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HUMAN AI INTERACTION THROUGH A PSYCHOLOGICAL LENS: EMOTIONS, COGNITION, AND BEHAVIOUR

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Abstract
The rapid integration of artificial intelligence (AI) into personal, social, and professional domains has fundamentally transformed how humans interact with technology. AI systems are no longer perceived solely as tools; instead, they increasingly assume quasi-social roles that influence human emotions, cognition, decision-making, and communication. From a psychological perspective, this study examines human–AI interaction by focusing on the dynamic interplay among emotion, cognition, and behavior. Drawing on insights from cognitive psychology, affective science, and human–computer interaction (HCI), the study explores how users construct meaning, develop trust, and negotiate control when engaging with AI systems.
The emotional dimension of human–AI interaction is examined through key affective responses such as trust, empathy, fear, and anxiety, particularly in high-stakes contexts including healthcare, education, and finance. The cognitive dimension focuses on attention, perception, reasoning, and adaptive learning processes that shape how users interpret, evaluate, and respond to algorithmic decisions. The behavioral dimension addresses patterns of adoption, resistance, and long-term reliance on AI systems, highlighting the socio-psychological consequences of sustained interaction with intelligent technologies. The study further considers ethical and societal implications, including risks of overreliance, cognitive offloading, and diminished human agency, alongside potential benefits such as empowerment, efficiency, and personalized support.
By integrating psychological theory with empirical inquiry, this research contributes to the growing literature on human–AI interaction and emphasizes the importance of transparency, explainability, and human-centered design in fostering trust and psychological well-being. Practical implications are offered for policymakers, designers, and stakeholders to promote responsible and psychologically informed AI integration.

INTRODUCTION

The rapid advancement of artificial intelligence (AI) has reshaped human experiences in ways that were once largely confined to science fiction. AI technologies are now embedded in everyday life, influencing employment practices, communication patterns, and decision-making processes. From recommender systems and virtual assistants to financial risk assessment tools, healthcare diagnostics, and autonomous vehicles, AI systems increasingly perform tasks that were traditionally associated with human intelligence.

As AI systems begin to exhibit adaptive, interactive, and decision-making capabilities, they challenge conventional understandings of technology as neutral tools. Instead, users often perceive AI as possessing agency, intentionality, and even personality. This shift raises critical psychological questions regarding how humans emotionally, cognitively, and behaviorally engage with intelligent systems. Understanding these processes is essential, as user experiences with AI are shaped not only by technical performance but also by subjective perceptions, emotional responses, and patterns of trust and reliance.

Psychological theory provides a valuable framework for examining human–AI interaction, as it addresses how individuals perceive, interpret, and adapt to complex environments. Emotional responses such as trust, empathy, fear, and anxiety play a central role in shaping acceptance or resistance to AI systems, particularly in high-stakes domains. Cognitive processes—including attention, reasoning, memory, and judgment—further influence how users interpret algorithmic outputs and assess their credibility. These emotional and cognitive processes ultimately manifest in observable behaviors, such as adoption, reliance, or resistance.

This study adopts a psychological perspective to examine human–AI interaction as a multidimensional phenomenon encompassing emotion, cognition, and behavior. By integrating theoretical insights with empirical investigation, the research seeks to clarify how psychological mechanisms influence engagement with AI systems and how AI design, in turn, shapes human experience.

Background

The relationship between humans and technology has long been a driving force in social and economic development. However, the emergence of artificial intelligence represents a qualitative shift in this relationship. Unlike earlier technologies, which were primarily viewed as passive tools, AI systems increasingly demonstrate adaptive behavior, autonomous decision- making, and interactive communication. These characteristics position AI systems as quasi- social actors rather than mere instruments.

In domains such as healthcare, education, finance, and customer service, AI systems are entrusted with tasks that involve judgment, prediction, and personalized interaction. Virtual assistants, recommendation engines, and decision-support systems routinely influence human choices and behaviors. As a result, issues of trust, collaboration, and perceived agency become central to human–AI interaction. Users may attribute intentions or competence to AI systems, raising complex psychological and ethical questions about responsibility, control, and reliance.

Traditional research in human–computer interaction (HCI) has emphasized usability, efficiency, and user experience. While these frameworks remain relevant, AI introduces new challenges that extend beyond conventional HCI assumptions. Autonomous decision-making, predictive analytics, and natural language interaction create relational dynamics in which users engage with AI systems in ways that resemble social interaction. Consequently, the focus shifts from usability alone to the broader psychological dimensions of interaction, including emotional engagement, cognitive understanding, and behavioral adaptation.

Psychological research offers foundational insights into these processes. Emotional responses influence whether users trust or distrust AI systems, particularly in contexts involving risk or uncertainty. Cognitive engagement determines how users allocate attention, interpret information, and evaluate recommendations generated by AI. Over time, these emotional and cognitive responses shape behavioral outcomes, including sustained use, resistance, or dependency. Together, these dimensions underscore the need for a psychological framework that captures the complexity of human–AI interaction.

Problem Statement

Despite the rapid integration of AI into daily life, the psychological consequences of sustained human–AI interaction remain insufficiently understood. Existing research has made significant advances in technical performance, ethical governance, and economic implications of AI systems. However, comparatively little attention has been devoted to the emotional, cognitive, and behavioral processes that shape user experiences with AI.

