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Who Do We Trust? Attachment, Anthropomorphism, and Age in Human–AI Relations

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Abstract

This study examined age-related differences in attachment styles, anthropomorphism, and trust in artificial intelligence. The primary aim was to examine emotional bonds and perceptions of AI systems change among adults at different developmental levels. A total of 92 participants aged 16 to 57 completed an online survey assessing attachment patterns, anthropomorphic perceptions, and trust in AI. Results indicated that younger adults demonstrated significantly higher levels of preoccupied (anxious) attachment compared to older groups. Trust in AI differed significantly across age groups, with middle-aged adults reporting the highest trust. Anthropomorphism did not significantly vary by age. Regression analysis showed that attachment styles did not significantly predict anthropomorphism overall, although dismissive attachment showed a modest individual association that should be interpreted cautiously due to the nonsignificant overall model. These findings suggest developmental differences in attachment anxiety and trust in AI, while anthropomorphic tendencies appear relatively stable across adulthood. However, given the modest sample size and cross-sectional design, findings should be interpreted cautiously and warrant replication in larger samples.

Keywords: *Artificial Intelligence; Trustworthiness; Anthropomorphism; Attachment Styles; Age Differences; Developmental Psychology*

1. Introduction

Artificial intelligence (AI) is increasingly embedded in everyday life, shaping how individuals work, communicate, and interact with digital systems. As AI technologies become more socially interactive, researchers have begun to examine whether individuals respond to AI using the same psychological mechanisms that govern human relationships. Three constructs are particularly relevant in this context: attachment, trust, and anthropomorphism. Attachment reflects enduring patterns of emotional bonding and expectations of support; trust refers to confidence in the reliability and dependability of an agent; and anthropomorphism involves attributing human-like characteristics to nonhuman entities. These constructs provide a theoretical framework for understanding how individuals emotionally and cognitively respond to artificial agents. Consistent with the Computers-Are-Social-Actors (CASA) paradigm, research demonstrates that individuals often apply social heuristics and interpersonal expectations when interacting with artificial agents (Nass & Moon, 2000). This suggests that core interpersonal psychological processes may shape how individuals perceive and trust AI systems.

1.1 Attachment

Attachment theory provides a framework for understanding how individuals form emotional bonds and regulate interpersonal relationships. Originally developed to explain infant–caregiver relationships, attachment patterns are shaped by early relational experiences and influence expectations of support, emotional regulation, and trust throughout adulthood (Bartholomew & Horowitz, 1991). Adult attachment is commonly categorized into four styles: secure, anxious (preoccupied), avoidant-dismissive, and fearful-avoidant (Sagone et al., 2023). Individuals with secure attachment tend to exhibit comfort with emotional closeness and autonomy, whereas anxious attachment is characterized by heightened concern about abandonment and a strong desire for reassurance. Avoidant-dismissive attachment involves emotional distancing and discomfort with dependence on others, while fearful-avoidant attachment reflects a combination of attachment anxiety and avoidance.

These attachment orientations influence not only interpersonal relationships but also interactions with nonhuman agents. Research suggests that individuals may transfer relational expectations formed in human relationships to artificial systems. For example, individuals with higher attachment anxiety have been found to exhibit lower trust in AI systems, potentially reflecting heightened sensitivity to uncertainty and reliability concerns (Gillath et al., 2020). Similarly, attachment insecurity has been associated with stronger emotional engagement and anthropomorphic perceptions toward artificial agents (Heng & Zhang, 2025; Yang & Oshio, 2025). These findings suggest that attachment processes may play an important role in shaping how individuals perceive and respond to AI.

1.2 Trust in AI

Trust is a multifaceted psychological construct that has been defined and operationalized in various ways across disciplines, reflecting its dependence on context, experience, and relational dynamics (Roundtable on Public Interfaces of the Life Sciences et al., 2015). Broadly, trust refers to a willingness to accept vulnerability based on positive expectations regarding the intentions or behavior of another agent (Matkin et al., 2023). Developmental research suggests that trust is shaped early in life through interactions with caregivers, forming internal working models that influence expectations of reliability and support in later relationships (Bosmans et al., 2019). Individuals with consistent and responsive caregiving experiences are more likely to develop secure expectations of others, whereas inconsistent or unreliable caregiving may foster skepticism and reduced willingness to rely on external agents. These foundational trust expectations extend beyond interpersonal relationships and may also shape how individuals evaluate and interact with nonhuman systems, including artificial intelligence, particularly when those systems display socially interactive features.

However, trust in AI differs from interpersonal trust in important ways, as AI systems operate based on programmed algorithms rather than independent intentions. As a result, scholars have argued that trust in AI is often more accurately conceptualized as confidence in system reliability and performance rather than traditional interpersonal trust (Ryan, 2020; Körber, 2018; Hancock et al., 2020).

Recent HRI research also shows that trust in AI depends not only on system performance but on human factors, including prior experiences and social expectations (Hancock et al., 2020; de Visser et al., 2020). Measures of trust in automation emphasize perceived competence, predictability, and responsibility (Körber, 2018), which align closely with the interpersonal trust mechanisms shaped by attachment history.

Although several validated instruments exist to assess trust in automation and artificial agents (e.g., Jian et al., 2000; Körber, 2018), there is no single universally adopted standard specifically tailored to modern conversational AI systems. Trust in AI is a multidimensional construct encompassing perceptions of competence, predictability, reliability, and ethical responsibility, and these dimensions may manifest differently depending on the technological context. Consequently, many recent studies have adapted existing trust measures or developed context-specific instruments to better capture users' perceptions of AI technologies. However, variation in measurement approaches continues to limit direct comparability across studies, highlighting the need for further refinement and validation of trust scales designed specifically for AI-mediated interactions. Accordingly, adapting existing trust-in-automation measures represents a common and accepted methodological approach when studying emerging AI technologies whose interaction characteristics differ from traditional automation systems.

The dependability and reliability of AI systems remain important research concerns (Min et al., 2022). Dependability and reliability refer to the extent to which a system can be trusted to perform as expected. As artificial intelligence is more involved in daily life, there have been more questions about the dependability and reliability of AI. These systems are trained to give quick responses, but the validity of the response is contingent on the data it's trained on (Hong et al., 2022). The quality of the data can vary, and incomplete, inaccurate, and biased datasets can easily impact the AI responses and negatively affect dependability and reliability on AI. It is important to note that artificial intelligence does not possess human-like understanding but instead generates outputs based on learned statistical patterns derived from training data. This can result in inaccurate or misleading outputs under certain conditions. Another aspect that affects the dependability of AI is algorithmic transparency. Many AI systems operate as so-called "black boxes," meaning their internal decision processes are not fully transparent to users or developers. This means that users have little to no understanding of how decisions are made with AI tools, and it makes it difficult to assess the credibility of these tools. For these reasons, it's relatively common for AI-generated content to be manipulated or weaponized, as shown in the recent increase of deepfake and algorithmic bias affecting social media feeds. While AI can potentially improve the quality of information, its dependability remains a significant concern. Lack of accuracy and general ambiguity about the sources behind the information that AI provides can lead to less trust in AI, which would lead to less dependability or reliability (Ryan, 2020). Trust calibration research further finds that users adjust their trust when AI errors accumulate, when explanations are missing, or when transparency decreases (de Visser et al., 2020), highlighting that dependability is a dynamic perception rather than a fixed system property. This highlights that trust in AI reflects a psychological perception shaped not only by system performance but also by individual differences, making it relevant to examine how attachment and age influence trust formation.

These findings underscore that trust in AI is influenced not only by technological factors but also by psychological processes, reinforcing the importance of examining individual differences in trust toward AI systems. Building on this foundation, the present study employed an adapted trust measure grounded in established trust-in-automation frameworks while specifically targeting governance, reliability, and accountability factors relevant to contemporary AI systems. These governance- and reliability-related perceptions represent core antecedents of trust in AI, as individuals' willingness to rely on AI systems is strongly influenced by their evaluation of system transparency, fairness, accountability, and safety (Körber, 2018; Hancock et al., 2020).

1.3 Anthropomorphism and Attachment to AI

Anthropomorphism is the tendency to attribute human-like characteristics to nonhuman entities, and it plays a significant role in the way people interact with artificial intelligence (Ryan, 2020). As AI systems become more advanced, they are designed to mimic human behaviors, emotions, and expressions, making them seem more relatable and trustworthy. This has led to a growing phenomenon where people develop emotional attachments to AI-powered entities, such as chatbots, virtual assistants, and social robots. Research consistently shows that anthropomorphic cues increase perceived warmth, competence, and trust in AI systems (Deng & Yan, 2025; Spatola et al., 2022). Because AI does not possess genuine emotional or cognitive experience, anthropomorphism toward AI reflects users' psychological perceptions rather than intrinsic properties of the system. This highlights the importance of measuring anthropomorphic perceptions as a user-level psychological construct.

Psychological research suggests that attachment to AI may stem from similar mechanisms as human attachment. People who struggle with human relationships or who experience social isolation are more likely to form strong emotional bonds with AI (Zimmerman et al., 2023). This is particularly evident in human-robot interactions, where users perceive AI as a comforting presence. While these attachments can provide companionship, they also raise ethical and psychological concerns. Over-dependence on AI companionship could impede genuine social development and exacerbate avoidant behaviors. Furthermore, AI does not possess genuine emotional experience, meaning perceived emotional reciprocity reflects users' psychological interpretation rather than actual emotional exchange. Understanding the implications of anthropomorphism and AI attachment is crucial in developing ethical AI systems that promote healthy interactions without fostering emotional dependence.

