Attachment to Artificial Intelligence: Development of the AI Attachment Scale, Construct Validation, and Psychological Correlates

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Abstract

Artificial intelligence (AI) systems are increasingly integrated into daily life, not only as tools but also as social partners that people may turn to for interaction and support. This raises important questions about whether, how, and why individuals form attachment-like bonds with AI, and what psychological implications such attachments may carry. Across five studies involving 1259 participants from Singapore and the US, the current work developed and validated the AI Attachment Scale and investigated the dispositional and motivational factors that predict attachment to AI, as well as its emotional and social outcomes. The AI Attachment Scale displayed strong psychometrics properties, including a reliable three-factor structure comprising of emotional closeness, social substitution, and normative regard subscales, strong convergent validity and discriminant validity, and high test–retest reliability. Examination of correlates revealed that time spent on AI, particularly for socioemotional purposes, was a strong predictor of AI attachment. Individuals higher in social anxiety, loneliness, and anxious attachment were also more likely to turn to AI as a compensatory surrogate when human connections were lacking. These tendencies were further linked to dispositional needs that AI fulfils, including closure through predictability, relatedness through socioemotional presence, and competence through affirming feedback. At the same time, stronger AI attachment is associated with heightened positive affect and life satisfaction, suggesting that AI attachment may satisfy the psychological needs and provide meaningful emotional benefits. These findings provide the first validated measure of attachment to AI and offer a foundation for future research on its psychological and societal implications.

Keywords. artificial intelligence, attachment, emotional closeness, social substitution, scale validation

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Artificial intelligence (AI) has become deeply embedded in everyday life, shaping the way people access information, automate tasks, and interact with digital systems (Lee, 2020; Poola, 2017; Raees et al., 2024). From voice assistants and chatbots to personalised recommendations and smart home devices, AI is now a familiar presence across multiple domains (Al-Emran et al., 2024; Bălan, 2023; Gupta et al., 2020). One of the most notable developments in recent years is the emergence of generative AI, which enables real-time, adaptive conversations rather than simply executing predefined commands (Chakraborty et al., 2023; Devi et al., 2023). Unlike traditional AI models that rely on fixed scripts, generative AI can analyse user input, detect sentiments of users, and tailor responses dynamically (Jang et al., 2024; Lund & Wang, 2023; Menon & Shilpa, 2023), making interactions feel more natural and human-like. As AI becomes more conversational and responsive, more people are beginning to use it for complex problem-solving, emotional support, learning assistance, and creative collaboration (Dahri et al., 2025; Wei et al., 2025). However, despite these advantages, the growing use of AI has raised questions about whether frequent AI use may influence human thought (e.g., through cognitive offloading), behaviour (e.g., reliance on AI for emotional or informational support), and relationships (e.g., inclusion of AI chatbots as companions), with prior work highlighting both potential benefits, such as increased accessibility of support (Brotosaputro et al., 2024; Shuford, 2023), and risks, such as reduced offline social engagement (Namvarpour, 2025).

One area that has received growing attention is the possibility that individuals may form emotional attachments to AI (Boine, 2023; Cherelus, 2024; Samuel, 2024). For example, users of Replika, an AI companion, have reported experiencing deep emotional connections, with some even referring to their AI as a significant other (Ho et al. 2025;

Laestadius et al., 2024; Skjuve et al., 2021). Even task-oriented generative AI models such as ChatGPT or Gemini have, after prolonged interaction, prompted emotional bonds (Huang & Huang, 2024; Zahira et al., 2023), especially following the introduction of voice capabilities (Duffy, 2024; Scharth, 2024; Todd, 2024). As prior research shows excessive dependence on technology can reduce interpersonal interaction and weaken social skills (Chen et al., 2021; Nizamani et al., 2024), similar patterns observed in AI interactions have led to growing concern that individuals may opt for these emotionally predictable agents over the complexities of human relationships (Goh et al., 2025; Huang et al., 2024). Indeed, extreme cases have emerged in which users developed such strong attachments to AI chatbots that they left their spouses (Roose, 2023) or took their own lives after being encouraged by the AI (Atillah, 2023; Montgomery, 2024). Taken together, these developments raise the possibility that getting attached to AI could, over time, undermine emotional resilience, displace investment in human relationships, and alter how individuals navigate intimacy and social connection. With AI systems becoming increasingly sophisticated and human-like in their responsiveness, the growing adoption of these technologies raises particular concern in situations where reduced investment in human relationships or diminished emotional resilience is seen as undesirable.

Despite the potential psychological and societal risks associated with emotional attachment to AI, there is currently no dedicated scale to measure it, making it difficult to systematically investigate its underlying mechanisms or consequences. While a handful of studies have attempted to examine attachment-related tendencies to AI, they tend to focus on specific contexts, such as customer service agents, therapeutic bots, or AI companions in gaming environments (Gillath et al., 2021; Yim et al., 2024). Furthermore, existing studies primarily adapt attachment scales originally designed for human-to-human relationships by substituting terminology relevant to AI (Yang & Oshio, 2025), which may overlook relational dynamics unique to AI attachment. AI agents differ from interpersonal or parasocial figures in being non-human yet consistently simulative of humanlike responsiveness, availability, and affirmation (Hu et al., 2025; Ventura et al., 2025; Wu et al., 2025). Parasocial attachments are more common among individuals who are drawn to admired or aspirational figures, and those who seek identification with the status, lifestyle, or values of distant figures such as celebrities or influencers. By contrast, attachment to AI may be more likely among individuals who place greater value on predictability and reciprocity in their social interactions, such as those who prefer guaranteed responsiveness, personalised feedback, and consistent availability. These differences suggest that attachment to AI represents a distinct form of relational bonding that cannot be adequately captured by existing attachment measures. Addressing this gap is necessary not only for conceptual clarity but also to enable empirical research on the psychological, behavioural, and social outcomes that may arise from such attachment. The current study therefore aims to develop and validate a psychometric tool specifically designed to assess attachment to AI, and to examine its associations with relevant psychological correlates. We adopt the theoretical foundations of attachment theory, while extending its application to a non-human, socially meaningful agent that, despite lacking consciousness, can simulate responsiveness and relational consistency in ways that foster perceived connection.