This gap is concerning because psychological mechanisms play a critical role in determining user trust, acceptance, resistance, and long-term reliance on AI technologies. AI systems occupy a dual role: they function as practical tools designed to enhance efficiency, while simultaneously acting as quasi-social agents that communicate, adapt, and make recommendations. This duality encourages anthropomorphism and emotional engagement, which may increase trust but also introduce risks such as overdependence, reduced critical thinking, and diminished human agency.

User responses to AI systems vary across contexts and individuals. In high-stakes domains such as healthcare or finance, some users exhibit strong reliance on AI recommendations, while others resist adoption due to concerns about transparency, errors, or loss of control. These divergent responses highlight the need for a systematic understanding of how emotional reactions and cognitive processes interact to shape behavioral outcomes in human–AI interaction.

Research Gap

Although artificial intelligence has become pervasive across multiple domains, existing scholarly literature remains disproportionately focused on technical efficiency, algorithmic design, and ethical governance. While these perspectives are essential, they provide only a partial understanding of human–AI interaction. In particular, there is a lack of integrative research that systematically examines the psychological dimensions of emotion, cognition, and behavior as interconnected processes.

Research on trust and transparency in AI has largely emerged from human–computer interaction and technology acceptance traditions. However, these frameworks often treat trust as a functional or technical outcome rather than as a complex emotional and psychological state that influences reasoning, decision-making, and long-term behavior. Similarly, studies of cognitive load, explainability, and user adaptation frequently overlook emotional responses and behavioral consequences, resulting in fragmented insights.

Moreover, empirical studies of human–AI interaction are often confined to specific application contexts, such as medical diagnostics, customer service chatbots, or autonomous vehicles. This context-specific focus limits theoretical generalization and hinders the development of a unified psychological framework applicable across domains. Consequently, there is a critical need for research that integrates emotional, cognitive, and behavioral perspectives into a coherent model of human–AI interaction.

Addressing this gap is essential for advancing theoretical understanding and informing the ethical, human-centered design of AI systems that support psychological well-being and responsible technology use.

Research Objectives

1. To examine what emotional states namely trust, empathy, fear and anxiety help or hinder user acceptance and user resistance to using AI systems.
2. To examine the cognitive mechanisms of attention, reasoning, judgments and adaptations that impact how people think about AI recommendations and decisions and respond to AI applications.
3. To examine the behavioural outcomes of the human AI interaction (adoption, reliance, and resistance) through both emotional and cognitive mechanisms.

Research Questions

1. In what ways do emotional responses (e.g., trust, empathy, fear and anxiety) impact people's willingness to engage with and utilize AI systems?
2. Which cognitive mechanisms (e.g., attention, reasoning and judgments), OUT of the cognitive mechanisms educational studies imply, mediate how humans interpret AI recommendations and decisions?
3. How do emotions and cognition in tandem, impact behavioural outcomes of adoption, resistance or reliance, in the human AI interaction?

Research Hypotheses

1. H1: Positive emotional responses (i.e., trust, empathy) will be found to positively correlate to the acceptance of AI technology and negative emotional responses (i.e., fear, anxiety) found to have a negative correlation to the acceptance of AI technology.
2. H2: Cognitive mechanisms (i.e., perceived transparency and ease of comprehension) are frequently found to mediate the relationship between emotional responses and adoption, resistance or reliance in the human AI interaction.
3. H3: Those who organize their thinking with a higher level of trust and clarity are more apt to follow AI suggestions than those who organize their thinking with skepticism and an uneasy level of cognitions.

Significance of the Study

This study is significant both theoretically and practically in furthering understanding of human AI interaction.

The study has theoretical implications because it addresses the need for integrating the psychological elements of emotions, cognition, and behaviour in artificial intelligence research following past. Concentrate on technical efficiency or regulatory ethics. The goal of this study was to develop the idea of artificial intelligence beyond a computer tool into a nearly societal agent capable of eliciting emotional, cognitive, and behavioural responses. Along with questioning current ideas in human computer interaction (HCI) and technology acceptance models (TAM), this contribution might present opportunities for more holistic perspectives. In some aspects of their lives, models on how to see human life have an artificial intelligence (AI) system. (Griffiths, 2015)

The research create repercussions for public policymakers, designers of artificial intelligence, and developers for practice. Knowing the emotions, thinking, and behaviour gives the practical understanding of how their user interacts with technology goes beyond human functional efficiencies (e.g.). Psychological adaptability, trust and human centred design).Thus, in AEWHAT for instance, emotions and trust in one finding or cognitive clarity in another will hint at tactics to AIs that provide transparent and explain ability to customers. At last, understanding of behaviourally produced results skim recommendations for ethical uses of artificial intelligence technology since as public good support in a responsible manner firstly numbering ethical systems and secondly as a guide against anything we need to caution.

At a more society level, this study raises serious issues concerning the consequences of artificial intelligence for human psychological experiences under the category of more Anxiety, irregular trust, or behavioural changes regarding decision making or selecting in/out.

Talking about these mental occurrences enables the initiative to interact with more general discussions on the ethical application of artificial intelligence, digital wellbeing, and a more positive attitude. Approach to life including smart technology.

