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

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Abstract

The growing application of artificial intelligence (AI) in personal, social, and work life has fundamentally changed people's interaction with technology. AI has come to be much more than simply a tool; AI now fills a near social duty reflected in emotion, decision making, and communication. From a psychological angle, this study looks at human AI interaction, emphasising the dynamic interplay among feeling, cognition, and behaviour. These develop user interest in artificial intelligence. Using insights from cognitive psychology, affective science, and human computer interaction studies, this article looks at the ways users create meaning, establish trust, and bargain control when using artificial intelligence systems. The emotional dimension of this life discusses how emotions in the form of trust, empathy, fear and anxiety develop in relation to AI systems particularly in sensitive contexts such as healthcare, education and finance. The cognitive dimension of this work focuses on attention, perception, reasoning and adaptive learning that contribute to how and for how long users are able to interpret or reconstruct algorithmic decision making in relation to their personal expectations. The behavioural layer considers user patterns of adoption, resistance, and long term use of AI, particularly as they reflect socio-psychological consequences of continued interaction with AI and technology whilst highlighting the dynamic interaction between humans and artificial systems in which human psychological states interact with systems use, as well as AI taking into consideration the emotional state of the user. The study also takes into account the ethical and societal ramifications of human AI interaction, which includes dangers of dependency or excessive reliance, cognitive offloading (which could allow the AI to perform entire tasks for the user), and disengagement or emotional distance, as well as the benefits of empowerment, efficiency, and personal, tailored support. It discusses ethical design principles, the importance of transparency in algorithmic decision making, and building user trust through human centric and empathic interfaces. Some practical suggestions for policymakers, designers, and stakeholders are provided to minimise harm and enhance psychological well-being through AI integration. In summary, the current study contributes to the growing academic research in this area, examining the user's psychology in understanding the interplay of emotion, cognition, and behaviour into human AI interaction. The gap in understanding the user's psychology contributes to human knowledge of AI as it relates to ethical considerations in human AI interaction, and it also has implications for creating this technology AI interaction and experience in practice..

***Keywords**: Human AI Interaction, Psychology, Cognition, Emotions, Behaviour, Trust, Ethics, User Experience*

Introduction

The rapid advancement of AI has altered the human experience in ways once unimaginable, including changes related to jobs, communication, and decision making. Expected in a genre of science fiction, AI is becoming part of many of our collective human experiences, from recommender systems and virtual assistants, to Among other such cases are financial risk analysis, healthcare diagnostics, and to autonomous vehicles. Systems' interactions with and acceptance of capacities typically attributed to humans bring to light a major concern of the extent of human interaction and what the psychological interpretation of that interaction could be. Having in mind experience problems, we have to examine the emotional, cognitive, and behavioural degree of human artificial intelligence involvement. (Nasir, 2025)

Psychology is flexible enough to investigate the cognitive/emotional techniques since the nature of logic has an interpretative character (Asghar et al., 2019) that incorporates human perception, decision making difficulties, and adaptability to interactions with artificial intelligence. The acceptance of artificial intelligence seems to be partly dependent on an emotional process involving trust, empathy, or fear concerns. In addition, cognitive processes involving attention, reasoning, memory, and judgement enable the methods by which one's interpretation of the output of an algorithm is processed. Once emotional or cognitive processes inform behaviours that could be observable, this represents the component of human behaviour and interaction that may lead to acceptance, resistance, or continued use of the system.

Collectively, emotions, cognition, and behaviour explain how humans cognitively engage with intelligent systems and in turn expand our understanding of how AI interfaces impacts human cognition. (Adadi, 2018)

Despite having offered useful beginnings for research in human computer interaction, the rise of artificial intelligence as a versatile pseudo-social partner invites further examination. Unlike legacy technologies, artificial intelligence systems are generally designed to interact in ways similar to human verbal, decision, and problem-solving behaviour. Therefore, users ascribe agency, intentionality, and sometimes personality to artificial intelligence systems. In other words, while a user anthropomorphizes artificial intelligence, that user could concurrently be preparing new avenues(Naeem, Khan, & Khaliq, 2020) of co-evolution, or introducing the possibility of overdependence, diminished criticality, or emotional disengagement. The possibilities and hazards of co-evolving call us to see human artificial intelligence interaction as more than a tool has it difficulties also as a psychology with its own difficulties. (Boden, 2016)