Attachment to AI

Drawing on foundational theories of attachment (Bowlby, 1969; Bowlby, 1988; Ainsworth, 1978), attachment to AI in the present research is conceptualised as reflecting a growing tendency by individuals to get attached to AI agents, relating to them as psychologically, social and morally meaningful entities. This includes feeling emotionally close to AI, engaging with it as a substitute or supplement to social interaction, and regarding it as deserving of appropriate treatment, experiences typically associated with human-to-human attachment relationships. As AI systems become increasingly embedded in daily life, supporting activities such as communication, emotional companionship, and decision-making (Lee, 2020; Poola, 2017; Raees et al., 2024), their consistent presence and responsiveness may gradually foster attachment. However, unlike traditional attachment figures such as humans or even pets, AI lacks actual human sentience or true reciprocal emotional capacity and is based on programmed responses, despite its simulating life-like replies (Lavelle, 2020; Shank et al., 2019), raising important questions about the psychological, social, and behavioural implications of forming attachment bonds with artificial entities.

Attachment, as originally defined by Bowlby (1969), refers to the emotional bond that forms between individuals, characterised by proximity-seeking behaviour, a sense of safety in the presence of the attachment figure, distress upon separation, and the use of the attachment figure as a secure base for exploration. Although attachment figures were initially defined as humans (Schneider, 1991; Shaver et al., 2008), subsequent research has expanded the scope of attachment to include non-human entities such as pets (Zilcha-Mano et al., 2011; Zilcha-Mano et al., 2012), deities (Beck, 2006; Sim & Loh, 2003), celebrities (Giles & Maltby, 2004; Stever, 2011), and even fictional characters (Rain & Mar, 2021; Rain et al., 2017). While these figures are often either non-sentient, lack emotional expressiveness, or are incapable of reciprocal interaction (Hoffner & Buchanan, 2005; Julius et al., 2012), research indicates that such figures can still fulfil core attachment functions, including providing a perceived safe haven in times of distress and serving as a symbolic secure base that facilitates emotional regulation and psychological comfort (Keefer et al., 2014; Kurdek & Kazak, 2009). This broadening of the attachment construct offers a conceptual foundation for understanding how attachment bonds may also emerge in the context of human–AI relationships.

In particular, pet attachment offers a particularly useful framework for theorising attachment to AI. Pets, though non-human, can display socially meaningful behaviours that elicit emotional bonds (Kurdek, 2008; Nagasawa et al., 2015; Sable, 2013). Similar to AI agents, pets are perceived as responsive, emotionally present, and capable of providing comfort and companionship, despite lacking full human-like cognition (Borgi & Cirulli, 2016; Prato-Previde et al., 2022). Importantly, the human–pet relationship is marked by relational asymmetry: humans typically retain ownership and control, mirroring human–AI interactions where the user often commands, and manages the AI agent. Furthermore, pets often offer social support without the complexity, unpredictability, or risk of rejection commonly associated with human attachment figures (Krause-Parello, 2012; McConnell et al., 2011; Zilcha-Mano et al., 2012), a parallel that may also apply to AI agents, which provide emotionally consistent interactions without distancing or conditional engagement. Additionally, unlike traditional interpersonal attachment, which generally assumes mutual autonomy and emotional reciprocity between two sentient humans (Deci & Ryan, 2014; Holmes, 1997), both pet and AI attachment involve relational structures where the human holds significantly more agency than the non-human target. It is, however, important to note that AI differs from pets such that AI agents simulate humanlike dialogue, emotion, and intentionality to a far greater extent than pets, potentially engaging social-cognitive systems evolved for human interaction rather than for interspecies bonds. At the same time, pets are embodied, tactile beings that require physical care and can provide warmth and comfort, relational dimensions not present in generative AI interactions.

Accordingly, the present research conceptualises attachment to AI by drawing on pet attachment frameworks, consisting of emotional closeness, substitute for human companionship, and the extension of personal regard or perceived moral consideration toward the AI agent. This definition draws from prior work on pet attachment, in particular the

Lexington Attachment to Pets Scale (LAPS; Johnson et al., 1992) serving as a core reference in shaping both the conceptual framing and item development. Emotional closeness refers to the experience of emotional intimacy or connection with AI, which may lead individuals to over-disclose and share highly personal and sensitive information they would not normally reveal in online settings, rely on the agent for emotional regulation, or experience distress when access to the AI is disrupted. Using AI as a substitute for human companionship captures both compensatory use (in response to social isolation or rejection) and preferential use (choosing AI over available human alternatives), which may contribute to reduced social motivation, avoidance of interpersonal relationships, or increased dependency on artificial interaction. Treating AI as personally significant or morally considerable reflects a pattern of interacting with the AI as if it were deserving of care, respect, or proper treatment. While this may reflect anthropomorphic tendencies, it may also blur boundaries between AI being solely regarded as a tool to being regarded as a socially and emotionally significant partner, raising concerns about distorted moral reasoning or misplaced empathy. Through this framework, the present study aims to capture how individuals can form meaningful but potentially maladaptive attachment bonds with artificial agents, and to examine the psychological patterns and consequences that emerge from such relationships.