Literature Review

Originally founded in computer science, artificial intelligence (AI) has become a converting power changing businesses, relationships, economic systems, and human life itself (Kaplan & amp; Haenlein, 2019). Contemporary uses of artificial intelligence technology include diagnostic systems that can help doctors and self-driving vehicles capable of navigating difficult terrain. Sophisticated conversational bots interacting in natural language that is, big language models and creative algorithms producing their own artistic output. These systems are increasingly demonstrating complex behaviours that can be interpreted. Notably, humans often observe and evaluate these behaviours through a psychological lens, irrespective of the underlying computational processes. This inclination towards anthropomorphism assigning human qualities, such as intentions, emotions, awareness, and beliefs, to non-human entities is a well-established psychological phenomenon (Epley et al., 2007). This is especially pronounced when individuals interact with AI systems that are specifically created for human conversation, social signals, or interactive behaviours (Nass & Moon, 2000), precisely because they tend to invoke such attribution.

Foundational theories of human information processing covering areas including attention, perceptual interpretation, memory and learning, language development and comprehension, and solving complex problems, judgment and decision making (Sternberg & Sternberg, 2016) provide important characteristics to analyze AI systems and approaches. For example, understanding how deep learning models encode, retain, and manipulate large datasets allows careful, but insightful, comparisons with the traditional connectionist or parallel distributed processing approach to human cognition (Rumelhart & McClelland, 1986). These studies could demonstrate similarities or differences in human and machine processing of information. The last few decades have also offered principles of judgment and decision making, cognitive biases (including confirmation bias that skews the search of information, or anchoring bias that skews an estimate based on a previous value) and reliance on heuristics (Kahneman, 2011), which also offer useful heuristics for understanding and reducing similar distortions in AI systems. The algorithmic biases identified often happen by accident as a result of using biased training data or underpinnings in architecture and optimization (Noble, 2018). Understanding how the machine bias could sometimes echo human bias is an important step toward developing fairer and more trustworthy AI.

Core theories within social psychology such as: social perception (how people develop impressions of others in addition to an AI), attribution theory (how an individual may use the human experience to make the connection of causes for behaviour regardless of whether is with other people or machines; Heider, 1958; Kelley, 1973); theories on attitude formation in relation to new communication technologies; theory on the stereotyping process affecting how an individual may categorize AI as an outcome; the inquiry about intergroup relations if

AI is considered an outgroup; and the inquiry into relationship formation would all provide context for some of the considerations about how AI agents are assorted in ways that move beyond broad generalizations (Fiske & Taylor, 2013). The literature on anthropomorphism (Epley et al, 2007); transference of trust in autonomous systems by way of transparency, reliability and perceived benevolence (Lee & See, 2004); and theories on socio-emotional and relation based on computer mediated communication (Walther, 1996) are also empirical bodies of work that provide context on the perception, interpretation, emotional engagement (or distancing) with artificial intelligence, and adoption (or resistance) of AI systems by users.

In particular, the concept of "mind perception," as highlighted by Gray and colleagues (2007), emphasizes the distinction of attributions of agency (planning and action) and a subjective experience (feeling and consciousness). This notion provides a basis to consider answers to how humans process and respond to AI or robots that design behaviours that resemble human agency, with more or less fluidity and ability to engage or even more precisely, respond as they would with other humans. Developmental psychology offers some insights into understanding these processes. Developmental aspects of social cognition connected to the emergence of Theory of Mind (ToM) that is, the ability to recognize beliefs, intentions, and wants in oneself and others to predict behaviour (Wellman, 1990) might shed light on how people of all ages view engagement with artificial intelligence at different degrees of sophistication. This begs the question of how adults interpret both cognitive understanding as well as developmental pathways as children. Social characteristic or mimicking behaviour artificial intelligence agents.

The notable advances in artificial intelligence in mental health highlight possibilities such diagnostic assistance tools using clinical notes to assist diagnose problems, predictive algorithms those These several uses raise important Concerns regarding ethical issues, psychological factors of the user, clinical efficacy, and limitations (e.g., lack of real empathy, etc.) of the user. Data security, non-human elements, or excessive reliance on artificial intelligence-generated advice might eventually compromise the quality of the therapeutic relationship. Destroy the clinician's ability to fulfil their professional commitments.

Another perspective that has been studied is bias and cognition. For example, harmful bias in the decision making of AI algorithms (e.g., discriminatory hiring decisions or misidentifications in facial recognition), has often been traced to biased datasets or algorithmic feedback loops or the choices of the developers (Buolamwini & Gebru, 2018; Noble, 2018). Investigating algorithmic bias using psychological concepts of stereotyping and prejudice may further lead to greater understanding of how AI technologies can be perceived comparably to human cognition. That said, whether AI systems in fact perform biases analogous to well-studied cognitive biases (e.g., confirmation bias) is an open question in need of investigation; nonetheless it is arguably an important ethical question.

The topic of intentionality and goal representation arises in discussions regarding AI behaviour too. It is not straightforward to assess whether AI actions could be viewed as goal

directed or intentional, and we need careful consideration of the system's planning structure, architecture, and performance context to determine this, while still remaining cognizant of the philosophical differences of human intentionality (Dennett, 1987).