From a psychological perspective, this article focus on human AI interaction, therefore including the interaction of feeling, cognition, and behaviour as the co-evolution of different types of processing. To start investigating some of the significant issues, the paper combine academic study theory driven thinking or empathic thought and empirical research. To be more specific: 1) What part does psychological processing play in establishing trust and accepted AI perception? 2) What cognitive eventually drives the algorithm for the decision is a collection of code? 3)How does apparently observable behaviour brings attention to the opportunities and dangers of the progressive deployment of artificial intelligence systems in daily life regardless of cognitive processing? Giving answers to these questions help to create moral and user centric AI systems as well as clarify the educational debate.

Background

Though the relationship between people and technology has always been a key factor in social progress, the connection with artificial intelligence (AI) marks a significant change in that relationship. Though artificial intelligence systems appear more and more to include adaptive, interactive, and decision making abilities demonstrating aspects of human thought, earlier technology has generally been viewed as tools. Furthermore than algorithms in social spheres like healthcare, education, and banking where artificial intelligence systems are used into virtual assistants (e.g., Siri, Alexa). Among the duties or responsibilities the technology begins to reveal the possibilities of decision making and information sharing are trust, teamwork, and decision making. Complex questions regarding how people interpret representative technology arise as humans push the boundaries of artificial intelligence to incorporate combined use of agency inside their knowledge sharing. That is picking and acting rather than just appearing technologically. (Chalmers, 2010)

Human computer interaction (HCI) has traditionally hypothesized these issues (usability, context aware interface design, user experience), but AI presents new challenges to some traditional assumptions of HCI, e.g. autonomous action by AI, natural language programming, and predictive analytics. Users no longer simply engage with a system, they engage in relational reciprocity with AI, and as a result of the relationship, AI can anticipate user needs, make recommendations and build knowledge of user action over time. Collectively, these issues of representation move us away from issues of usability central to our consideration, to issues of psychological interaction. (Dietvorst, 2015)

Research in psychology provides useful starting points to investigate these new propositions in HCI. Emotion describes whether a user feels trust versus scepticism towards AI, especially in high stakes situations which require investigation of the implications of a decision made by an AI, e.g. automobile driving but also in assessing accuracy of medical diagnoses. Cognitive engagement considers how user's attention, reasoning, and judgement provides understanding to think and respond to AI decisions and then when they shape perception for trust in an AI. Behavioural responses acknowledge how, with time, users may emerge as a) adopters, b) resistors, or c) develop dependency on a technology like AI. (Nasir, 2025) Together these three domains provide a starting place in descriptions of the complexity of human AI interaction. At the same time, there are possible complications for reliance on AI, and concerns for the erosion of human agency, and ethical risk from algorithmic opacity and bias. Although much of the existing literature addresses technical and ethical issues of AI, there is relatively little literature that attends to a psychology of AI. In the context of the existing literature, a psychology of AI is critical for understanding individual experiences, and for framing ethical design and governance of AI solutions which support human well-being.

Problem Statement

AI is rapidly altering the ways we live, work, and interact with each other, but we have not thought through the psychological consequences. While research has advanced notably in terms of documenting technical performance, ethical conversations and economic implications, there is far less research spent on the emotional, cognitive, and/or behaviours associated with interacting with AI. We are concerned about this as we know the outcomes of psychological mechanisms affecting user trust, acceptance, opposition, and long term use of an artificial intelligence solution. The problems with these situations come from AI's bi-modal use as a practical good regarded as a means that finishes jobs effectively and actually or maybe as a sort of social actor who, like a human would, interacts with, changes to, and makes judgments. These features can cause anthropomorphized, emotional, and anxious conversation. Given all this knowledge about engagement and interaction, the artificial intelligence system might risk an erosion of trust, increased dependence, and a diminishing of human agency. (Epley, 2007)