To measure the variable of anthropomorphism, various standardized scales are widely used, such as the Anthropomorphic Tendencies Scale (ATS), developed by Chin et al. (2005), the Specific Object Anthropomorphism Scale (SOAS), developed by David et al. (2025). These scales provide a strong theoretical foundation for measuring anthropomorphism and are commonly adapted in research examining emerging technologies. However, while validated anthropomorphism scales exist, fewer instruments have been specifically designed to assess anthropomorphic perceptions toward modern conversational AI systems. Therefore, the present study developed an anthropomorphism measure adapted from established theoretical frameworks and existing scales.

This research investigates the dynamics of emotional attachment, trustworthiness, dependability, and reliability within the context of artificial intelligence systems, examining both the underlying factors and possible risks related to these psychological and technical aspects. With AI's continuous advancement and growing presence across multiple domains of everyday existence, the nature of human-AI interactions has become progressively more complex. Attachment represents a key element shaping individuals' connections with AI technologies, often rooted in childhood experiences and emotional requirements. People exhibiting insecure attachment patterns, especially those demonstrating anxious or avoidant characteristics, may experience difficulties in interpersonal relationships and consequently form emotional connections with AI-powered systems, including digital assistants, conversational agents, or robotic companions with human-like features. Although such connections may offer a form of social support, they could simultaneously promote isolation from society and impede the growth of authentic emotional capacities in face-to-face interactions.

Trust in AI is another key factor that shapes user interactions with these technologies. Trust is often built on past experiences and the perceived reliability of a system. While AI can fulfill aspects of "rational trust," such as consistency in outputs, it lacks true understanding and accountability. The misrepresentation of AI as "trustworthy" can lead to ethical dilemmas, shifting responsibility from humans to machines, particularly when AI systems fail or cause harm. The reliability of AI is further complicated by issues such as biased data, misinformation, and algorithmic opacity. AI systems operate as "black boxes," where even developers may not fully understand how certain decisions are made. This lack of transparency raises concerns about AI's dependability, as errors in training data or biased algorithms can lead to misleading or false information, reducing overall trust.

Collectively, these findings highlight the importance of examining how attachment, anthropomorphism, and trust interact to shape human responses to AI systems. As AI becomes increasingly integrated into everyday life, individuals may vary in whether they perceive AI as a functional tool, a social entity, or an emotionally meaningful presence. Understanding how these psychological processes differ across age groups is essential for clarifying how individuals relate to AI and how developmental factors influence trust and anthropomorphic perceptions. The present study addresses this question by examining age-related differences in attachment, anthropomorphism, and trust in AI.

2. Methodology

2.1 Aim of the study:

The present study aims to investigate how attachment styles, anthropomorphism, and trust in artificial intelligence differ across age groups, and to explore the interrelationships among these psychological constructs in shaping human–AI interaction.

2.2 Objectives

1. To examine whether secure, fearful, preoccupied, and dismissive attachment styles vary significantly across different adult age groups.
2. To analyze age-related differences in the tendency to anthropomorphize AI systems.
3. To assess whether cognitive trust in AI differs across younger, middle-aged, and older adults.
4. To explore correlations among attachment styles, anthropomorphism, and trust in AI.
5. To identify whether attachment styles significantly predict anthropomorphic tendencies toward AI.

2.2.1 Supplementary objectives for descriptive figures

6. To examine the distribution of positive emotional responses (excitement, optimism, and relaxation) toward artificial intelligence among respondents.
7. To examine the distribution of negative emotional responses (worry, fear, and outrage) toward artificial intelligence among respondents.
8. To describe respondents' overall willingness to trust artificial intelligence.
9. To assess respondents' acceptance of the use of artificial intelligence in general contexts.
10. To examine respondents' self-perceived familiarity with artificial intelligence technologies.
11. To explore respondents' beliefs regarding the impact of artificial intelligence on employment outcomes.
12. To identify the artificial intelligence tools most commonly used by respondents.

2.3 Hypothesis

H1: There will be a significant difference between the 3 categories of the independent variable, *Age group*, on the dependent variable of secure attachment style.
H2: There will be a significant difference between the 3 categories of the independent variable, *Age group*, on the dependent variable of fearful attachment style.
H3: There will be a significant difference between the 3 categories of the independent variable, *Age group*, on the dependent variable of preoccupied attachment style.
H4: There will be a significant difference between the 3 categories of the independent variable, *Age group*, on the dependent variable of dismissive attachment style.

H5: There will be a significant difference between the 3 categories of the independent variable, *Age group*, on the dependent variable of anthropomorphism.
H6: There will be a significant difference between the 3 categories of the independent variable, *Age group*, on the dependent variable of trust in AI
H7: There will be a correlation between the subscales of attachment, anthropomorphism, and trust in AI
H8: Attachment styles will be a significant predictor of anthropomorphism towards AI.

2.3.1 Supplementary Hypothesis

In addition to the primary inferential hypotheses, supplementary hypotheses were formulated to guide the interpretation of frequency-based graphical analyses presented in Figures 1–11.

H9. Respondents will report predominantly moderate to high levels of positive emotions (excitement, optimism, and relaxation) toward artificial intelligence.
H10. Respondents will report predominantly low to moderate levels of negative emotions (worry, fear, and outrage) toward artificial intelligence.
H11. Respondents will most frequently report a neutral level of willingness to trust artificial intelligence.
H12. Respondents will report moderate to high levels of acceptance of artificial intelligence use.
H13. Respondents will report moderate to high levels of perceived familiarity with artificial intelligence.
H14. Respondents will most frequently endorse neutral or mixed beliefs regarding whether artificial intelligence will create more jobs than it will eliminate.
H15. One artificial intelligence platform will emerge as the most frequently used tool among respondents.

2.4 Participants

A total of 92 individuals participated in the study. Data were collected from May to July 2025 using an online survey distributed through a snowball sampling strategy, in which initial respondents were encouraged to share the survey within their personal networks. Inclusion criteria required participants to be 16 years or older and proficient in English. Although the a priori power analysis indicated that a minimum of 159 participants would be required to reliably detect medium effect sizes, the final sample consisted of 92 participants who completed the survey in full and met inclusion criteria. A larger number of individuals were approached through the snowball distribution process; however, not all initiated participants completed the questionnaire or provided usable responses.

The participants were between the ages of 16 and 57, with 30.5% being between the ages of 16 and 25, 31.5% being between the ages of 26 and 41, and 38.1% being between the ages of 42 and 57. These age categories (16–25, 26–41, and 42–57 years) were deliberately chosen based on recognized developmental and psychosocial differences among early, middle, and late adulthood.

The current study categorized the age range into three groups: 16-25, 26-41, and 42-57. Ages 16–25 signify late adolescence to emerging adulthood, characterized by transitions towards autonomy, identity exploration, intensified emotional reactivity, and heightened vulnerability to peer influence. Cognitive control systems are still developing at this stage, which makes this group different from others in terms of social behavior and coping skills. Ages 26 to 41 correspond to early to mid-adulthood, a time when people usually solidify their roles at work, in relationships, and in their families. Emotional regulation becomes stable, and studies indicate a plateau in novelty-seeking and impulsivity compared to younger adults. Ages 42 to 57 mark the shift from mid- to late adulthood, distinguished by accumulated life experiences, more defined cognitive strategies, and contemplative coping mechanisms. People in this stage may see stress and social interactions differently because they are more selective about their emotions and social interactions.

The sample consisted of 59.4% females and 40.6% males. 22.9% of the people had a high school diploma, 27.1% had an undergraduate degree, 43.8% had a postgraduate degree, and 6.3% had a doctorate. 70.8% of them had jobs, 24% were students, 3.1% were not working, and 2.1% were skilled professionals.

As participation was voluntary and recruitment relied on peer referral, completion rates were influenced by respondent availability and engagement.

2.5 Research Design

The study used a quantitative and cross-sectional research design, utilizing self-report surveys to measure participants' familiarity with artificial intelligence (AI), trust toward AI, anthropomorphism, emotional reactions, and attachment styles.

2.6 Instruments

1. **Trust-Related Perceptions of AI.** Trust-related perceptions of artificial intelligence were assessed using a 9-item scale adapted from the *KPMG Trust in Artificial Intelligence Survey* (Gillespie et al., 2025). Participants rated the importance of key factors influencing their trust in AI systems, including data privacy and security, transparency and explainability, accountability, fairness, and human oversight (see Appendix B). These items capture core dimensions underlying trust formation in AI, reflecting participants' evaluation of the conditions required for AI systems to be considered trustworthy.

   Responses were recorded on a 5-point Likert scale ranging from 1 (not at all important) to 5 (extremely important). Item responses were summed to create a composite trust score, with higher scores indicating stronger trust-related perceptions and greater importance placed on trust-enabling characteristics of AI systems.

   The adapted scale demonstrated excellent internal consistency in the present study (Cronbach's α = .94), with corrected items, total correlations ranging from .69 to .86, indicating strong coherence among items. Given the high reliability of the scale and the absence of any improvement in reliability when individual items were removed, all nine items were retained for analysis. This strong internal consistency supports the use of the scale for assessing trust-related perceptions of AI in the present sample. The items focused specifically on trust-enabling governance and reliability factors rather than emotional reactions, ensuring clear construct definition.