Finally, in discussions regarding anthropomorphism and mind perception, both machine driven features and human driven factors contribute to feelings of human like qualities attributed to AI. The traits of the system, such as naturalistic language, embodiment, responsiveness, and pseudo emotional displays, interaction with human difference (e.g., loneliness, cognitive closure needs, cultural context) contributes to how the user perceives AI intentions/consciousness (Waytz et al., 2010).

Theoretical Framework

1. Emotion Theory (Appraisal Theory of Emotions Lazarus, 1991)

Emotional reactions fundamentally inform our attitudes toward AI. Appraisal theory indicates people analyze circumstances depending on their significance to individual objectives, which results in reactions such as trust, fear, or anxiety. In relation to AI, how users perceive factors such as autonomy, control, and transparency dictate whether they experience emotions that are perceived as positive (i.e., trust or empathy) or negative (i.e., fear or uncertainty).

2. Cognitive Psychology (Information Processing & Cognitive Load Theory Sweller, 1988)

Cognitive processes dictate how humans interpret, process, and respond to outputs from AI. Information processing theories suggest that users' judgments about an AI system affected by attention, perception, and reasoning. Cognitive load theory also describes how when AI outputs are complex or opaque users may become overwhelmed, thus limit understanding and creating hostile attitudes. Cognitive clarity and transparency, therefore, represent key mediating factors between AI design and acceptance.

3. Behaviour Models (Technology Acceptance Model Davis, 1989; Theory of Planned Behaviour Ajzen, 1991)
Technological behaviour characterized by attitudes, perceived usefulness, social norms, and intention to act, can signal both acceptance, trust, and inhibition with AI. The Technology Acceptance Model (TAM) provides guidance relating to how perceived usefulness and perceived ease of use can be leveraged by the user to determine whether to adopt. The Theory of Planned Behaviour (TPB) extends this discussion by arguing subjective norms and perceived behavioural control incorporates social and contextual influences in relation to both the intention to act and behaviour with AI systems.

4. Socio-technical Framework (Human–Computer Interaction and Anthropomorphism Theory)
Engaging with an AI system may be seen differently than interacting with traditional technologies, because we think of AI systems as though they are responsive, communicative, and socially capable. Anthropomorphism lends some validity to this analogy of understanding since as people begin to interpret or assign human traits eventually this might have consequences of trust, empathy, related to investigatory/reliability or harm in response to the type of engagement, especially around harm reduction. Emphasizing the activity that is social and technical, the socio-technical perspective emphasizes the action whether with the AI as just a tool. A device that merely reacts is like a cognition and emotional complex as a kind of implementation.

Foundation of the Research.
Utilizing these theoretical techniques, the study aims to place human artificial intelligence engagement as an emergent process whereby:

- Emotions (trust, empathy, fear, and anxiety) impact initial impressions and openness towards the AI. Cognition (including attention, reasoning, and comprehension) acts as a mediator in how individuals interpret and evaluate AI outputs
- Behaviour (adoption, reliance, and resistance) conveys the outcome of emotional and cognitive processes, mediated by social norms and perceived control

Methodology
Research Design
The research study qualitative in design and use a survey method for data gathering. A survey method give permission us to systematically measure emotional, cognitive, and behavioural psychological constructs related to human AI interaction. Although a correlational approach allows us to examine relationships among variables, we examine our research hypotheses through regression and mediation.

Population and Sample
Our purpose population is individuals who have human-AI interactions in their daily or work lives such as interacting with virtual assistants (i.e., Siri, Alexa), chatbots, recommender systems, and decision support.

- **Sampling Approach/Technique:** We employed a stratified random sampling method to ensure representation of different demographic groups (i.e., age, education, and work background).
- **Sample size:** We survey a minimum of 300 participants to align with sample size recommendations related to structural equation modeling (SEM) and multivariate analysis and to support generalizability and power.

Instruments for Data Collection
- **Emotions**: Adapted from the Positive and Negative Affect Schedule (PANAS) and trust anxiety methods from human AI studies.
- **Cognition**: A set of items focused on the participants perceptions of transparency and ease of understanding and cognitive load relative to Cognitive Load Theory.
- **Behaviour**: A set of items measuring behaviour related to adoption, reliance and resistance, adapted from the Technology Acceptance Model (TAM) and Theory of Planned Behaviour (TPB).

The questionnaire is use five-point Likert scale.

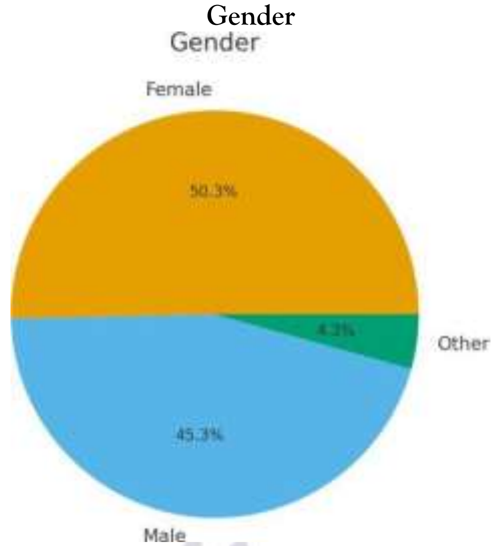
Data Collection Procedure
Participants are recruited using online platforms, professional networks, and in academic settings. Informed consent is obtained prior to participation and anonymity is assured. The survey take place online to enhance participant access and reach.