Antecedents and Consequences of Attachment to AI

Beyond scale development, the current work also aims to identify the possible antecedents that drive attachment to AI, as well the consequences that could arise from it. When considering antecedents of attachment to AI, the social surrogacy hypothesis (Derrick et al., 2009) offers a useful framework for understanding the psychological and motivational foundations of attachment to AI. This perspective suggests that individuals may turn to symbolic or mediated figures to fulfil social and emotional needs, particularly when meaningful human relationships are absent, strained, or emotionally costly (Derrick et al., 2009). In such contexts, people often seek alternative sources of stability and perceived social presence. Although initially applied to media use (Derrick et al., 2019; Schäfer & Eerola, 2020), this framework can be extended to interactions with AI, wherein artificial agents function as modern surrogates: consistently accessible, responsive, and seamlessly integrated into everyday life (Ventura et al., 2025; Wu et al., 2025). Their predictable behaviour, non-judgemental presence, and continual availability make AI systems especially well-suited to provide the sense of safety and consistency that characterises attachment bonds (Wu et al., 2025; Zhang & Li, 2025). Moreover, compared to the complexity, unpredictability, and potential rejection embedded in human relationships (Romero-Canyas et al., 2010; Vaillancourt et al., 2024), AI may present a lower-risk, emotionally reliable alternative. Social-surrogacy choices of this kind can be viewed as one expression of a broader adaptive inclination to secure dependable relational bonds (Allen et al., 2021; Baumeister & Leary, 1995); when preferred human partners are unavailable, the attachment system generalises to whatever agent, even non-human, that offers consistent, socially meaningful cues. Thus, attachment to AI may serve both compensatory and preferential functions, arising not only in the absence of human connection, but also when existing human relationships fail to adequately meet an individual's psychological needs.

Several psychological and situational factors may increase the likelihood of individuals forming attachments to AI, which could again be viewed through the perspective of the social surrogacy hypothesis. For instance, as the social surrogacy hypothesis suggests individuals who seek surrogate attachment figures lack satisfying attachment figures (David et al., 2019; Knowles, 2013), it is plausible that those suffering from chronic loneliness, experiences of social rejection, or low perceived social support may be more likely to turn to AI to fulfil their attachment needs as they offer consistent availability, low risk of judgement, and a controllable social presence (Ventura et al., 2025; Wu et al., 2025; Zhang & Li, 2025).

Furthermore, individuals high in attachment anxiety may also prefer AI as it enables emotional proximity without the threat of abandonment, a pattern aligned with social surrogacy mechanisms observed in relationships with pets and media figures, where emotionally supportive bonds are formed with non-threatening, reliably available targets (Gabriel et al., 2017; Liebers, 2022). People who find traditional social navigation effortful or overwhelming, such as those with neurodivergence, social anxiety, or chronic environmental isolation, may also turn to AI as a social surrogate, drawn to AI's predictable and low-demand interaction style to fulfil relational needs in ways that feel safer and more manageable than human alternatives. In addition, individuals who are predisposed to attribute psychological and social meaning to non-human agents due to traits such as empathy, openness to relational technologies, or a tendency to anthropomorphise may also be more likely to experience stronger attachment to AI.

In turn, once individuals form attachment to AI, it may have a range of psychological, behavioural, and social consequences, many of which can be similarly understood through the lens of the social surrogacy hypothesis. Just as media figures or pets can provide perceived social fulfilment in the absence of human connection (Derrick et al., 2019; Gabriel et al., 2017), strong attachments to AI may offer emotional regulation, perceived companionship, and a sense of social embeddedness, particularly for those who struggle to meet relational needs through traditional means (e.g., Cann, 2025; Giordano, 2024; Yang et al., 2025). However, reliance on artificial surrogates may also dampen social initiative, reduce tolerance for emotional complexity, or contribute to avoidance of interpersonal vulnerability. Evidence from media-based social surrogacy research suggests that turning to non-human symbolic surrogates such as fictional or television characters is associated with social withdrawal tendencies (Arbeau et al., 2012; Closson et al., 2019). As such, it is possible that individuals who experience emotional closeness with AI may increasingly turn to it in moments of distress, reducing reliance on human support systems and limiting opportunities to develop interpersonal resilience (e.g., Cann, 2025; Samuel, 2024; Yang et al., 2025). Similarly, those who substitute AI for human companionship may become less inclined to engage with the demands of human relationships, such as navigating conflict, ambiguity, or rejection, potentially reinforcing avoidant relational patterns (e.g., Buontempo, 2025; Heritage, 2025; Wei, 2025). Taken together, these outcomes suggest that while AI attachment may serve adaptive short-term functions in managing relational strain, it may also recalibrate longer-term relational expectations to favour emotionally risk-free interactions, constant availability, and unilateral control, which human relationships cannot reliably provide.