2. **Anthropomorphism Scale.** A self-constructed 10-item measure was created to evaluate the extent to which individuals ascribe human-like attributes to AI, encompassing agency, intentionality, emotionality, and moral concern. Responses used a 5-point Likert scale. Item responses were summed to produce a composite anthropomorphism score, with higher scores indicating stronger anthropomorphic perceptions. An example item from the questionnaire is: *"AI seems to have a mind of its own."*(Refer to Appendix A).

   This scale was based on the theoretical framework established by Waytz et al. (2010), who differentiate between cognitive anthropomorphism (attributing mental capacities such as intention or autonomous decision-making) and affective anthropomorphism (attributing emotional states or feelings). Items were constructed to reflect both dimensions.

   Overall Cronbach's alpha for the scale was α = .79 (Table 1). While internal consistency was acceptable, the scale's factor structure and convergent validity were not examined, and findings involving anthropomorphism should therefore be interpreted cautiously. Tukey's HSD post hoc tests were used to control for multiple comparisons.

3. **Attachment Styles Questionnaire (ASQ).** The ASQ (Van Oudenhoven, Hofstra, & Bakker, 2003) was used to measure attachment. It is based on Bartholomew and Horowitz's (1991) four-category model. The ASQ is made up of 20 items that are rated on a 5-point Likert scale, measuring four different attachment styles: secure, fearful, preoccupied, and dismissing. An example item is: *"I find it easy to get engaged in close relationships with other people."* The ASQ has demonstrated acceptable cross-cultural reliability (Polek, 2008). In the present study, internal consistency reliability was acceptable to good across subscales, with Cronbach's alpha coefficients of .84 for secure attachment, .85 for fearful attachment, .67 for preoccupied attachment, and .60 for dismissive attachment. These values are consistent with previously reported reliability ranges for the ASQ and support the use of the scale in the current sample.

2.7 Procedure

People were asked to fill out the online questionnaire using the Google Forms survey. Before starting, participants were given a summary of the study, and they were assured that participation was voluntary. It took about 10 to 12 minutes to finish the survey on average.

2.8 Ethical Consideration

The study followed established ethical guidelines for human subjects research. Before taking part, people gave their informed consent electronically. Participants were assured of anonymity and confidentiality, and they were informed that they could withdraw at any time without consequence. Survey items were designed to minimize psychological risk, and participants were provided with contact information for further inquiries or concerns.

2.9 Data Analysis

Data were analyzed using DataTab statistical software. Descriptive statistics were computed for all variables. One-way analysis of variance (ANOVA) was conducted to examine age-group differences in attachment styles, anthropomorphism, and trust in AI. When significant main effects were observed, Tukey's HSD post hoc tests were performed for significant ANOVA results to control for familywise Type I error. Pearson correlation analysis was conducted to examine relationships among attachment styles, anthropomorphism, and trust in AI. Multiple linear regression analysis was used to assess whether attachment styles predicted anthropomorphism.

2.9.1 Assumption testing and screening

Assumptions of normality were assessed using Shapiro–Wilk, Kolmogorov–Smirnov, and Anderson–Darling tests, supplemented by visual inspection of Q–Q plots. Although some normality tests were statistically significant, visual inspection indicated approximately normal distributions with minor tail deviations. Given the sample size ($N = 92$) and the robustness of parametric procedures, parametric analyses were retained. Homogeneity of variance was assessed using Levene's test and was satisfied for all ANOVA analyses ($p > .05$). No cases exceeded conventional thresholds, indicating no influential outliers were present. These results supported the use of parametric statistical analyses.

2.9.2 Power Analysis

An a priori power analysis was conducted using G*Power 3.1 to estimate the sample size required to detect medium effect sizes ($f = .25$) at an alpha level of .05 with statistical power of .80 for a one-way

ANOVA with three groups. The analysis indicated that a minimum of 159 participants would be required to reliably detect medium effects. The present sample size of 92 provides adequate power to detect large effects but reduced power for detecting small-to-medium effects. Therefore, nonsignificant findings should be interpreted cautiously.

3. Results

Figure 1

The extent to which respondents feel excited about AI

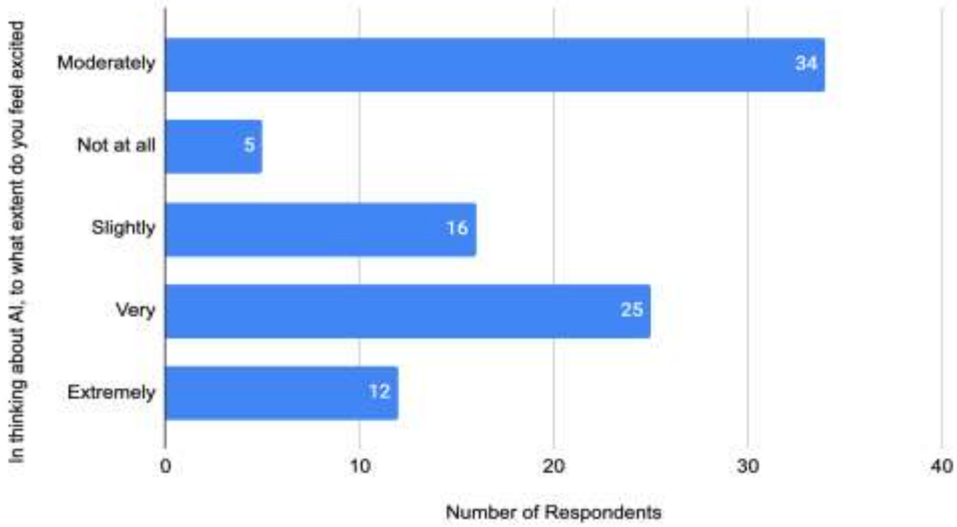

Figure 1 shows the response to "In thinking about AI, to what extent do you feel excited?" The majority of the respondents (n = 34) held that they feel moderately excited, whereas n = 25 respondents claimed that they were "very excited" about AI. A very small number of respondents (n = 5) stated that they did not feel excited about AI.

Figure 2

The extent to which respondents feel optimistic about AI

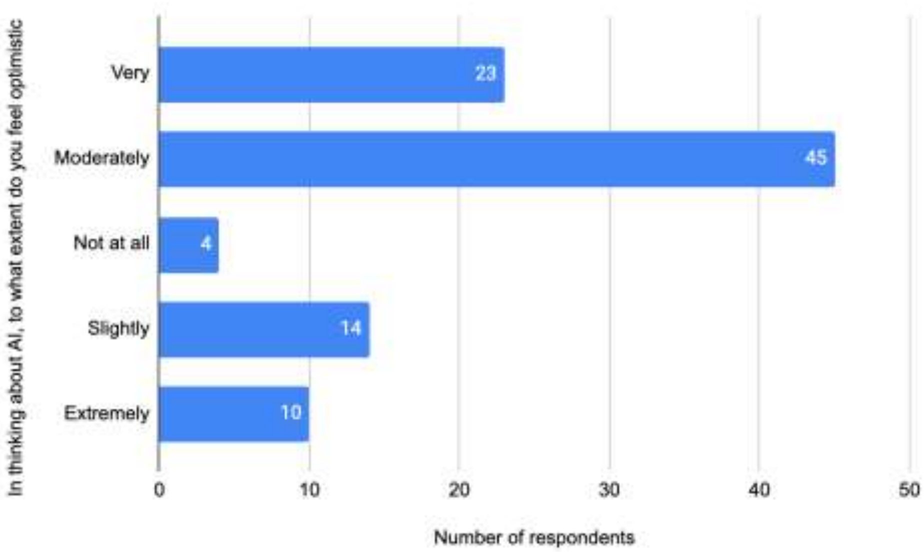

Figure 2 illustrates respondents' levels of optimism regarding AI. The majority of participants (n = 45) reported feeling moderately optimistic, making it the most common response. A substantial number (n = 23) indicated that they felt very optimistic, while smaller groups expressed either slight optimism (n = 14) or extreme optimism (n = 10). Only a small minority (n = 4) stated that they did not feel optimistic at all about AI.

Figure 3

The extent to which respondents feel relaxed about AI

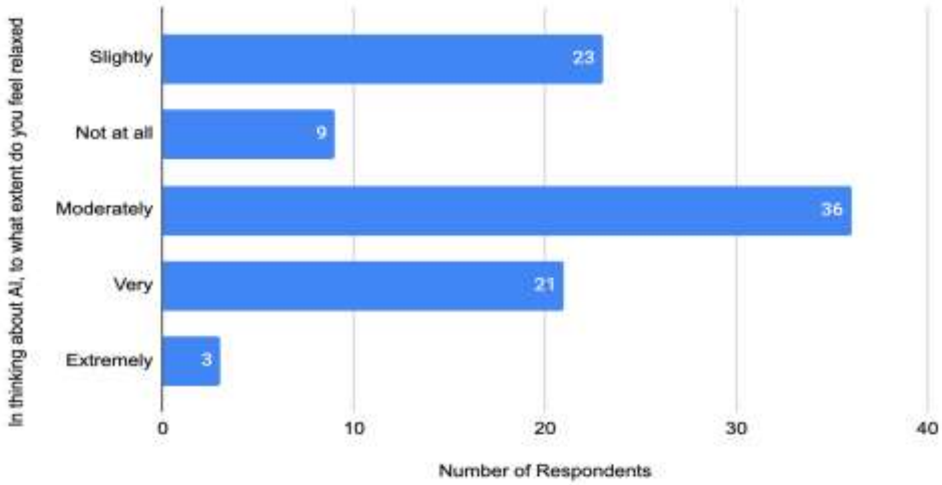

Figure 3 displays how relaxed respondents feel when thinking about AI. Most participants (n = 36) reported feeling moderately relaxed, followed by a considerable number who felt slightly relaxed (n = 23). A smaller portion of respondents stated that they felt very relaxed (n = 21), while a few expressed no relaxation at all (n = 9). Only a very small number (n = 3) indicated feeling extremely relaxed about AI.

