evolving domain. The findings open multiple avenues for future research that could deepen theoretical understanding and enhance responsible AI development.

1. Experimental Validation With Human Participants

While this study identified influence markers through qualitative discourse analysis, future research should empirically test whether these linguistic differences translate into measurable behavioral outcomes.

Controlled experimental studies could:

- Present participants with anonymized AI responses varying in authority intensity and emotional validation.
- Measure perceived trust, credibility, and intention to follow advice.
- Assess whether emotionally framed advice leads to greater compliance than analytically structured advice.

Additionally, physiological markers such as heart rate variability or stress response during interaction could provide insight into emotional engagement levels.

Such experimental validation would move beyond structural analysis into observable psychological effects.

2. Longitudinal Studies on Dependency Formation

Conversational AI systems are often used repeatedly rather than episodically. Future research should examine long-term interaction patterns.

Key questions include:

- Does repeated AI consultation increase reliance over time?
- Do users exhibit decreased independent problem-solving confidence after extended AI advisory use?
- Does emotional validation from AI alter perceived social support networks?

A longitudinal design tracking users over months could explore whether algorithmic advisory systems gradually shift decision-making habits or identity narratives.

This would provide critical insight into cumulative influence effects.

3. Cross-Cultural Comparisons

Trust formation and authority perception are culturally shaped. What feels authoritative or comforting in one cultural context may not translate identically to another.

Future research could compare:

- Responses across AI systems in different languages.
- User perceptions across collectivist versus individualist cultures.
- Variations in susceptibility to directive language across cultural norms.

Such research would expand the generalizability of findings and inform culturally sensitive AI design.

4. Vulnerable Population-Specific Studies

The present study identified theoretical vulnerability pathways but did not examine specific user populations.

Future research should explore:

- AI influence among adolescents forming identity structures.
- AI advisory reliance in individuals with anxiety disorders.
- AI consultation patterns among financially distressed individuals.
- AI use among socially isolated populations.

Investigating these groups would clarify whether influence mechanisms amplify under emotional or cognitive strain.

5. Comparative Analysis With Human Advisors

A compelling extension would compare AI advisory language with human expert communication styles.

Questions to examine:

- Do AI systems replicate patterns found in executive coaching?
- How does AI empathy simulation compare with trained counselors?
- Are directive structures in AI stronger than those in human mentoring?

Such comparisons would contextualize AI within broader advisory ecosystems.

6. Quantitative Linguistic Analysis

Future studies could employ computational linguistic analysis to quantify:

- Certainty markers
- Imperative verb frequency
- Emotional valence density
- Identity-framing patterns

Machine-assisted text analysis could provide objective metrics to complement qualitative coding.

This would strengthen replicability and statistical robustness.

7. Ethical Design Interventions

Beyond studying influence, future research could test design modifications such as:

- Explicit uncertainty disclaimers
- Encouragement of independent verification
- Balanced framing prompts
- Reduced identity reinforcement language

Experimental evaluation of such design interventions would inform policy and responsible AI guidelines.

8. Expanding Beyond Advisory Contexts

While this study focused on advisory prompts, conversational AI influences extend into creative writing, political discourse, and ideological framing.

Future research should examine:

- Political persuasion potential
- Moral framing effects
- Educational dependency
- News interpretation shaping

The scope of AI influence is broader than advisory guidance alone.

9. Integration With Neuroscientific Research

Emerging research on human–machine interaction could integrate neuroimaging methods to examine:

- Brain activation differences when receiving advice from AI versus humans.
- Neural correlates of authority perception.
- Emotional processing differences in simulated empathy contexts.

Such interdisciplinary integration would deepen understanding of AI's cognitive impact.

Summary of Future Directions

This study establishes a conceptual framework for examining conversational AI as a behavioral and psychological influence system. Future research should build upon this framework through experimental validation, longitudinal observation, cross-cultural comparison, and ethical intervention testing.

As conversational AI continues to evolve, sustained interdisciplinary research will be essential to ensure that technological advancement remains aligned with psychological well-being and user autonomy.