The Current Study

The current study aims to develop and validate a psychometric tool for measuring attachment to AI, and to examine how it relates to both antecedents such as psychological dispositions and motivational tendencies, as well as potential consequences, including behavioural reliance, emotional outcomes, and patterns of social interaction. To this end, a series of studies will be conducted for scale development, validation, and application. Studies 1 and 2 will focus on generating and refining a multidimensional item pool to capture stable individual differences in attachment to generative AI. Study 3 will conduct an exploratory factor analysis to assess the underlying factor structure of the AI Attachment Scale. In Study 4, confirmatory factor analysis (CFA) will be used to test the scale's structural validity and psychometric robustness, as well as convergent and discriminant validity and test-retest reliability. Study 4 will also assess test–retest reliability of the scale. Study 5 will be used to investigate how attachment to AI correlates to a range of possible antecedents and consequences, such as loneliness, social anxiety, need to belong, anthropomorphic tendencies, and attachment styles. We will also test for measurement invariance across sex and cultural contexts. By developing a psychometrically sound tool, this study aims to equip researchers with a foundational measure for examining attachment with artificial agents. Beyond its theoretical contributions to attachment and human–technology interaction research, the scale may support practical efforts to anticipate or address shifts in social behaviour, emotional dependence, and relationship norms in increasingly AI-integrated societies.

Transparency and Openness (Studies 1–5)

The current study's design and analysis plan were not pre-registered. Data collection for the current work was approved by the author's university institutional review board prior to data collection [IRB-25-146-E030-M2(925)]. The relevant materials, dataset, and R analytic code will be publicly available on ResearchBox (#4639; https://researchbox.org/4639) upon publication.

All analyses for the current work were conducted in R version 4.4.3 (R Core Team, 2025). Data cleaning was performed using *dplyr* version 1.1.4 (Wickham et al., 2023), and descriptives were calculated using *psych* version 2.5.3 (Revelle, 2024). Data visualisations were created using the *ggplot2* version 3.5.2 (Wickham, 2016). Confirmatory factor analyses were conducted using the *lavaan* package version 0.6-19 (Rosseel, 2012). Intra-class correlation coefficients (ICC) for test-retest reliability were calculated using *merTools* version 0.6.2 (Knowles et al., 2024).

Study 1: Scale Development, Content Validation, and Item Refinement

Method

Item Generation

An initial pool of approximately 50 items was developed for the AI attachment scale through a theory-driven process. A theory workbook was created to guide item generation, drawing from established frameworks of attachment (e.g., Bowlby, 1969; Ainsworth, 1979), with a focus on pet attachment measures (Johnson et al., 1992; Lexington Attachment to Pets Scale [LAPS]). Theoretical constructs such as anthropomorphism (Epley et al., 2007; Salles et al., 2020), technophilia (Martínez-Córcole et al., 2017; Osiceanu, 2015), and parasocial interaction (Dibble et al., 2016; Xu et al., 2023) were also reviewed to refine the operational definition of attachment to AI. Items were edited to reflect AI-specific characteristics, such as the ability to simulate reciprocal social responses, including verbal interaction and adaptive feedback, unlike pets or inanimate technologies.

Expert Review & Item Refinement

The item pool underwent multiple rounds of revision based on feedback from three senior scholars and two graduate students with expertise in psychological scale development and technology use. Items were evaluated for clarity, redundancy, and theoretical alignment, resulting in a set of 30 items that reflected comprehensive coverage of the construct. Specifically, 10 items were drafted for each of the three proposed dimensions of attachment to AI (emotional closeness, social substitution, and normative regard), ensuring that each aspect of the construct was adequately represented. This balanced distribution was intended to provide both theoretical breadth and empirical comparability across the dimensions.

Results and Discussion

Readability Analysis

A readability analysis was then conducted using the Flesch-Kincaid metrics, which estimate reading difficulty based on average syllables per word and words per sentence (Ravens-Sieberer et al., 2014). Prior research suggests that the average adult in the United States reads at roughly a 7th-grade level, with a Flesch Reading Ease score between 60 and 70 (Stockmeyer, 2009). The final scale achieved a Flesch-Kincaid Grade Level of 5.3 and a Reading Ease score of 75.2, indicating that the items are easily understood by a general U.S. population. Furthermore, research indicates that readability benchmarks for native English speakers (such as US populations) are also comparable with non-native English speakers (Prakash, 2025), supporting the scale's applicability across diverse participant groups. While readability scores alone do not guarantee conceptual clarity, ensuring items are easy to process helps increases the likelihood that respondents will understand and interpret the items as intended.

Content Validity Assessment

Further content validation was carried out following methods outlined by Anderson and Gerbing (1991), and the evaluation guidelines indicated by Colquitt et al. (2019). As recommended by Anderson and Garbing (1991) in their approach, this study employed individuals unfamiliar with the constructs as evaluators. Accordingly, six undergraduate students were engaged to serve as judges. Each rater received both a set of descriptions outlining the different dimensions of the AI attachment scale (i.e., emotional closeness, social substitution, normative regard) and the pool of drafted items. Their task was to review the items and assign each one to the dimension they believed it best represented.