Still, the behavioural effects of what it means to be a person using an artificial intelligence system differ according on the circumstances. Speaking to task domains such health care or finances, some people have a lot of faith in the recommendations made by the Conversely, some stay away from the artificial intelligence system out of worries about mistake, relinquishing transparency or control. People respond differently to the AI's advice or guidance, underlining the necessity of knowledge of the directional connections, roles, and emotional response interaction. Behaviour and cognition to develop some insight of group and individual interactions with artificial intelligence. (Fiske, 2019)

The primary challenge is the absence of knowledge and systematic knowledge on the psychological aspects of human A.I. interaction; the roles of emotion, cognition, and behaviour, for individuals and groups. In order to advance theoretical knowledge and ensure that new A.I. technologies are developed and harnessed to respect and enhance people's psychological needs, we ultimately need to address this important gap in knowledge.

Research Gap

In spite of A.I. now being omnipresent in many areas of human engagement from health and finance to education and entertainment AI. Related scholarly literature is mostly focused on the technical efficiencies, algorithms and ethical governance of A.I. systems. These researches contribute to an understanding of the performance of political systems and what are the social consequences of having algorithms make decisions; however very little work, has actually examined the psychological dimensions in engagement with A.I., for example, little or no work in reframing and reframing the experience of engagement with A.I. through emotions, cognitive impressions and behaviours. (Nasir, 2025)

The current research on user trust and transparency in regard to fostering a positive user experience with artificial intelligence has a vast precedent in human computer interaction (HCI) literature and technology acceptance that can help internal stakeholders understand usability, trust, and adoption although, again, these frameworks do not capture the much more complicated set of complexities presented in artificial intelligence engagement. Artificial intelligence is not merely a technology or tool, but is rather an adaptive, quasi-social actor that communicates with, predicts, and can make decisions for a user. This is a fundamentally different phenomenon, and engagement with it produces complicated psychological responses that can involve anthropomorphism, empathy, anxiety, and over dependence. At this stage, theorising is fairly limited and largely undermines the phenomena and unrealised implications related to engagement with AI. (Nasir, 2024)

Ultimately, while there is an increasing interest and focus on trust and transparency in the design of AI, the majority of investigation has focused too narrowly on these issues in isolation from other cognitive and behaviour processes. Trust is overwhelmingly examined in terms of technical and ethical roles, without fully appreciating trust as an emotional or psychological state, and one that plays a role in

reasoning, decision making and longer term behaviours. Likewise, studies of cognitive load and user adaptation seldom incorporate emotional or behavioural outcomes into their investigations, leading to a patchwork of the holistic human AI experience. (Fiske and Taylor, 2013)
In addition, empirical investigation focusing on user experiences of AI operate within limited contexts (e.g., medical diagnosis, customer service chatbots, or autonomous vehicles), without creating a unified psychological framework that spans contexts. In doing so, both theoretical advancement, and therefore user-centred designs of AI systems that fit human needs, are stymied. (Gray, 2007)

Consequently, the gap in research is due to a lack of a unified psychological frame of reference for human AI interaction that simultaneously captures emotional responses, cognitive processes, and behavioural outcomes. Working towards this gap is needed to build an overall understanding of how humans interact with AI, as well as support ethical, user centred design of future intelligent systems.

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.

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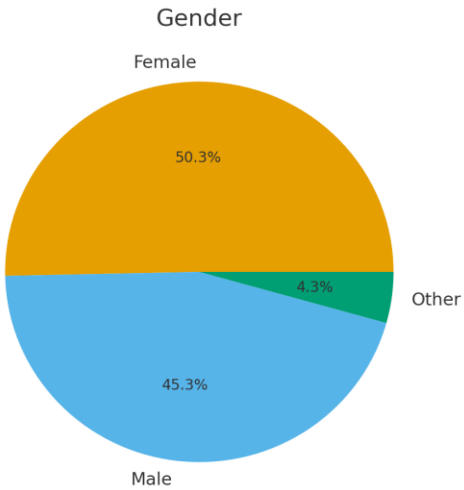
Data Collection Procedure
Participants are recruited using online platforms, professional networks, and in academic settings. Informed consent is obtained prior to participation and anonymity is assured. The survey take place online to enhance participant access and reach.