The findings supported H9, as most respondents reported moderate to high levels of excitement, optimism, and relaxation toward AI.

Figure 4

The extent to which respondents feel worried about AI

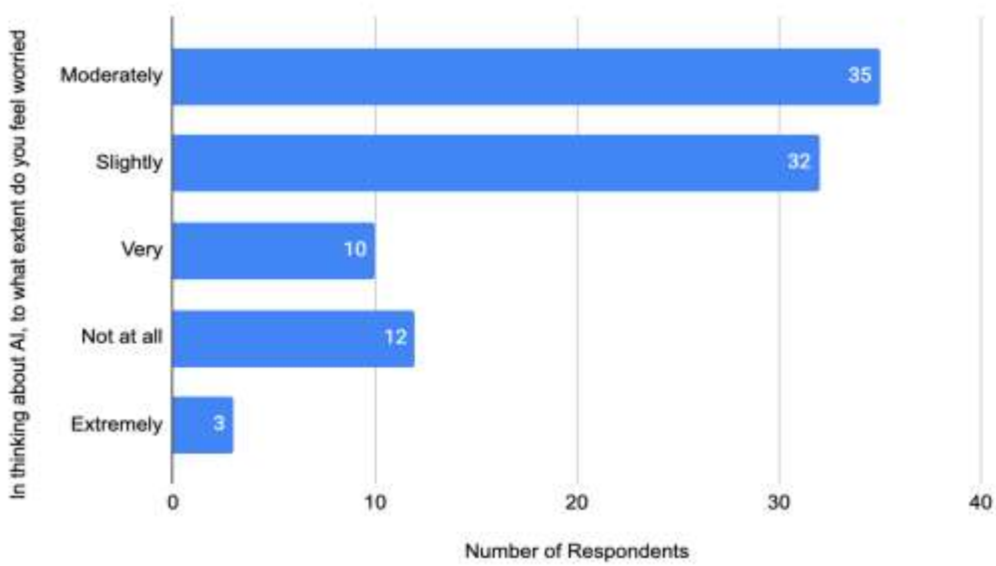

Figure 4 shows the extent to which respondents feel worried about AI. The two most common responses were moderately worried (n = 35) and slightly worried (n = 32), indicating that mild to moderate concern is relatively widespread. Fewer participants reported feeling not at all worried (n = 12) or very worried (n = 10). Only a minimal number of respondents (n = 3) stated that they felt extremely worried about AI.

Figure 5

The extent to which respondents feel fearful about AI

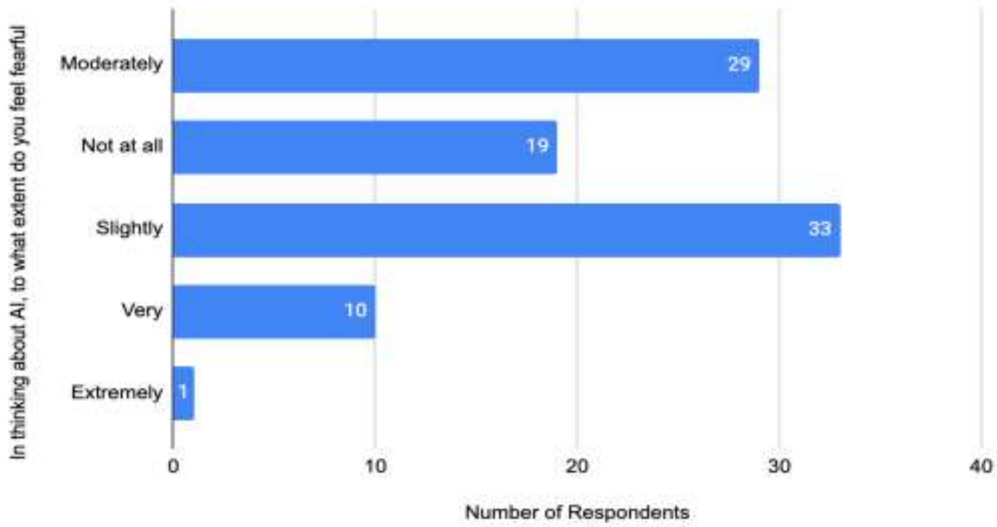

Figure 5 illustrates the degree to which respondents feel fearful when thinking about AI. The most common response was slightly fearful (n = 33), followed by those who felt moderately fearful (n = 29). A notable portion of participants reported feeling not at all fearful (n = 19). Fewer respondents indicated stronger levels of fear, with n = 10 feeling very fearful, and only a single respondent (n = 1) reporting feeling extremely fearful about AI.

Figure 6

The extent to which respondents feel outraged about AI

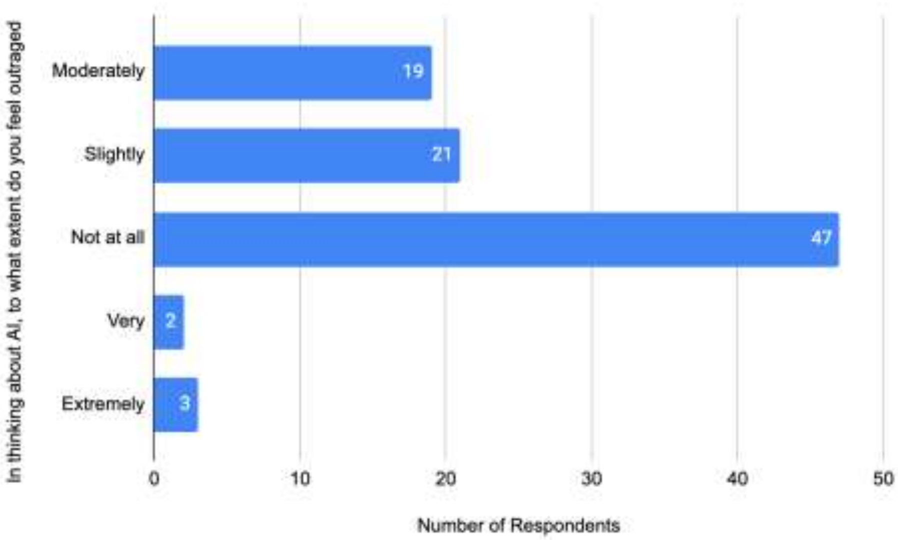

Figure 6 shows that feelings of outrage toward AI were generally low among respondents. Nearly half (n = 47) stated that they felt not at all outraged, making this the dominant response. Smaller groups reported feeling slightly outraged (n = 21) or moderately outraged (n = 19). Very few respondents expressed stronger emotional reactions, with only n = 3 reporting feeling extremely outraged and n = 2 feeling very outraged about AI.

H10 was largely supported, as responses for worry and fear clustered primarily in the slight to moderate range, while feelings of outrage were generally low, with most respondents indicating little to no outrage toward AI.

Figure 7

The explore the extent to which respondents are willing to trust AI

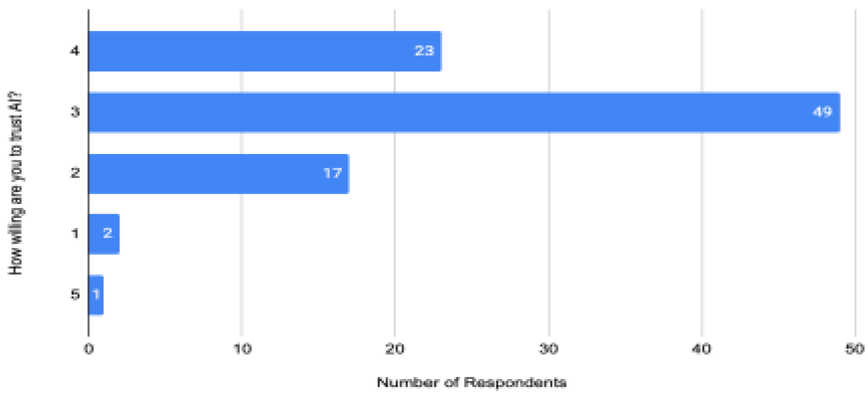

Figure 7 presents respondents' willingness to trust AI. Participants responded on a 5-point Likert scale, where 1 = very low trust, 3 = neutral, and 5 = very high trust. The majority of respondents (n = 49) selected level 3, indicating a neutral level of trust in AI. A notable proportion of respondents reported a relatively higher level of trust (level 4; n = 23), whereas fewer respondents indicated lower trust (level 2; n = 17). Only very small groups indicated minimal trust (level 1; n = 2) or very high trust (level 5; n = 1). Consistent with H11, the modal response reflected a neutral level of willingness to trust AI, with fewer respondents expressing extreme levels of trust or distrust.