To evaluate content adequacy, two indices were employed: the proportion of substantive agreement (p_{sa}) and the substantive validity coefficient (c_{sv}). The p_{sa} was computed as the proportion of judges who assigned an item to its intended dimension, whereas the c_{sv} was derived by subtracting the highest number of alternative assignments from the number of correct assignments and dividing this value by the total number of judges (Colquitt et al., 2019). In line with Colquitt and colleagues' (2019) guidelines, items were retained only if they exceeded the cut-offs of .72 for p_{sa} and .51 for c_{sv}. All items in the present study surpassed these thresholds, with values greater than .83 on both indices, allowing the full set of 30 items to be carried forward (refer to Supplement 1 in ResearchBox #4639 for the full item set).

Study 2: Preliminary Item Evaluation

Following the generation and content validation of items in Study 1, Study 2 was designed as a preliminary evaluation of the scale. Specifically, this study aimed to pilot test the item pool with a small sample of participants to examine whether the items were understandable, to evaluate their distributional properties, and to identify any potential issues such as floor or ceiling effects.

Method

Participants & Procedure

To further evaluate item performance and optimise wording clarity, a total of 62 participants ($n_{\text{Singapore}}$=30 and n_{US}=32 participants) were recruited. Singaporean participants were recruited through convenience sampling from a local university in Singapore, using word-of-mouth and peer referrals, while US participants were recruited via Prolific. This sample size is considered adequate for initial item review and qualitative feedback during early scale development, consistent with recommendations for preliminary item testing before factor analysis (Boateng et al., 2018). Data collection was conducted via an online survey hosted on Qualtrics. Participants were presented with the 30-item version of the AI attachment scale, and instructed to complete the survey remotely on their personal devices, at a time and location of their choosing. Prior to rating the items, they were shown a brief preamble defining generative AI in accessible language. Items were then presented in randomised order and rated on a 5-point Likert scale (1=*Strongly disagree*, 5=*Strongly agree*).

Analytic Plan

The primary aim of Study 2 was to evaluate the clarity, distribution, and overall performance of the initial item pool. Descriptive statistics (means, standard deviations, minimum and maximum values) were computed for each item in the Singapore and US samples separately. Subsequently, histograms were generated to visually inspect the distribution of responses and assess whether items show evidence of normal response patterns as well as any potential floor or ceiling effects. Only items that perform consistently across both the Singaporean and US samples were retained for subsequent studies to ensure applicability in different cultural contexts.

Results and Discussion

In the Singapore sample, item standard deviations ranged from 1.02 to 1.50, and skewness values ranged from -0.64 to 2.66 (M_{SD}≈1.24, M_{skew}≈0.48), and full observed ranges for 25 out of 30 items. In the US sample, item standard deviations ranged from 1.04 to 1.57, and skewness values ranged from -1.08 to 1.22 (M_{SD}≈1.38, M_{skew}≈0.19), and full observed ranges for all items. Histograms for each item were additionally inspected to check distributional patterns (see Supplement 2). Upon inspection of both skewness values and item distributions, three items with extreme skewness were removed from the scale, resulting in a revised scale of 27 items, with 9 items per dimension (see Supplement 3 for full item set). After item removal, the remaining items showed distributions that were neither highly skewed nor restricted in range (Singapore: M_{SD}≈1.26, Range_{SD}=[1.02, 1.50], M_{skew}≈0.30, Range_{skew}=[-0.64, 1.12]; US: M_{SD}≈1.40, Range_{SD}=[1.04, 1.57], M_{skew}≈0.10, Range_{skew}=[-1.08, 0.95]), and visual inspection confirmed response patterns consistent with the intended constructs. Thus, the refined pool was conceptually and linguistically clear and suitable for subsequent psychometric validation.

Study 3: Exploratory Factor Analysis

Following the findings from Study 1 and Study 2, Study 3 was conducted to examine the underlying factor structure of revised Attachment to AI Scale using exploratory factor analysis (EFA). To strengthen the generalisability of the results, samples were drawn from both Singapore and the United States, allowing the factor structure to be evaluated across distinct cultural contexts.

Method

Participants & Procedure

Study 3 recruited two independent samples, one in Singapore and one in the United States, to ensure that refinement of the scale's factor structure was evaluated in a manner compatible across cultural contexts. Following guidelines recommending a minimum of 10 participants per item for exploratory factor analysis (Boateng et al., 2018), the target sample size was set at 270.The final samples consisted of 339 participants (M_{age}=24.43, SD_{age}=4.49, $range_{age}$=[18-39]) from Singapore and 302 participants (M_{age}=41.48, SD_{age}=12.39, $range_{age}$=[19-78]) from the US (refer to Supplement 4 for participant demographics). In Singapore, participants were drawn from local universities using online subject pool system or Telegram channels. In the United States, participants were recruited through the crowdsourcing platform Prolific. To ensure participants had sufficient familiarity with AI, only individuals who reported using generative AI at least once a week were eligible to take part. Informed consent was obtained electronically from all participants prior to the start of the survey. In exchange for their participation, participants in the Singapore sample received 2 SGD, while participants in the US sample received 1.55 USD.

Measures

Attachment to AI. Attachment to AI was measured using the revised 27-item version of the Attachment to AI Scale developed in Study 2. Items were rated on a 5-point Likert scale (1=*Strongly disagree*, 5=*Strongly agree*).

Demographics. Participants were asked to report their demographic information, including age, sex (male or female), ethnicity, and nationality, as well as objective and subjective social status. Objective social status was measured using a single item assessing monthly household income on a six-point scale (1=*Less than 2,000 SGD*, 6=*More than 20,000 SGD*) for the Singapore sample, and a single item assessing yearly household income on an eight-point scale (1=*Less than 15,000 USD*, 8=*More than 150,000 USD*) for the US sample . Subjective social status was measured using the MacArthur Scale of Subjective Social Status (Adler et al., 2000), where participants will indicate their perceived standing in society on a 10-point scale (1=*Lowest status*, 10=*Highest status*).