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.

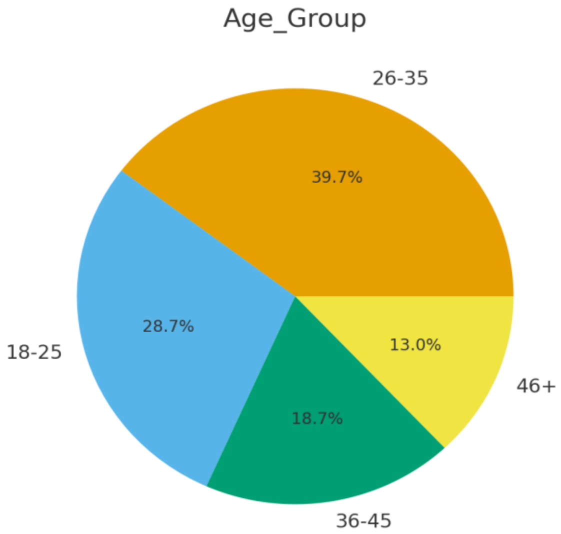
Data Analysis
1. **Gender**



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.

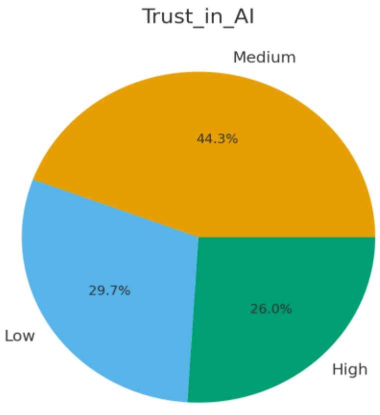
2. Age Group



Age Group	Frequency
26-35	119
18-25	86
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.

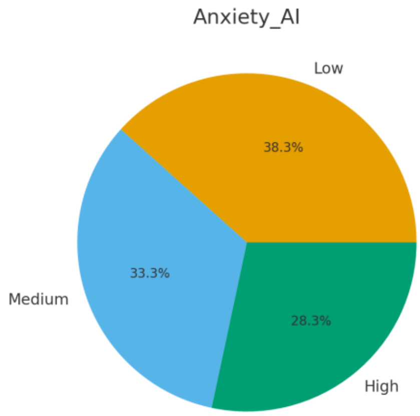
3. Trust in AI



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.

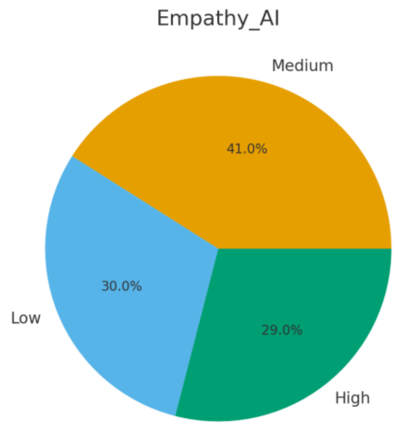
4. Anxiety AI



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.

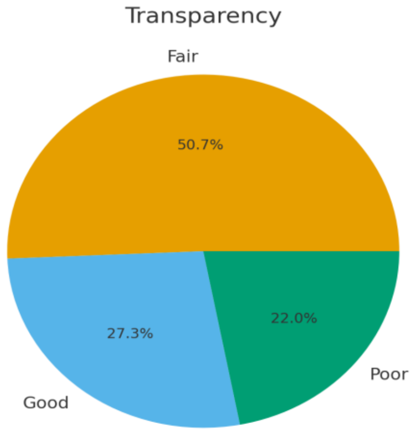
5. Empathy AI



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.