Figure 8

To explore the extent to which respondents accept the use of AI

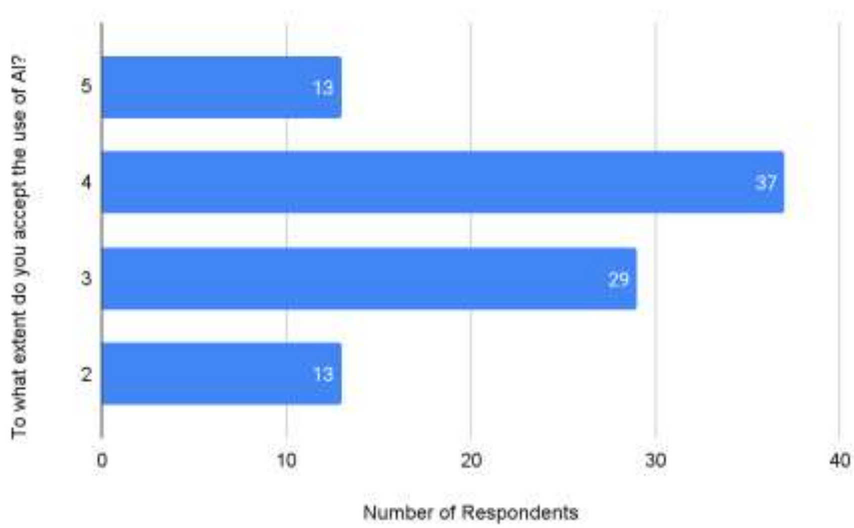

Figure 8 depicts how strongly respondents accept the use of AI. The most common level of acceptance was 4 (n = 37), followed by level 3 (n = 29). Smaller groups selected level 5 (n = 13) and level 2 (n = 13), indicating relatively high overall acceptance. No respondents selected level 1, suggesting that outright rejection of AI use was absent among participants. The results supported H12, as most participants reported relatively high acceptance of AI use, and no respondents indicated complete rejection of AI.

Figure 9

To gauge how familiar do respondents perceive they are with AI

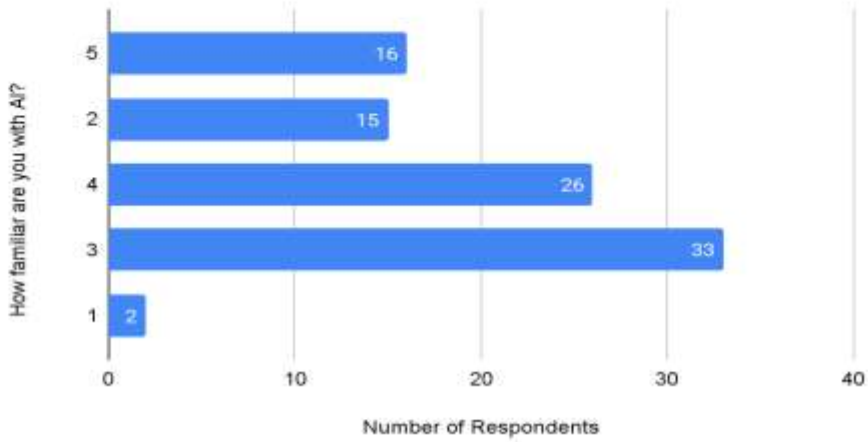

Figure 9 shows respondents' self-reported familiarity with AI. The most common rating was 3 (n = 33), indicating a moderate level of familiarity among participants. This was followed by respondents who rated their familiarity as 4 (n = 26) or 5 (n = 16), suggesting that many participants feel relatively knowledgeable about AI. Smaller groups reported lower familiarity levels: 2 (n = 15) and 1 (n = 2). Overall, the distribution reflects a generally well-informed respondent group, with most participants falling in the mid-to-higher familiarity range. The findings supported H13, with the majority of respondents reporting moderate to high familiarity with AI technologies, indicating that the sample was generally well informed about AI.

Figure 10

The extent to which respondents believe AI will create more jobs than it will eliminate

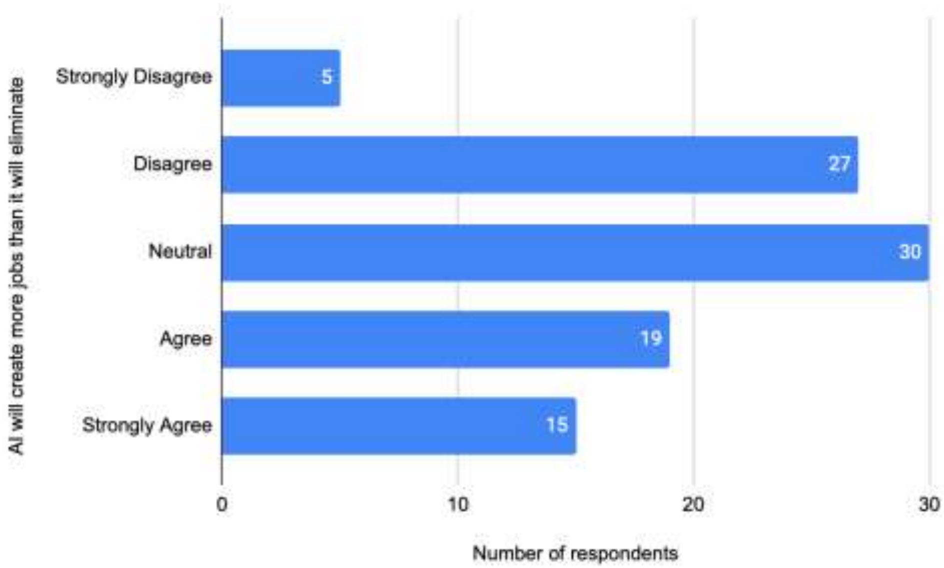

Figure 10 illustrates respondents' beliefs regarding whether AI will create more jobs than it will eliminate. The largest proportion of participants selected Neutral (n = 30), indicating uncertainty about AI's net impact on employment. A substantial number of respondents disagreed with the statement (n = 27), while a smaller group agreed (n = 19). Fewer participants expressed stronger stances, with n = 15 reporting that they strongly agree and n = 5 stating that they strongly disagree. Consistent with H14, neutrality emerged as the most common response regarding AI's impact on employment, reflecting uncertainty or mixed expectations about AI-related job creation and job loss.

Figure 11
AI tools commonly used by respondents.

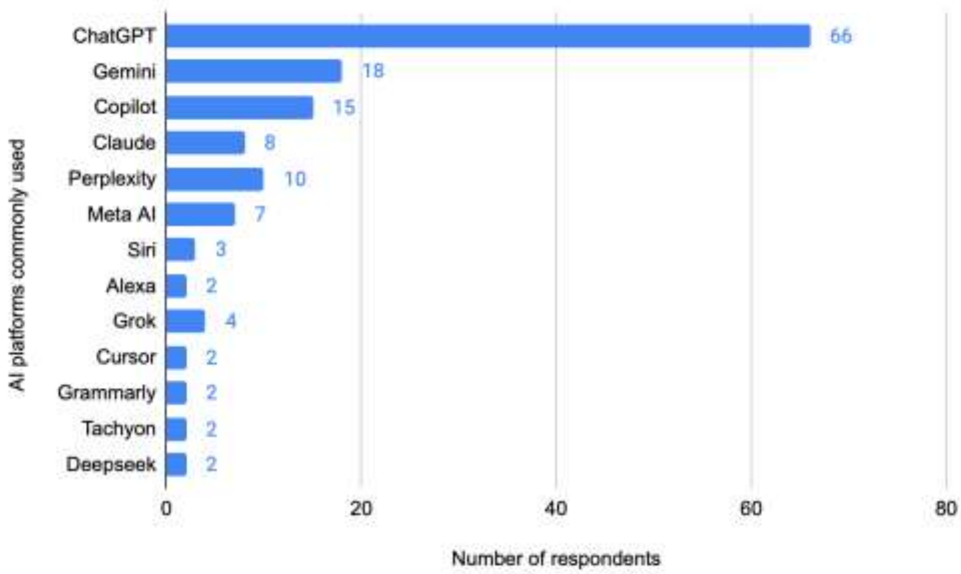

Figure 11 presents the range of AI platforms that respondents reported using. Since participants were allowed to select more than one tool, the totals exceed the number of respondents and reflect overall usage patterns rather than exclusive choices. The data show a strong preference for ChatGPT, which was selected by the majority of respondents (n = 66), making it by far the most widely used platform. Other commonly used tools included Gemini (n = 18) and Copilot (n = 15). Moderate levels of usage were reported for Perplexity (n = 10), Claude (n = 8), and Meta AI (n = 7). A small number of respondents reported using tools such as Grok (n = 4), Siri (n = 3), Alexa, Cursor, Grammarly, Tachyon, and Deepseek (each n = 2). The results supported H15, as one AI platform - ChatGPT - was reported as being used by a substantially larger proportion of respondents compared to all other AI tools, indicating a clear concentration of AI usage.

Table 1
Internal Consistency Reliability of the Anthropomorphism Scale (N = 10 items)

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
ANT_1	0.28	0.79
ANT_2	0.57	0.76
ANT_3	0.43	0.77
ANT_4	0.25	0.79
ANT_5	0.38	0.78
ANT_6	0.56	0.75
ANT_7	0.47	0.77
ANT_8	0.59	0.75
ANT_9	0.53	0.76
ANT_10	0.52	0.76

Note. Overall Cronbach’s alpha for the scale was α = .79 (10 items).

The Anthropomorphism Scale demonstrated good internal consistency, with a Cronbach’s alpha of .79, indicating acceptable reliability for research purposes. Corrected item–total correlations ranged from .25 to .59, with most items exceeding the commonly recommended threshold of .30, suggesting that the majority of items contributed meaningfully to the overall construct. Items ANT_1 and ANT_4 showed relatively lower item–total correlations (.28 and .25, respectively). However, deletion of these items did not result in an improvement in overall reliability (α remained .79), indicating that their retention does not adversely affect the scale’s internal consistency. Furthermore, Cronbach’s alpha if item deleted ranged from .75 to .79, suggesting no single item disproportionately influenced scale reliability. Overall, the findings support the retention of all 10 items and indicate that the Anthropomorphism Scale is a reliable measure for assessing the construct in the present sample.