Analytic Plan

EFA. An exploratory factor analysis (EFA) was conducted to examine the underlying structure of the revised AI attachment scale. This approach allows the identification of latent dimensions without imposing a pre-defined structure, enabling the detection of cross-loadings, weak items, or unexpected loading patterns prior to confirmatory testing. Separate EFAs were conducted for the Singaporean and U.S. samples to ensure that the factor structure is broadly comparable across cultural contexts and to inform item trimming in a culturally sensitive manner. To further evaluate the cross-cultural applicability of the scale, measurement invariance testing was also conducted following EFA, allowing us to identify items that do not function equivalently across groups, thereby ensuring that the final scale retains only items that are invariant and thus interpretable across both samples.

To assess the suitability of the data for factor analysis, Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was first computed. A significant Bartlett's test and KMO values exceeding .60 indicate that the data are adequately factorable (Shrestha, 2021). EFA was then performed using principal axis factoring with oblimin rotation, which allows for correlation among factors. The number of factors to retain was determined using a combination of visual inspection of the scree plot, retaining factors up to the point at which eigenvalues drop sharply before levelling off (Shrestha, 2021), as well as the Bayesian Information Criterion (BIC; Preacher et al., 2013) and theoretical interpretability.

Measurement Invariance. Measurement invariance across sex (male and female) and culture (U.S. and Singapore) was tested using multi-group CFA. For comparisons across cultures, Singapore sample and US sample of the current study were used. The first step involved assessing configural invariance, which tests whether the same factor structure holds across groups without any parameter constraints. Model fit was evaluated using commonly accepted thresholds: comparative fit index (CFI) and Tucker–Lewis index (TLI) values ≥ .90 (Hopwood & Donnellan, 2010; Perry et al., 2015), and root mean square error of approximation (RMSEA) ≤ .06 and standardised root mean square residual (SRMR) ≤ .08 (Hu & Bentler, 1999; Shi & Maydeu-Olivares, 2020). Metric (weak) invariance was then tested by constraining factor loadings to be equal across groups and comparing to the configural model. Scalar (strong) invariance was tested next by constraining both factor loadings and item intercepts to equality and comparing to the metric model. A model was considered to demonstrate invariance if the comparative fit index changes by no more than .01 (ΔCFI≤.01), and if the model shows lower AIC and BIC values relative to the less constrained model (Cao & Liang, 2022; Cheung et al., 2024). If scalar invariance was not fully supported, partial scalar invariance was explored by selectively freeing specific intercept constraints based on model modification indices and comparative fit improvements. Finally, residual (strict) invariance was tested by constraining both item residuals and residual covariances to equality across groups and comparing this model to the scalar invariance model.

Results and Discussion

Exploratory Factor Analysis

The factorability of the data was first examine. For the Singapore sample, the KMO value (.96) was excellent, with all individual item KMOs exceeding .88, and Bartlett's test was significant ($\chi^2(351)=5557$, $p<.001$). For the US sample, the KMO value (.97) was similarly excellent, with all individual item KMOs exceeding .94, and Bartlett's test was significant ($\chi^2(351)=7703$, $p<.001$). This indicated that data in both samples were suitable for factor analysis.

Factor retention decisions were based on both scree plot examination (see Figure 1) and BIC values. While the scree-plot suggested a three-factor solution, both two- and three-factor solutions were examined. In the Singapore sample, the two-factor solution showed the lowest BIC (-1032), followed by the three-factor model (-1016). In the US sample, the three-factor model was strongly favoured, with the lowest BIC (-853), as compared to the two-factor model (-785.1). Given strong theoretical support for a three-factor structure, as well as the US sample clearly favouring the three-factor model, the three-factor solution was retained. Iterative re-analysis was conducted in both samples until all items demonstrated substantial primary factor loadings (>.45), minimal cross-loadings (<.35), and communalities >.43 in both Singapore and US samples. The final EFA yielded a 15-item, three-factor scale that accounted for 58% variance in the Singapore sample, and 70% variance in the US sample. This structure also aligned with the theoretical dimensions of the construct and was retained for confirmatory factor analysis. Factor intercorrelations ranged from .35 to .77 (Singapore) and .56 to .77 (US), consistent with a multidimensional but related construct. Internal consistency was examined with Cronbach's α for each subscale and the total scale. The three subscales demonstrated good reliability (Singapore: α=.85–.92; US: α=.91–.94), and the overall 15-item also displayed good reliability (Singapore: α=.95; US: α=.97). The final 15 items are presented in Table 1, and the factor loadings of the final EFA for both samples are presented in Supplement 5.