Data Analyses
- **Descriptive Statistics:** To summarize demographic variables and general trends.
- **Reliability and Validity Tests:** Using Cronbach alpha and Confirmatory Factor Analysis (CFA) to measure instrument reliability and construct validity.

- **Correlational Analysis:** To assess the relationship between emotions, cognition, and behaviour.
- **Regression and Mediation Analysis:** To assess Hypotheses 1 through Hypothesis 5 (e.g., whether cognition acts as a mediator between emotions and behavioural outcomes).
- **Structural Equation Model (SEM):** To assess the structural relationship between the overall conceptual framework and path relationships.

Data Analysis

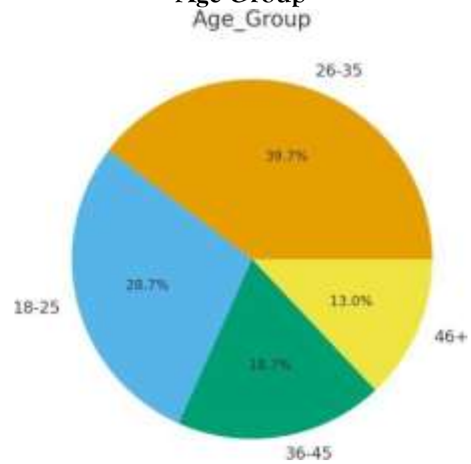
Gender



Gender	Frequency
Female	151
Male	136
Other	13

Discussion: The distribution of gender reveals significant patterns. The chart and table both imply how participant's experienced, or perceived, gender leading to insights about psychological dimensions involved in human AI interaction.

Age Group



Age Group	Frequency
26-35	119
18-25	86

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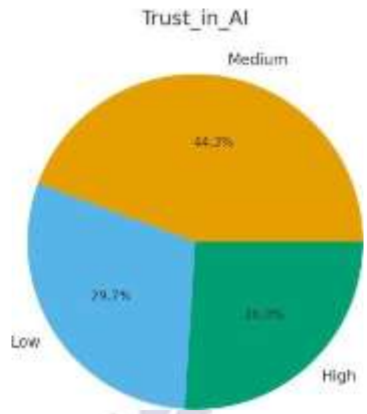
36-45	56
46+	39

Discussion: The distribution of age reveals significant patterns. The chart and table both imply how participant's experienced, or perceived, age , leading to insights about psychological dimensions involved in human AI interaction.

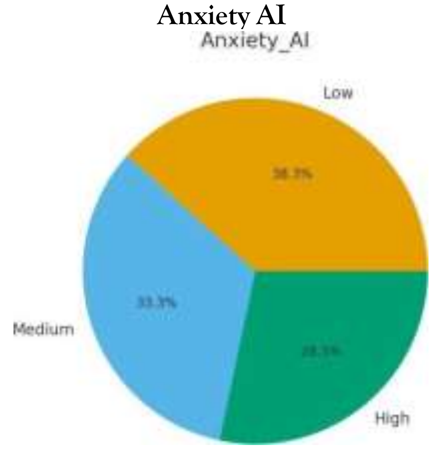
Trust in AI



Trust in AI	Frequency
Medium	133
Low	89
High	78

Discussion: The distribution of trust reveals significant patterns. The chart and table both imply how participant's experienced, or perceived, trust, leading to insights about psychological dimensions involved in human AI interaction.

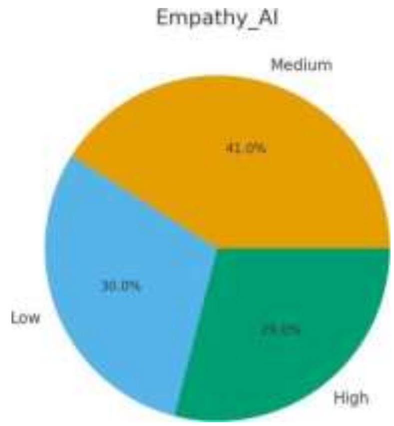
Anxiety AI



Anxiety-AI	Frequency
Low	115
Medium	100
High	85

Discussion: The distribution of anxiety AI reveals important patterns. The chart and table suggest how participants experienced or perceived anxiety AI which offers indications regarding the psychological dimensions of human AI interaction.

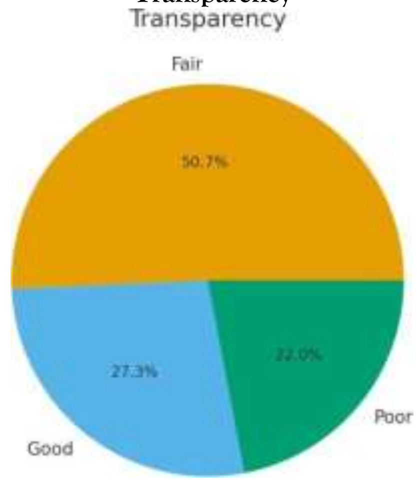
Empathy AI



Empathy AI	Frequency
Medium	123
Low	90
High	87

Discussion: The distribution of empathy AI reveals significant patterns. The chart and table both imply how participant's experienced, or perceived, empathy AI, leading to insights about psychological dimensions involved in human AI interaction.