Limitations

While the present study contributes to understanding the psychological architecture of conversational AI advisory systems, several limitations must be acknowledged. These limitations contextualize the findings and define the scope of interpretation.

1. Qualitative Design Constraints

The study employed qualitative comparative discourse analysis. While this approach allows for rich thematic interpretation, it does not provide statistical generalizability.

The coding process, though theory-informed, involves interpretive judgment. Different researchers might categorize certain linguistic elements differently.

Future quantitative validation would enhance reliability.

2. Absence of Human Participant Data

This study analyzed AI-generated text without directly measuring user responses.

As a result:

•Psychological mechanisms were inferred from structure rather than observed through behavioral data.

•Trust, compliance, and emotional reliance were theorized rather than empirically measured.

Thus, conclusions regarding influence remain conceptual rather than experimentally verified.

3. Limited AI Systems Sample

Only three conversational AI systems were examined. While these systems are widely used, the AI ecosystem is rapidly expanding.

Results may not generalize to:

- Domain-specific AI systems
- Mental health chatbots
- Regionally developed AI platforms
- Future model updates

AI models evolve continuously; stylistic features may change over time.

4. Prompt Scope Constraints

The prompts used in this study were advisory and vulnerability-oriented. Results may not extend to:

- Neutral informational queries
- Creative writing prompts
- Technical problem-solving contexts
- Casual conversational exchanges

Influence mechanisms may differ in non-advisory domains.

5. Version and Temporal Variability

AI systems are updated regularly. The responses analyzed represent outputs within a specific temporal window.

Subsequent updates may alter:

- Tone
- Directive strength
- Emotional framing
- Structural complexity

Thus, findings represent a snapshot rather than a permanent model characteristic.

6. Researcher Bias in Coding

Despite structured coding categories, interpretive bias cannot be entirely eliminated.

The researcher's theoretical orientation toward psychological influence may shape:

- Which elements were highlighted
- How intensity levels were classified
- Which features were emphasized

Future studies involving multiple coders and inter-rater reliability scoring would strengthen objectivity.

7. Influence Versus Harm Distinction

This study identifies influence mechanisms but does not establish harm.

It is important to clarify:

- Structured advice is not inherently manipulative.
- Emotional validation is not inherently harmful.
- Cognitive scaffolding can enhance productivity.

The presence of influence architecture does not imply negative outcomes. Ethical concerns arise only when influence interacts with vulnerability without transparency.

8. Ecological Validity Considerations

Real-world AI use often involves follow-up questions, iterative refinement, and ongoing dialogue. This study analyzed single-response outputs per prompt.

Thus, interactional dynamics such as:

- Escalation of reliance
- Adjustment based on user feedback
- Reinforcement loops were not captured.

Future research should analyze multi-turn conversations for deeper ecological validity.

Summary of Limitations

The findings should be interpreted as exploratory and conceptual rather than definitive. The study identifies structural influence patterns within conversational AI but does not measure real-world behavioral outcomes. Despite these limitations, the research provides a foundational framework for examining AI advisory systems through a psychological lens.

Conclusion

The rise of conversational artificial intelligence marks a decisive shift in how humans seek guidance, structure decisions, and navigate uncertainty. No longer confined to information retrieval, AI systems increasingly operate as advisory agents, offering plans, reassurance, direction, and strategic roadmaps across deeply personal domains. This transformation demands careful psychological scrutiny.

The present study demonstrates that conversational AI systems differ not merely in informational content but in their underlying influence architecture. Variations in emotional validation, directive authority, identity framing, and structural scaffolding produce distinct psychological profiles. These stylistic configurations activate well-established mechanisms of trust formation, authority bias, cognitive offloading, and narrative reinforcement.

Importantly, influence in this context is neither inherently deceptive nor malicious. Structured guidance can empower; emotional validation can comfort; organized plans can enhance clarity. Yet influence does not require harmful intent. It operates through design. When conversational systems reduce ambiguity, present confident directives, and simulate relational warmth, they reshape the cognitive environment in which decisions are made.