Figure 1

Scree Plot for EFA

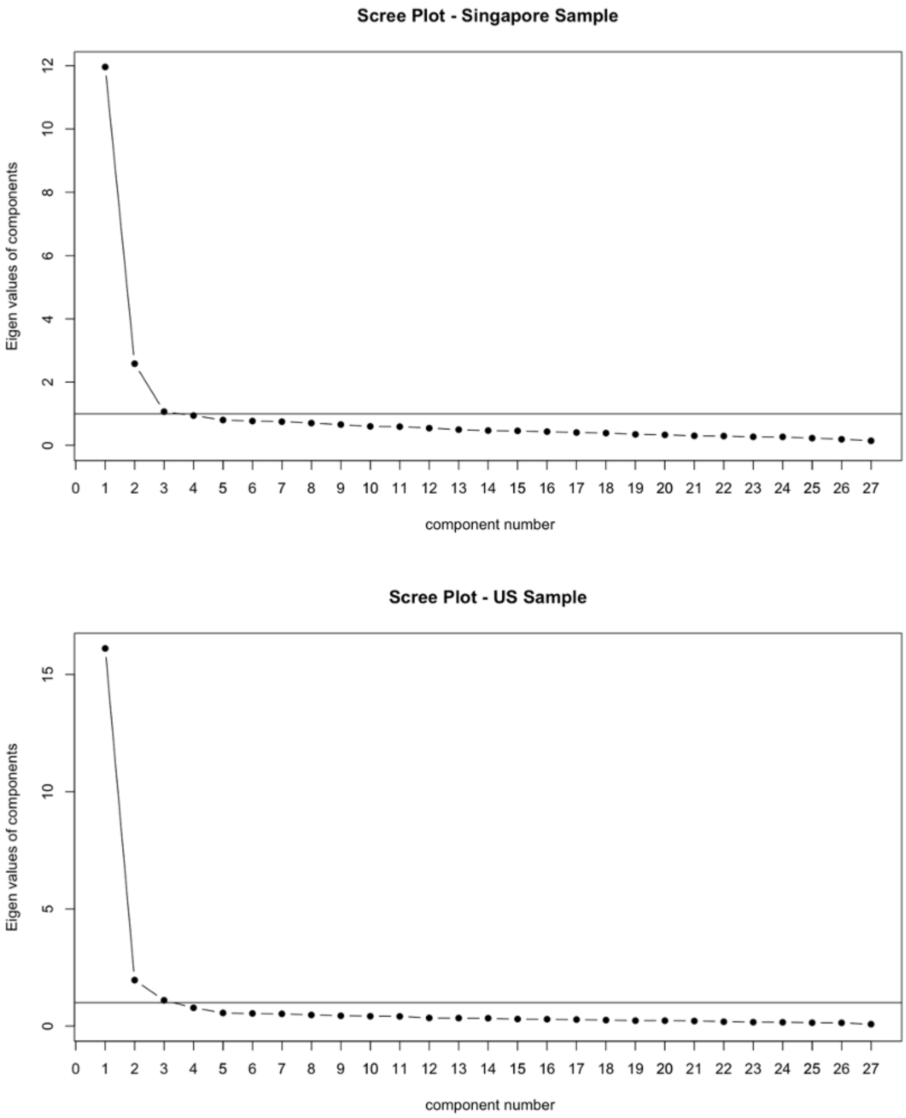

Table 1

Final Items of the AI Attachment Scale

Artificial intelligence (AI) refers to computer systems designed to perform tasks that typically require human intelligence. This questionnaire focuses on generative AI; systems that produce text, images, or other content in response to user input by drawing on patterns learned from existing large datasets from the internet. Examples include ChatGPT, Replika, DALL·E, DeepSeek, and similar technologies that simulate conversation. Please think of the generative AI system/systems you use most often and rate how much you agree or disagree with each of the following statements based on your experience.

	1 = Strongly disagree	2 = Disagree	3 = Neither agree nor disagree	4 = Agree	5 = Strongly agree
Emotional Closeness					
My exchanges with AI feel personally meaningful.	☐	☐	☐	☐	☐
There is a sense of familiarity in how I engage with AI.	☐	☐	☐	☐	☐
I look forward to interacting with AI.	☐	☐	☐	☐	☐
I feel a sense of closeness and comfort in my interactions with AI.	☐	☐	☐	☐	☐
I would feel uneasy if AI suddenly became unavailable.	☐	☐	☐	☐	☐
Social Substitution					
I sometimes find myself turning to AI when I need someone to talk to.	☐	☐	☐	☐	☐
I often talk to AI when I face problems.	☐	☐	☐	☐	☐
I sometimes prefer talking to AI because I don’t have to worry about being judged.	☐	☐	☐	☐	☐
I turn to AI when I feel unsupported by people in my life.	☐	☐	☐	☐	☐
When there’s no one to talk to, I sometimes end up interacting with AI.	☐	☐	☐	☐	☐
Normative Regard					
I try to treat AI respectfully.	☐	☐	☐	☐	☐

It feels wrong to be dismissive when responding to AI.	☐	☐	☐	☐	☐
I try not to be rude to AI, even if it doesn't understand me.	☐	☐	☐	☐	☐
I act friendly towards AI.	☐	☐	☐	☐	☐
I think it's important to be considerate when talking to AI.	☐	☐	☐	☐	☐

Measurement Invariance

Sex. The baseline configural model, estimated without cross-group constraints, showed good fit ($\chi^2(174)=395.31$, $p<.001$, CFI=.97, TLI=.96, RMSEA=.06, SRMR=.04), suggesting that the proposed three-factor structure was consistent for both males and females. After imposing equality constraints on factor loadings, metric invariance was supported, as indicated by a minimal change in fit (ΔCFI=.001) alongside lower BIC values. Scalar invariance was likewise upheld (ΔCFI=.004), with further reductions in BIC. Finally, residual invariance was achieved (ΔCFI=.001), again with lower BIC values. Taken together, these findings indicate that scalar invariance across sex was established, permitting valid comparisons between male and female participants (see Table 2).