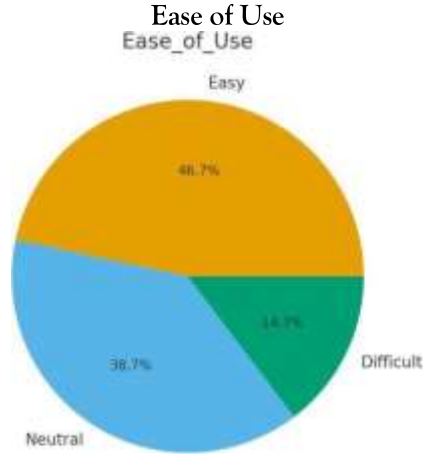
Transparency



Transparency	**Frequency**
Fair	152
Good	82
Poor	66

Discussion: The distribution observed for transparency is revealing. Together the chart and table provide an implication for how participants experience or perceive transparency, which provides insight into the psychological dimensions of human experience with AI.

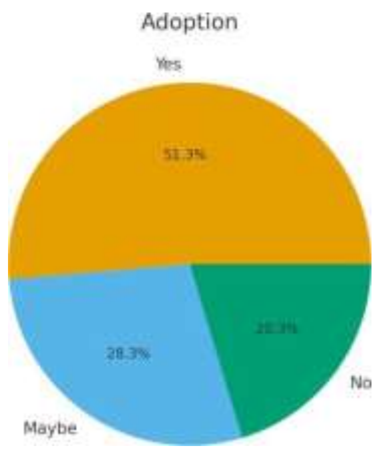
Ease of Use



Ease of Use	Frequency
Easy	140
Neutral	116
Difficult	44

Discussion: The distribution of ease of use reveals significant patterns. The chart and table both imply how participant's experienced, or perceived, ease of use, leading to insights about psychological dimensions involved in human AI interaction.

Adoption



Adoption	Frequency
Yes	154
Maybe	85
No	61

Discussion: The distribution of adoption reveals significant patterns. The chart and table both imply how participant's experienced, or perceived, adoption, leading to insights about psychological dimensions involved in human AI interaction.

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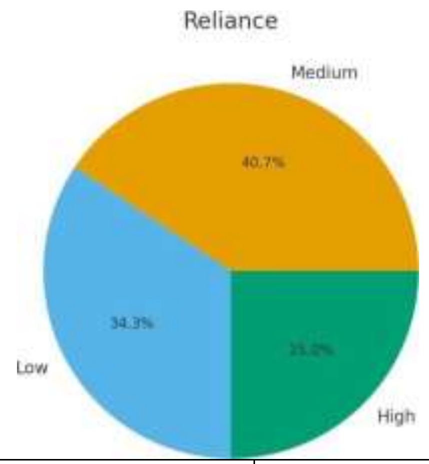
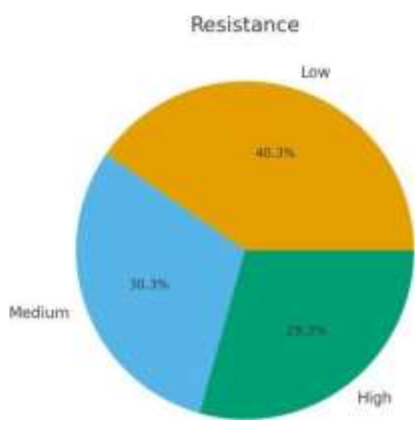
Reliance



Reliance	**Frequency**
Medium	122
Low	103
High	75

Discussion: The distribution of reliance reveals significant patterns. The chart and table both imply how participant's experienced, or perceived, reliance, leading to insights about psychological dimensions involved in human AI interaction.

Resistance



Resistance	**Frequency**
Low	121
Medium	91

High	88

Discussion: The distribution of resistance reveals significant patterns. The chart and table both imply how participant's experienced, or perceived, resistance, leading to insights about psychological dimensions involved in human AI interaction.

Findings

The findings of this study provide empirical insight into the emotional, cognitive, and behavioral dimensions of human–AI interaction. Descriptive analyses were conducted to examine participant characteristics and distributions across key study variables, followed by interpretive synthesis aligned with the study's conceptual framework.

Demographic Characteristics

The sample consisted of 300 participants, with a relatively balanced gender distribution. Female participants represented the largest group, followed by male participants, with a smaller proportion identifying as other. The age distribution indicated that the majority of participants were between 18 and 35 years of age, reflecting a younger population that is typically more exposed to and familiar with AI technologies. Older age groups were represented to a lesser extent but provided meaningful variation for comparative interpretation.

These demographic patterns suggest that the findings primarily reflect the perceptions and experiences of individuals who are actively engaged with AI systems in their daily or professional lives.

Emotional Responses Toward AI

Participants reported varied emotional responses to AI systems. Levels of trust in AI were predominantly moderate, with fewer participants reporting high trust and a substantial minority expressing low trust. Similarly, empathy toward AI systems was most frequently reported at moderate levels, while fear and anxiety were distributed across low, medium, and high categories.

Overall, the data indicate that emotional responses toward AI are not uniformly positive or negative but instead reflect a nuanced psychological landscape. Participants who reported higher trust and empathy also tended to express greater openness toward AI use, whereas elevated anxiety and fear were associated with more cautious or skeptical attitudes. These findings support the view that emotional responses are central to shaping initial engagement with AI technologies.