Table 2
Internal Consistency Reliability of the Trust Scale (N = 9 items)

	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
TRUST_1	0.76	0.94
TRUST_2	0.8	0.94
TRUST_3	0.81	0.94
TRUST_4	0.86	0.93
TRUST_5	0.84	0.93
TRUST_6	0.78	0.94
TRUST_7	0.76	0.94
TRUST_8	0.69	0.94
TRUST_9	0.77	0.94

Note. Overall Cronbach's alpha for the scale was α = .94 (9 items).

The Trust Scale demonstrated excellent internal consistency, with a Cronbach's alpha of .94, indicating a very high level of reliability. Corrected item–total correlations ranged from .69 to .86, well above the recommended minimum threshold of .30, suggesting that all items were strongly and consistently related to the underlying construct of trust in AI. Cronbach's alpha values if an item were deleted ranged from .93 to .94, indicating that removal of any individual item would not result in a meaningful improvement in overall reliability. This pattern suggests that all nine items contribute positively to the scale and that the Trust in AI Scale is internally coherent and psychometrically robust.Overall, the results support the retention of all nine items and confirm that the Trust Scale is a highly reliable measure suitable for use in subsequent analyses.

Table 3
ANOVA for age groups and secure attachment style

	n	M	SD	df	F	p	η2
16-25	28	27.04	3.88	2	0.15	.881	0
42-57	35	26.91	4.33				
26-41	29	26.48	4.9				

Table 3 shows the ANOVA scores for participants in different age groups on the dependent variable of secure attachment style. Respondents in the age range of 16-25 reported higher scores (M = 27.04, SD = 3.88) than respondents aged 26-41 (M = 26.91, SD = 4.33) and those aged 42-57 (M = 26.48, SD = 4.9). However, the difference in their scores was not statistically significant with $F = 0.15$, $p = .881$ ($p>0.05$). The η2 value of 0 indicates no effect. Therefore, H1 was rejected.

Table 4

ANOVA for age groups and fearful attachment style

	n	M	SD	df	F	p	η2
16-25	28	11.57	3.02	2	1.69	.19	0.04
42-57	35	10.37	3.37				
26-41	29	11.86	3.93				

Table 4 shows the ANOVA scores for participants in different age groups on the dependent variable of fearful attachment style. Respondents in the age range of 26-41 reported higher scores ($M = 11.86$, $SD = 3.93$) than respondents aged 16-25 ($M = 11.57$, $SD = 3.02$) and those aged 42-57 ($M = 10.37$, $SD = 3.37$). However, the difference in their scores was not statistically significant with $F = 1.69$, $p = .19$ ($p>0.05$). The η2 value of 0.04 indicates a small to moderate effect size. Therefore, H2 was rejected.

Table 5

ANOVA for age groups and preoccupied attachment style

	n	M	SD	df	F	p	η2
16-25	28	19.54	5.83	2	8.82	<.001	0.17
42-57	35	14.69	3.85				
26-41	29	16.83	3.89				

Table 5 shows the ANOVA scores for participants in different age groups on the dependent variable of preoccupied attachment style. Respondents in the age range of 16-25 reported higher scores ($M = 19.54$, $SD = 5.83$) than respondents aged 26-41 ($M = 14.69$, $SD = 3.85$) and those aged 42-57 ($M = 16.83$, $SD = 3.89$). The difference in their scores was statistically significant with $F = 8.82$, $p < .001$ (this indicates that the p value is less than 0.05). The η2 value of 0.17 indicates a large effect size. Hence, H3 was accepted.

Table 6

Tukey's HSD Post Hoc Comparisons for Preoccupied Attachment Style Across Age Groups

	Mean Diff.	p	95% CI lower limit	95% CI upper limit
16-25 - 42-57	4.85	<.001	2.10	7.60
16-25 - 26-41	2.71	.069	-0.17	5.58
42-57 - 26-41	2.14	.153	-0.58	4.87

Tukey's HSD post hoc analysis was conducted to examine pairwise differences in *preoccupied attachment style* scores among the three age groups. Results revealed that participants aged 16–25 years (M = 19.54, SD = 5.83) scored significantly higher than those aged 42–57 years (M = 14.69, SD = 3.85), $p < .001$. The mean difference between the 16–25 and 26–41 groups approached significance ($p = .069$), while the difference between the 42–57 and 26–41 groups was not significant ($p = .153$). These findings indicate that younger adults (16–25) tend to exhibit a more preoccupied attachment style compared to older adults (42–57), suggesting that attachment anxiety may decrease with age and emotional maturity.

Table 7

ANOVA for age groups and dismissive attachment style

	n	M	SD	df	F	p	η2
16-25	28	11.14	2.24	2	0.6	.553	0.01
42-57	35	11.09	1.99				
26-41	29	11.62	2.06				

Table 7 shows the ANOVA scores for participants in different age groups on the dependent variable of dismissive attachment style. Respondents in the age range of 26-41 reported higher scores (M = 11.62, SD = 2.06) than respondents aged 16-25 (M = 11.14, SD = 2.24) and those aged 42-57 (M = 11.09, SD = 1.99). However, the difference in their scores was not statistically significant with F = 0.6, p = .553 (p>0.05). The η2 value of 0.01 indicates a small effect size. Hence, H4 was rejected.

Table 8

ANOVA for age groups and anthropomorphism

	n	M	SD	df	F	p	η2
16-25	28	26.86	7.51	2	0.48	.621	0.01
42-57	35	25.46	6.3				
26-41	29	26.83	5.96				

Table 8 shows the ANOVA scores for participants in different age groups on the dependent variable of anthropomorphism. Respondents in the age range of 16-25 reported higher scores (M = 26.86, SD = 7.51) than respondents aged 26-41 (M = 26.83, SD = 5.96) and those aged 42-57 (M = 25.56, SD = 6.3). However, the difference in their scores was not statistically significant with F = 0.48, p = .621 (p>0.05). The η2 value of 0.01 indicates a small effect size. Therefore, H5 was rejected.

Table 9
ANOVA for age groups and trust in AI

	n	M	SD	df	F	p	η2
16-25	28	36.68	8.13	2	5.11	0.008	0.1
42-57	35	34.06	8.13				
26-41	29	40.03	5.67				

Table 9 shows the ANOVA scores for participants in different age groups on the dependent variable of trust in AI. Respondents in the age range of 26-41 reported higher scores (M = 40.03, SD = 5.67) than respondents aged 16-25 (M = 36.68, SD = 8.13) and those aged 42-57 (M = 34.06, SD = 8.13). The difference in their scores was statistically significant with F= 5.11, p = 0.008 ($p<0.05$). The η2 value of 0.1 indicates a moderate effect size. Therefore, H6 was accepted.

Table 10
Tukey's HSD Post Hoc Comparisons for Trust in AI Across Age Groups

	Mean diff.	p	95% CI lower limit	95% CI upper limit
16-25 - 42-57	2.62	.351	-1.88	7.12
16-25 - 26-41	3.36	.21	-1.35	8.06
42-57 - 26-41	5.98	.005	1.52	10.43

Post hoc comparisons using Tukey's HSD indicated that participants aged 26–41 years (M = 40.03, SD = 5.67) scored significantly higher on trust in AI than those aged 42–57 years (M = 34.06, SD = 8.13), $p = .005$. No significant differences were observed between the 16–25 group (M = 36.68, SD = 8.13) and either of the other two age groups ($p > .05$). These results suggest that individuals in early to mid-adulthood (26–41 years) tend to display greater levels of trust in AI compared to older adults (42–57 years). This pattern may reflect developmental and contextual factors, such as increased professional and social responsibility during early adulthood, which often requires greater reliability and consistency in interpersonal relationships. Though this has not been directly assessed in the present study. Conversely, the decline in trust in AI scores among older adults may relate to shifts in social priorities or changing interpersonal expectations over time.

Table 11
The correlation between attachment subscales, anthropomorphism, and trust towards AI

		S.A.	F.A.	P.A.	D.A.	ANT	AI-T
S.A.	Correlation	1	-0.52	-0.22	0.03	-0.03	0.12
	p		<.001	.034	.742	.766	.244
F.A.	Correlation	-0.52	1	0.46	0	0.09	0
	p	<.001		<.001	.99	.379	.988
P.A.	Correlation	-0.22	0.46	1	-0.22	0.15	-0.03
	p	.034	<.001		.038	.158	.807
D.A.	Correlation	0.03	0	-0.22	1	0.19	0.07
	p	.742	.99	.038		.069	.497
ANT	Correlation	-0.03	0.09	0.15	0.19	1	0.17
	p	.766	.379	.158	.069		.097
AI-T	Correlation	0.12	0	-0.03	0.07	0.17	1
	p	.244	.988	.807	.497	.097	

**S.A. = Secure attachment, F.A. = Fearful attachment, P.A. = Preoccupied attachment, D.A. = Dismissing attachment, ANT = Anthropomorphism, AI-T = Trust in AI scale*

The Pearson correlation shows that secure attachment had a statistically significant moderate negative correlation with fearful attachment ($r = -0.52$, $p < .001$), a weak negative correlation with preoccupied attachment ($r = -0.22$, $p = .034$), and no significant correlation with dismissing attachment ($r = 0.03$, $p = .742$), anthropomorphism ($r = -0.03$, $p = .766$), or trust in AI (AI-T) ($r = 0.12$, $p = .244$). Fearful attachment was significantly positively correlated with preoccupied attachment ($r = 0.46$, $p < .001$), but showed no significant correlation with dismissing attachment ($r = 0.00$, $p = .99$), anthropomorphism ($r = 0.09$, $p = .379$), or AI trust ($r = 0.00$, $p = .988$). Preoccupied attachment had a weak negative correlation with dismissing attachment ($r = -0.22$, $p = .038$), and no significant correlation with anthropomorphism ($r = 0.15$, $p = .158$) or AI trust ($r = -0.03$, $p = .807$). Dismissing attachment showed no significant correlation with anthropomorphism ($r = 0.19$, $p = .069$) or trust in AI ($r = 0.07$, $p = .497$). Anthropomorphism was not significantly correlated with trust in AI ($r = 0.17$, $p = .097$).