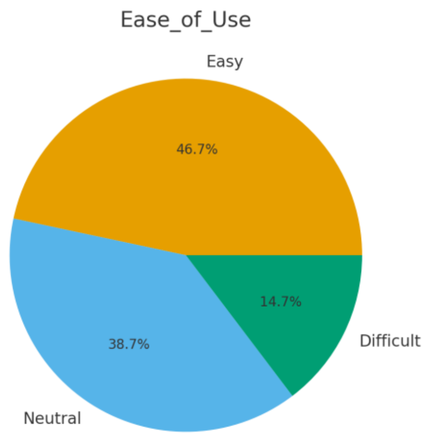
6. **Transparency**



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.

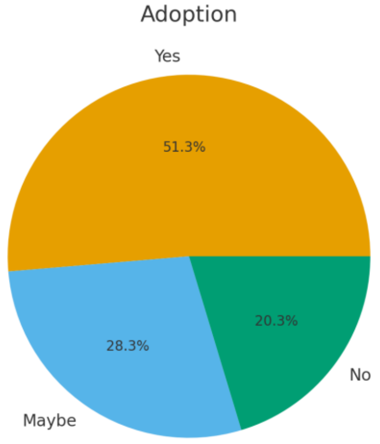
7. **Ease of Use**



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.

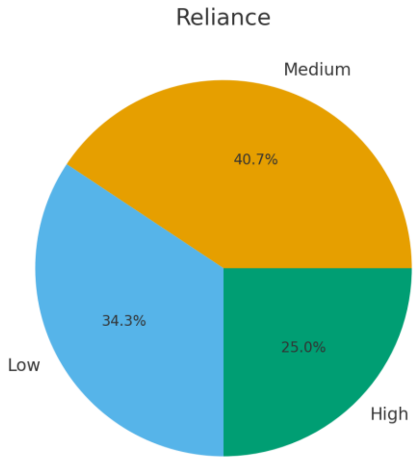
8. Adoption



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.

9. 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.

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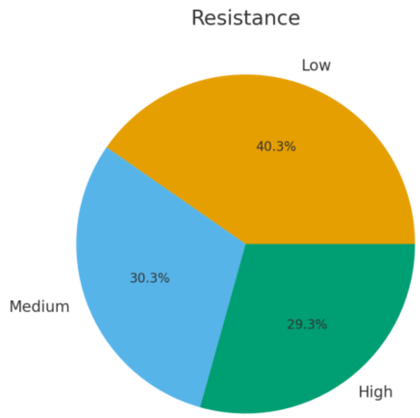
10. Resistance



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 research presented some important implications for the psychology of how humans engage with AI:

1. **Emotions**: Both trust and empathy are significant facilitators of the use of AIs, while fear and anxiety are barriers. Participants who reported the most trust at the outset showed the most willingness to interact with AIs across multiple domains of work, including health care, finance, and education.
2. **Cognition**: The feelings of transparency and usability are strongly associated with how participants drew meaning from AI recommendations. Cognitive overload or feelings of uncertainty also affected acceptance and increased resistance.
3. **Behaviour**: Positive emotional states and clearly defined cognitive processes are related to willingness to adopt and trust AIs, while anxiety or a clear lack of transparency in the decision maker increased resistance to using AIs from participants.
4. **Demographics**: Younger participants (18-35 years) are related to greater willingness to adopt and rely on AIs, while older participants expressed more scepticism and resistance to learning and using AIs.
5. **Integrated pattern**: Overall, the findings confirmed the original hypothesised model by indicating that emotions influence cognition (or thinking), and cognition starts to influence behavioural outcomes overall.

Conclusion

This research indicates that human interactions with AI are not simply a matter of technology, but rather they are a complex, psychological phenomenon. Trust, anxiety, and other human emotions, as well as cognitive aspects of transparency and understanding and behavioural outcomes of adoption or resistance, are interconnected. The results demonstrate that positive emotions with a clear cognitive understanding enable acceptance and trust in AI, while negative emotions, coupled with ambiguity in cognitive processing, impair trust and enhance resistance. Taken together, this article supports a bidirectional framework in which human psychology influences technology usage, while the design of AI systems influences the human experience. In the end, the study supports the need to grow AI from a psychological perspective to ensure human systems are enhancing rather than undermining well-being.

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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