Cognitive Perceptions of AI Systems

Cognitive evaluations of AI systems revealed that most participants perceived AI transparency and ease of use as moderate to good. A smaller proportion of respondents reported difficulties in understanding AI outputs or experienced AI systems as cognitively demanding.

Perceived transparency and ease of understanding appeared closely linked to users' confidence in interpreting AI recommendations. Participants who reported greater cognitive clarity expressed fewer concerns regarding AI decision-making processes, whereas those who perceived AI systems as opaque or difficult to understand demonstrated higher levels of uncertainty and hesitation. These results underscore the importance of explainability and cognitive accessibility in shaping user perceptions of AI.

Behavioral Outcomes: Adoption, Reliance, and Resistance

Behavioral responses to AI systems reflected a spectrum of engagement patterns. A majority of participants indicated willingness to adopt AI technologies, either definitively or conditionally. However, a notable proportion remained uncertain or expressed reluctance, highlighting ongoing ambivalence toward AI use.

Reliance on AI systems was most frequently reported at moderate levels, suggesting that participants generally viewed AI as a supportive tool rather than a fully autonomous decision- maker. Resistance to AI use was present across the sample, with low to moderate resistance being most common, though a subset of participants reported high resistance.

These patterns indicate that adoption, reliance, and resistance coexist as behavioral tendencies, influenced by users' emotional and cognitive evaluations rather than by technological exposure alone.

Age-Based Patterns in Human–AI Interaction

Age-related differences emerged across emotional, cognitive, and behavioral dimensions. Younger participants (18–35 years) demonstrated greater willingness to adopt and rely on AI systems, accompanied by higher levels of perceived ease of use and lower reported anxiety. In contrast, older participants exhibited more cautious attitudes, characterized by increased skepticism, greater concern about transparency, and higher resistance to AI adoption.

These findings suggest that generational differences may play a role in shaping psychological responses to AI, potentially reflecting variations in technological familiarity, trust formation, and perceived control.

Integrated Patterns Across Emotion, Cognition, and Behavior

When examined collectively, the findings reveal an integrated pattern consistent with the study's theoretical framework. Emotional responses toward AI appear closely linked to cognitive evaluations of transparency and understanding, which in turn correspond with behavioral outcomes such as adoption, reliance, or resistance.

Participants who reported positive emotional responses, combined with clear cognitive understanding of AI systems, were more likely to express willingness to engage with and rely on AI technologies. Conversely, negative emotional states—particularly anxiety and fear— coupled with perceptions of opacity or cognitive difficulty, were associated with increased resistance and reduced trust.

Taken together, these findings support the proposed view that human–AI interaction is best understood as a psychologically interconnected process in which emotion, cognition, and behavior dynamically interact.

Discussion

The present study contributes to the growing body of research on human–AI interaction by demonstrating that engagement with artificial intelligence is fundamentally psychological in nature, shaped by the dynamic interplay of emotional responses, cognitive evaluations, and behavioral outcomes. Rather than functioning solely as technical tools, AI systems are experienced as quasi-social agents that elicit trust, anxiety, understanding, and resistance— processes that jointly influence adoption and reliance.

Emotional Dimensions of Human–AI Interaction

Consistent with Appraisal Theory of Emotion (Lazarus, 1991), the findings indicate that emotional responses play a foundational role in shaping users' willingness to engage with AI systems. Trust and empathy emerged as facilitators of openness and acceptance, while fear and anxiety were associated with skepticism and resistance. These patterns align with prior research suggesting that affective evaluations strongly influence technology acceptance, particularly in contexts involving uncertainty or perceived risk (Lee & See, 2004; Fiske et al., 2019).

Importantly, emotional responses toward AI were not polarized but rather distributed across moderate levels, suggesting that users occupy an ambivalent psychological position. This ambivalence reflects the dual role of AI as both a supportive tool and a potential threat to autonomy or control. Such findings reinforce concerns in the literature regarding overreliance and emotional attachment, as well as the need to design AI systems that foster calibrated, rather than blind, trust.

Cognitive Processing and Perceived Transparency

Cognitive evaluations—particularly perceptions of transparency and ease of understanding— were closely linked to emotional responses and behavioral tendencies. Participants who reported clearer cognitive understanding of AI systems expressed greater confidence and lower anxiety, whereas perceptions of opacity and cognitive difficulty were associated with hesitation and resistance. These results support cognitive load theory, which posits that excessive mental demands can undermine comprehension and increase negative affect (Sweller, 1988).

The findings also resonate with research on explainable AI, which emphasizes that interpretability and clarity are essential for meaningful human oversight and trust. Cognitive clarity appears to function as a mediating mechanism through which emotional responses are translated into behavioral outcomes. In this sense, transparency does not merely enhance usability but plays a critical psychological role in enabling users to feel competent and in control when interacting with AI systems.

Behavioral Outcomes: Adoption, Reliance, and Resistance

Behavioral patterns observed in this study reflect the combined influence of emotional and cognitive processes. While many participants expressed willingness to adopt AI technologies, reliance tended to remain moderate, suggesting cautious engagement rather than unquestioned dependence. This pattern aligns with existing research on algorithm aversion and selective reliance, where users balance perceived benefits against concerns about accuracy, accountability, and loss of agency (Dietvorst et al., 2015).