Table 12
Multiple linear regression between attachment styles and anthropomorphism

Predictor	**B**	**SE B**	**β**	**t**	**p**	**95% CI for B**
Constant	13.27	7.75	—	1.71	.091	[−2.14, 28.67]
Secure attachment	0.01	0.18	.01	0.05	.958	[−0.35, 0.37]
Fearful attachment	0.01	0.25	.00	0.03	.975	[−0.49, 0.51]
Preoccupied attachment	0.26	0.16	.20	1.65	.102	[−0.05, 0.58]
Dismissing attachment	0.73	0.34	.23	2.19	.031	[0.07, 1.40]

Note. N = 92. Dependent variable = anthropomorphism.
Model fit: R^2 = .07, adjusted R^2 = .03, $F(4, 87)$ = 1.74, p = .148.

A multiple linear regression analysis was conducted to examine whether attachment styles predicted anthropomorphism toward AI. The overall regression model was not statistically significant, F = 1.74, p = .148, accounting for a small proportion of variance in anthropomorphism (R^2 = .07, adjusted R^2 = .03). This indicates that attachment styles, as a set of predictors, explained limited variance in anthropomorphic tendencies toward AI. Although one predictor, namely dismissive attachment, reached statistical significance (B = 0.73, β = .23, SE = 0.34, t = 2.19, p = .031), this finding should be interpreted cautiously because the overall regression model was not significant. Therefore, this individual association should be considered exploratory and requires replication in larger samples. Accordingly, H8 was not supported.

4. Discussion

The present study set out to examine age-related differences in attachment styles, anthropomorphism, and trust in artificial intelligence, as well as the interrelationships among these constructs. Overall, the findings partially supported the proposed hypotheses. Consistent with H3, significant age-group differences emerged for preoccupied (anxious) attachment, with younger adults (16–25 years) reporting substantially higher levels of attachment anxiety than middle-aged and older adults, suggesting a developmental decline in attachment-related insecurity. H6 was also supported: trust in AI differed significantly across age groups, with adults aged 26–41 reporting higher levels of trust than older adults, indicating that trust in AI may peak during early to mid-adulthood. In contrast, H1, H2, and H4 were not supported, as secure, fearful, and dismissive attachment styles did not significantly vary across age groups. Likewise, H5, which predicted age differences in anthropomorphism, was rejected;

participants showed similar tendencies to attribute human-like qualities to AI regardless of age. Finally, correlational analyses partially supported H7 by revealing significant associations among several attachment dimensions, although not all predicted relationships with anthropomorphism and AI trust were observed. H8 was also only partially supported: while attachment styles as a set did not significantly predict anthropomorphism, dismissive attachment emerged as a unique significant predictor.

In addition to these primary hypotheses, several supplementary hypotheses (H9–H15) were examined to provide descriptive insight into participants' emotional responses, trust tendencies, acceptance, familiarity, beliefs about AI's societal impact, and patterns of AI platform use.Taken together, the pattern of accepted and rejected hypotheses suggests that age is differentially related to components of attachment and AI trust, while anthropomorphism appears comparatively age-invariant in this sample.

The current findings suggest that age has minimal impact on certain interpersonal and AI-related orientations, while other dimensions do vary by age. Specifically, secure attachment style and avoidant attachment styles (including dismissive and fearful) showed no significant differences across the young adult, middle-aged, and older adult groups. All age groups reported very similar levels of attachment security and avoidance. In contrast, preoccupied (anxious) attachment and trust in AI displayed clear age-related patterns. Younger adults exhibited much higher attachment anxiety and somewhat lower skepticism toward AI, whereas older participants (approaching late midlife) were less anxiously attached but also less trusting of AI. These patterns largely align with prior research and developmental theory, though the limited sample size and age range warrant caution in interpretation. Below, we discuss each set of findings in detail, supported by relevant literature.

All three age groups had comparable levels of secure attachment as well as dismissive and fearful avoidant attachment. The mean differences were very small, and the ANOVA results were non-significant, indicating that being in one's late teens versus one's forties or fifties did not substantially influence how securely or avoidantly attached a person was. This outcome is consistent with a body of research suggesting that adult attachment orientations remain relatively stable across adulthood. For example, Segal et al. (2009) found no significant age differences in secure or avoidant attachment between a group of 22-year-olds and a group of 68-year-olds. In that study, older adults scored as high on attachment security and as low on avoidance (including dismissing and fearful styles) as younger adults did. Such evidence supports the notion that, barring major life changes, attachment security and avoidance tend to persist at similar levels through adult life (Segal et al., 2009). Similarly, a cross-sectional analysis by Chopik et al. (2012) reported only minor age-related variance in attachment avoidance from early adulthood into old age, with no dramatic shifts in avoidant tendencies across different age cohorts. Overall, the findings reinforce the idea that core attachment orientations of security vs. avoidance are largely age-invariant in adulthood.

It is important to acknowledge, however, that the oldest group (ages 42–57) may not have been old enough to capture certain later-life changes in attachment. Some longitudinal research focusing on adults in their late 60s and beyond suggests a possible uptick in dismissing-avoidant attachment at more advanced ages. For instance, in a 14-year follow-up study of adults who were in their mid-40s to late 60s, older participants in that range were more likely to exhibit a dismissing attachment style than younger participants (Platts et al., 2023). The authors observed that within the 44–68 age group, the proportion of dismissively attached individuals increased with age, whereas preoccupied attachment became less common in the older subset (Platts et al., 2023). This implies that certain attachment shifts might emerge in the transition from midlife to late life—shifts that the study, capped at 57 years old, would have missed. Additionally, each of the age cohorts contained 92 individuals, limiting statistical power to detect subtle differences. These sample limitations mean that while we did not find age effects on attachment security or avoidance, small true differences cannot be ruled out. Still, taken together with prior research, the evidence suggests that an individual's level of secure or avoidant attachment is more strongly influenced by personal and relationship factors than by age or generation per se.

In contrast to the stable patterns for security and avoidance, attachment anxiety (preoccupied style) showed a pronounced age-related decline. Younger adults had markedly higher preoccupied attachment scores than both middle-aged and older adults. In the data, the late-teen/early-20s group reported the highest attachment anxiety, and anxiety levels dropped substantially in the 26–41 group and even further in the 42–57 group. Statistically, this age effect was significant and large, indicating a meaningful decrease in attachment-related anxiety from the youngest to the more mature groups. This finding is strongly supported by existing literature: attachment anxiety tends to be higher in younger people and diminishes with age. Longitudinal studies have documented that as individuals progress from adolescence into mid-adulthood, average attachment anxiety declines significantly (Chopik et al., 2019). In a 59-year longitudinal analysis, Chopik et al. (2019) found that attachment anxiety decreased steadily with age, particularly from young adulthood through middle age. Cross-sectional comparisons similarly show that older adults report far less anxious/preoccupied attachment than younger adults. For example, Segal et al. (2009) noted that older participants experienced anxious attachment feelings less frequently than their younger counterparts, and Chopik et al. (2013) observed that attachment anxiety was highest among people in their twenties and progressively lower in older age groups. The results mirror these patterns.

Several factors might explain this developmental trajectory. As people age and accumulate relationship experiences, they often develop greater emotional security, self-regulation skills, and confidence in their social bonds, which can reduce the fears of abandonment that underlie anxious attachment. Over time, individuals may learn that relationships can endure conflicts or separations, and they become less preoccupied with seeking constant reassurance. Socioemotional selectivity theory also offers insight: as adults get older, they tend to prioritize close, positive relationships and downsize their social networks to those who provide the most emotional support. This focus on high-quality relationships and emotional regulation in later adulthood could naturally contribute to lower attachment anxiety (Charles & Carstensen, 2010).

Hypothesis 5, which anticipated age-group differences in the tendency to anthropomorphize AI, was not supported. Participants' anthropomorphism scores were very similar across the 16–25, 26–41, and 42–57 age brackets. The one-way ANOVA showed no significant differences by age and a negligible effect size. This suggests that within the adult age range we sampled, a person's likelihood of perceiving AI agents as having human-like qualities does not depend much on their age. This null finding adds to the limited literature on age and anthropomorphism, which so far has not revealed any consistent age trend. If anything, some studies have found that older adults may anthropomorphize robots more than younger adults under certain conditions. For example, Morillo-Méndez et al. (2024) conducted a human–robot interaction experiment with young, middle-aged, and older adults (age 65+) and found that the older group perceived the social robot as significantly more anthropomorphic, warm, and competent compared to the younger and middle-aged groups. The researchers interpreted this as a potential novelty effect, as the older participants, having had less lifetime exposure to advanced robots, were more inclined to ascribe human traits to the new technology (Morillo-Méndez et al., 2024). In this case, the oldest participants were in their 40s and 50s rather than truly elderly, and most were familiar with modern technology. This familiarity may have blunted any novelty-based anthropomorphism, resulting in uniform perceptions across ages.