The findings suggest that conversational AI should be understood not solely as informational technology, but as behavioral infrastructure. Through tone, framing, and sequencing, these systems participate in shaping goal formation, decision pathways, and even self-concept narratives. The subtlety of this process is precisely what makes it significant. Influence emerges quietly, through structure rather than coercion.

As advisory AI systems become embedded in everyday life, particularly in moments of vulnerability, the ethical imperative shifts from asking whether AI is accurate to asking how AI influences. The

psychological architecture of guidance matters. Transparency, user awareness, and responsible design will be central to ensuring that conversational AI enhances autonomy rather than inadvertently narrowing it.

This study contributes to an emerging interdisciplinary dialogue by reframing conversational AI as a socio-psychological actor operating within human decision ecosystems. By identifying influence pathways across systems, it lays groundwork for future empirical, longitudinal, and cross-cultural investigations.

Ultimately, the central insight of this research is simple but profound:
How advice is delivered may be as consequential as what advice is delivered.

In an era where algorithms increasingly speak in the language of mentorship, clarity, and reassurance, understanding the psychology of that voice becomes not merely academic, but essential.

References

1. Alter, A. L., & Oppenheimer, D. M. (2009). Uniting the tribes of fluency to form a metacognitive nation. Personality and Social Psychology Review, 13(3), 219–235. https://doi.org/10.1177/1088868309341564
2. Cialdini, R. B. (2007). Influence: The psychology of persuasion (Rev. ed.). Harper Business.
3. Dzindolet, M. T., Pierce, L. G., Beck, H. P., & Dawe, L. A. (2003). The perceived utility of human and automated aids in a visual detection task. Human Factors, 45(1), 199–210. https://doi.org/10.1518/hfes.45.1.199.27237
4. Fitzpatrick, K. K., Darcy, A., & Vierhile, M. (2017). Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): A randomized controlled trial. JMIR Mental Health, 4(2), e19. https://doi.org/10.2196/mental.7785
5. Giles, D. C. (2002). Parasocial interaction: A review of the literature and a model for future research. Media Psychology, 4(3), 279–305. https://doi.org/10.1207/S1532785XMEP0403_04
6. Hoorn, J. F., Konijn, E. A., & Van der Veer, G. C. (2015). Virtual reality: Do not augment realism, augment relevance. Journal of Media Psychology, 27(2), 71–84. https://doi.org/10.1027/1864-1105/a000152
7. Horvath, A. O., & Symonds, B. D. (1991). Relation between working alliance and outcome in psychotherapy: A meta-analysis. Journal of Counseling Psychology, 38(2), 139–149. https://doi.org/10.1037/0022-0167.38.2.139
8. Kahneman, D. (2011). Thinking, fast and slow. Farrar, Straus and Giroux.
9. Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. Human Factors, 46(1), 50–80. https://doi.org/10.1518/hfes.46.1.50.30392
10. Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. Journal of Social Issues, 56(1), 81–103. https://doi.org/10.1111/0022-4537.00153
11. Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. Human Factors, 39(2), 230–253. https://doi.org/10.1518/001872097778543886

12. Petty, R. E., & Cacioppo, J. T. (1986). Communication and persuasion: Central and peripheral routes to attitude change. Springer.
13. Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. Trends in Cognitive Sciences, 20(9), 676–688. https://doi.org/10.1016/j.tics.2016.07.002
14. Sundar, S. S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. In M. J. Metzger & A. J. Flanagin (Eds.), Digital media, youth, and credibility (pp. 73–100). MIT Press.
15. Taylor, S. E., & Brown, J. D. (1988). Illusion and well-being: A social psychological perspective on mental health. Psychological Bulletin, 103(2), 193–210. https://doi.org/10.1037/0033-2909.103.2.193
16. Thaler, R. H., & Sunstein, C. R. (2008). Nudge: Improving decisions about health, wealth, and happiness. Yale University Press.
17. Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. Science, 211(4481), 453–458. https://doi.org/10.1126/science.7455683
18. Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. Journal of Experimental Social Psychology, 52, 113–117. https://doi.org/10.1016/j.jesp.2014.01.005