Resistance to AI use, though not dominant, was consistently present, underscoring the importance of recognizing resistance as a meaningful psychological response rather than a mere barrier to adoption. From a behavioral perspective informed by the Technology Acceptance
Model and the Theory of Planned Behavior, resistance may reflect perceived lack of control, unfavorable attitudes, or social norms that discourage AI reliance in certain contexts.

Age-Related Differences and Generational Perspectives

The observed age-related differences further highlight the role of experiential and contextual factors in shaping human–AI interaction. Younger participants demonstrated greater openness to adoption and reliance, accompanied by lower anxiety and higher perceived ease of use. In contrast, older participants exhibited greater skepticism and resistance, potentially reflecting lower familiarity with AI technologies, heightened concerns about transparency, or stronger preferences for human judgment.

These generational differences suggest that psychological responses to AI are not uniform and may evolve over time as exposure, literacy, and societal norms surrounding AI change.

Addressing these differences through targeted education and inclusive design may help reduce anxiety and foster equitable engagement across age groups.

Integrative Implications for Human–AI Interaction

Taken together, the findings support an integrative model in which emotional responses shape cognitive evaluations, which in turn influence behavioral outcomes. This interconnected pattern underscores the inadequacy of approaches that examine trust, transparency, or adoption in isolation. Human–AI interaction emerges as a holistic psychological experience in which emotions, cognition, and behavior mutually reinforce one another.

By empirically grounding this integrative framework, the study advances theoretical understanding of human–AI interaction and highlights the importance of psychologically informed AI design. AI systems that account for emotional sensitivity, cognitive capacity, and behavioral tendencies are more likely to promote ethical use, sustainable trust, and psychological well-being.

Conclusion

This study demonstrates that human–AI interaction is not merely a technological phenomenon but a deeply psychological process shaped by the interrelated dimensions of emotion, cognition, and behavior. As artificial intelligence systems increasingly permeate everyday life, understanding how users emotionally experience, cognitively evaluate, and behaviorally respond to these systems becomes essential for responsible and effective AI integration.

The findings indicate that emotional responses— particularly trust, empathy, fear, and anxiety— play a foundational role in shaping users' openness to AI systems. These emotions influence how individuals cognitively interpret AI outputs, especially in terms of perceived transparency, ease of understanding, and mental effort. In turn, cognitive evaluations mediate behavioral outcomes, including adoption, reliance, and resistance. This interconnected pattern supports the study's integrative framework and highlights the limitations of examining psychological components of human–AI interaction in isolation.

From a theoretical perspective, this research contributes to the literature by offering a unified psychological framework that bridges emotion theory, cognitive psychology, behavioral models of technology use, and socio-technical perspectives. By conceptualizing AI systems as quasi- social agents rather than neutral tools, the study extends traditional human–computer interaction and technology acceptance models and emphasizes the importance of psychological mechanisms in shaping AI engagement.

Practically, the findings underscore the need for AI systems that prioritize transparency, explainability, and cognitive accessibility. Designers and developers should adopt human- centered approaches that account for users' emotional sensitivities and cognitive capacities, particularly in high-stakes domains such as healthcare, education, and finance. Policymakers and organizational stakeholders may also benefit from these insights by developing ethical guidelines and educational initiatives that promote calibrated trust, reduce anxiety, and support informed decision-making.

Despite its contributions, the study has several limitations that warrant consideration. The use of a cross-sectional survey design limits causal inference, and reliance on self-reported measures may introduce response bias. Additionally, while the sample provided meaningful variation in demographic characteristics, the findings may not fully capture cultural or contextual differences in human–AI interaction across global populations. Future research would benefit from longitudinal designs, mixed-method approaches, and cross-cultural comparisons to further explore the long-term psychological impacts of AI use.

In conclusion, as artificial intelligence continues to evolve and integrate into human systems, its success will depend not only on technical performance but also on its alignment with human psychological needs. By foregrounding the roles of emotion, cognition, and behavior, this study offers a psychologically informed foundation for the ethical, sustainable, and human-centered development of artificial intelligence.

Recommendations

Recommendations are suggested based on the findings:

1. **Designers and Developers:** Designers and developers should put a high emphasis on explain ability and transparency in AI systems to reduce cognitive overload and build trust in users. Designers and developers should include human centred design principles that are aimed at addressing user emotions and cognitive needs.
2. **Policymakers and Regulators:** Policymakers and regulators should develop and outline clear ethical guidelines that ensure that AI systems are developed and used in a way that protects people's psychological well-being. Policymakers and regulators should create awareness raising campaigns to help reduce fear and anxiety due to the introduction of AI.
3. **Organizations and Stakeholders:** Organizations and stakeholders should establish training modules that can be used to increase users' cognitive understanding of AI applications. Organizations and stakeholders should employ a participatory approach that allows end users to provide feedback related to the development and implementation of AI.
4. **Future Research:** Future research should specifically broaden the scope of studies to different cultural contexts to also understand possible differences in emotional, cognitive and behavioural responses to AI. Future research could look into the long term effects of AI use on psychological states such as trust, dependency, and critical thinking.

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