Lastly, age had a notable effect on trust in AI systems, supporting Hypothesis 6. The highest trust in AI was reported not by the youngest cohort but by the middle-aged adults in the sample. Participants aged 26–41 expressed the most trusting attitudes toward AI on average, slightly higher than the 16–25 group, while the older group (42–57) was the most skeptical. This pattern aligns with broader generational trends observed in other studies and surveys. Research consistently finds that older adults are more wary of AI technologies, whereas younger generations tend to be more comfortable and trusting.

For example, a 2023 survey of over 10,000 U.S. consumers revealed a large generational gap in AI trust: about 31% of consumers under age 45 said they “mostly or completely” trust AI, but only 8% of those over age 55 expressed that level of trust (Stockton, 2023). Likewise, Kubovics (2025) found that younger people showed greater trust in the benefits of AI and were more willing to share personal data, whereas older individuals were more concerned about risks such as data misuse. The author concluded that greater digital exposure and familiarity among the young lead to more benevolent views of AI, while older adults’ lower digital trust and higher privacy concerns temper their willingness to adopt AI (Kubovics, 2025).

5. Conclusion

The present study explored how attachment styles, anthropomorphism, and trust in AI vary across different adult age groups. The findings revealed two statistically significant differences: younger adults (16–25) reported significantly higher levels of *preoccupied attachment* (attachment anxiety), and middle-aged adults (26–41) reported significantly higher levels of trust in AI compared to both younger and older groups. These patterns are consistent with prior psychological and sociotechnical literature, which suggests that attachment anxiety typically declines with age, while trust in technology tends to peak during stages of life when individuals have both exposure and professional engagement with emerging tools like AI.

While other attachment styles (secure, dismissive, fearful) and anthropomorphism scores did not significantly differ across age groups, this too is in line with research showing that these variables tend to remain relatively stable throughout adulthood. Together, these results highlight important developmental and generational differences in how people emotionally relate to both other humans and intelligent machines. The findings have implications for mental health professionals, human-computer interaction designers, and developers working on AI trustworthiness. This suggests that both emotional maturity and age-based familiarity with AI systems play a role in shaping user perceptions and behavior. These findings should be interpreted as preliminary and require replication in larger and more diverse samples.

5.1 Limitations

1. Small Sample Size and Sampling Method: There were a total of 92 participants in the study; this relatively small sample size limits the ability to draw broadly generalizable conclusions. Although a larger number of individuals were approached through the snowball recruitment process, only 92 participants completed the survey in full and met inclusion criteria. This discrepancy reflects typical completion challenges in voluntary online survey research. Since each age group consisted of a relatively small number of participants, statistical power was reduced, particularly for detecting smaller effects. This limitation is consistent with the a priori power analysis, which indicated that a larger sample size would be required to detect medium-sized effects with adequate statistical power. Although the sample size was adequate for detecting large effects, it was underpowered to reliably detect small-to-medium effect sizes. Additionally, snowball sampling reduces representativeness, as recruitment may be biased toward individuals within shared social networks. The non-random nature of this sampling method limits generalizability to the broader population. Consequently, nonsignificant findings should be interpreted cautiously, and future research with larger, more diverse samples is needed.
2. Age Range Restriction: The participants in the study were not older than 57 years. Adults over 60 were deliberately excluded from this research. This older demographic may differ significantly in both attachment tendencies and trust in AI. According to Chopik et al. (2012), older adults tend to have lower anxiety associated with attachment. Additionally, older participants tend to trust AI less than younger participants (Kullgren et al., 2025). Consequently, this age restriction critically

limits the study's ability to fully understand and generalize trends related to attachment and AI trust across the complete spectrum of the adult lifespan, particularly concerning the growing older adult population and their unique perspectives on AI adoption.

3. Self-Report Bias: All metrics were derived from self-report questionnaires. These methods are inherently vulnerable to various systemic errors, one being social desirability bias, where participants alter their responses to align with perceived social norms or expectations, rather than reporting true opinions or behaviours. Furthermore, the reliance on participants' memory makes the data susceptible to recall inaccuracies (or recall bias), particularly when assessing behaviors or events over extended periods. Additionally, individuals may have restricted introspective access to their own internal states or the reasons for their behaviors, further limiting the accuracy of their self-perceptions. These combined factors have the potential to seriously compromise the overall validity and reliability of the collected data and the subsequent study conclusions.
4. Cross-Sectional Design: The study utilized a cross-sectional design, which inhibits the evaluation of how participants' attachment styles and trust in AI may change over time. Longitudinal designs are essential to document temporal variations in attitudes or behaviors regarding AI.
5. Lack of Standardized Measures for AI Trust: There are no widely validated and standardized scales for measuring AI usage and trust because trust in AI is an emerging field of study. There are some standardsized general scales for trust, such as the Interpersonal Trust Scale (ITS), developed by Rotter (1967), and the Propensity to Trust Scale (PTS) developed by Frazier et al. (2013), but nothing is widely validated for trust in AI specifically. Consequently, the study depended on the KPMG report (Gillespie et al., 2025), which focuses on AI and was the most appropriate source available. However, the lack of a standardized scale makes the results less generalizable across different studies.This dependence highlights the necessity for more rigorous and validated instruments in subsequent research.
6. Lack of Validated Anthropomorphism Measures: Anthropomorphism in human–technology interaction has been widely studied; however, standardized instruments specifically designed for contemporary AI systems, particularly conversational and generative AI, remain comparatively limited. Existing measures, such as the Anthropomorphic Tendencies Scale (Chin et al., 2005) and the Specific Object Anthropomorphism Scale (SOAS; David et al., 2025), provide validated approaches for assessing humanlike attributions toward nonhuman entities. However, these instruments were not originally developed for modern AI systems characterized by dynamic, language-based interaction. Consequently, the present study employed adapted items to better capture anthropomorphic perceptions in the context of current AI technologies. Although internal consistency was acceptable in the present sample, the lack of extensive prior validation may limit comparability with other studies. Future research should prioritize further validation of anthropomorphism measures specifically tailored to AI contexts.
7. Regression Model Limitations: Although regression analysis was conducted to examine whether attachment styles predicted anthropomorphism, the overall regression model was not statistically significant. This suggests that the predictive relationships observed may be weak or influenced by sample size limitations. Therefore, these findings should be interpreted cautiously, and future research with larger samples is needed to confirm these relationships.
8. Lack of Covariate Controls: The present study did not control for potential covariates such as gender, education level, or prior familiarity with AI, which may influence both trust and anthropomorphic perceptions. These factors could contribute to individual differences in how AI systems are perceived and evaluated. Future research should incorporate these variables as covariates to better isolate the effects of attachment and age on trust and anthropomorphism toward AI.

5.2 Future Research and Recommendations

1. Longitudinal Approaches: Subsequent studies should track how attachment styles, AI trust, and anthropomorphic perceptions evolve to better understand developmental and experiential changes across the lifespan.
2. Cross-Cultural Comparison: Research should explore whether age-related patterns in attachment, trust in AI, and anthropomorphism are consistent across cultures with varying technological frameworks and cultural norms pertaining to AI use.
3. Expanded Age Range: Including adults over 60 would help capture late-life shifts in trust, attachment tendencies, digital literacy, and anthropomorphism toward AI.
4. Development of Standardized Measures: There is a significant demand for empirically validated scales that evaluate both trust in AI and anthropomorphism towards AI. Future researchers should prioritize the development and validation of standardized instruments to enhance measurement reliability, enable cross-study comparisons, and reinforce theoretical clarity in this nascent field.
5. Design age-sensitive AI interfaces by incorporating transparency and reliability cues for older adults and personalization features for younger users.
6. Tailor digital mental health and support tools to account for individuals' attachment styles and emotional needs, enabling more effective and ethical AI-based interventions.
7. Implement AI literacy and education initiatives to reduce unwarranted skepticism or overtrust, particularly among older adults with limited familiarity with AI systems.

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APPENDIX

APPENDIX A
Anthropomorphism Scale

(All items are on a Likert scale of 1 = Strongly Disagree, 2 = Disagree, 3= Neutral, 4 = Agree, 5 = Strongly Agree)

1. AI seems to have a mind of its own
2. AI can understand what I am thinking.
3. I believe the AI makes decisions based on its own intentions.
4. I feel that AI has preferences or goals.
5. I would feel bad if I were rude to AI.
6. I talk to AI as if it were a person.
7. I give AI a name or personality.
8. When I interact with AI, I feel like I’m talking to someone, not something.
9. AI deserves to be treated with respect.
10. I would feel guilty if I ignored or disrespected AI.

APPENDIX B
Trust in Artificial Intelligence Scale

Trust in artificial intelligence was assessed using items adapted from the KPMG Trust in Artificial Intelligence Survey (Gillespie et al., 2025).

Participants responded to the following prompt:

How important are the following factors for you to trust artificial intelligence systems?

Responses were recorded using a 5-point Likert scale:

1 = Not at all important
2 = Slightly important
3 = Moderately important
4 = Highly important
5 = Extremely important

Items:

1. Data privacy and security
2. Technical robustness and safety
3. Transparency and explainability
4. Risk and impact mitigation
5. Accountability and contestability
6. Human agency and oversight
7. Fairness, inclusion, and non-discrimination
8. AI literacy
9. Ethical code of conduct and governance