Culture. The configural model showed good fit ($\chi^2(174)=463.44$, $p<.001$, CFI=.96, TLI=.95, RMSEA=.07, SRMR=.05), indicating that the proposed three-factor structure was consistent across cultures. Metric invariance was supported as the metric model resulted in only a small change in fit (ΔCFI=.003) and lower BIC values. Scalar invariance for the full model was not supported (ΔCFI=.015) with a higher BIC value. Modification indices suggested intercept non-invariance in one item ("I feel a sense of closeness and comfort in my interactions with AI"). Freeing the intercept of the item lead to partial scalar invariance, with minimal change in fit (ΔCFI=.007) and a lower BIC value. Residual invariance was also supported for the partial model, with only a small change in fit (ΔCFI=.006) and a smaller BIC value. Overall, these results provide evidence for partial scalar invariance across cultures (Table 2).

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Table 2

Summary of Model Fit Statistics for Measurement Invariance (Study 3)

Model	Sex				Culture			
	CFI	ΔCFI	AIC	BIC	CFI	ΔCFI	AIC	BIC
Configural	.968		25179.40	25607.85	.957		25002.10	25430.55
Metric (vs Configural)	.967	.001	25165.83	25531.80	.955	.003	25005.56	25371.53
Scalar (vs Metric)[1]	.963	.004	25183.19	25500.06	.948	.007	25042.20	25363.54
Residual (vs Scalar)[1]	.964	.001	25165.47	25415.40	.941	.006	25070.85	25325.24

Note. ΔCFI=change in CFI relative to the previous model. Lower AIC and BIC values indicate better model fit. All ΔCFI values are below the recommended cutoff of .01 (Cheung & Rensvold, 2002). [1]For cultural invariance, both scalar and residual invariance model fits reported are from the partial models after freeing the intercept of one item.

Study 4: Confirmatory Factor Analysis, Construct Validation, and Test-Retest Reliability

Building on the results of Studies 1–3, Study 4 aimed to confirm the three-factor structure of the Attachment to AI Scale using confirmatory factor analysis (CFA). This stage also evaluated the construct's convergent and divergent validity to determine whether the scale demonstrated the expected theoretical relations with relevant constructs. Specifically, convergent validity was assessed through associations with AI anthropomorphism and AI interaction positivity, as perceiving AI as socially capable and engaging positively is fundamental to attachment-like processes. Divergent validity was examined through comparison with broader dispositional traits (Big Five personality traits) and related but conceptually distinct constructs (e.g., pet attachment, parasocial attachment), which, while sharing superficial similarities, differ from the relational orientation reflected in AI attachment.

Method

Participants & Procedure

Participants were recruited from a local university in Singapore through the university subject pool system. A minimum sample size of 200 participants was targeted, in line with commonly accepted guidelines for confirmatory factor analysis to achieve stable parameter estimates (MacCallum et al., 1999). A total of 255 participants took part (M_{age}=21.47, SD_{age}=2.03, range$_{age}$=[18-31]; refer to Supplement 6 for participant demographics), of whom 234 completed the second session (91.76% completion rate). To ensure sufficient familiarity with AI, only individuals who reported using generative AI at least once a week were eligible to participate. Informed consent was obtained electronically prior to participation. The study comprised two sessions, separated by a one-week interval. In the first session, participants completed the Attachment to AI Scale along with measures of convergent and divergent validity. In the second session, held one week later, participants completed only the Attachment to AI Scale. The one-week interval was chosen to balance the need to reduce potential memory-related carryover effects while still allowing meaningful assessment of stability over time (Duff, 2014; Windle, 1955). Participants received either one course credit or 5 SGD as compensation.

Measures

Attachment to AI. The revised 15-item version of the AI Attachment Scale was used to measure attachment to AI. Items were rated on a 5-point Likert scale (1=*Strongly disagree*, 5=*Strongly agree*).

AI Psychological Anthropomorphism. AI psychological anthropomorphism was measured using the 16-item AI Psychological Anthropomorphism Scale (Shen et al., 2024). Participants will be asked to indicate the extent to which they feel AI has anthropomorphic qualities (e.g., “I feel AI has the ability to think like a human”, “I feel AI can actively understand my needs”) on a five-point scale (1=*Strongly disagree*, 5=*Strongly agree*). Items were averaged to create an overall AI psychological anthropomorphism score (α=.91), with higher scores indicating higher levels of AI psychological anthropomorphism.

AI Interaction Positivity. Positivity in interaction with AI was measured using the four-item AI-Interaction Positivity Scale (Montag & Elhai, 2025). Participants were asked to indicated their agreement on four statement regarding their feelings when interactions with AI (e.g., “When I interact with products that have artificial intelligence built in, I am satisfied”, “When I interact with products that have artificial intelligence built in, I am happy”) on a five-point scale (1=*Strongly disagree*, 5=*Strongly Agree*). Items were averaged to create an overall AI interaction positivity score (α=.92), with higher scores indicating higher levels of positivity towards AI interaction.

Big Five Personality. Big Five personality traits of participants was measured using the Big Five Inventory-2-Short Scale developed by Soto and John (2017). Each subscale of the measure consisted of six items measured on a five-point scale (1=*Strongly disagree*, 5=*Strongly agree*): agreeableness ("Is compassionate, has a soft heart"; α=.74), conscientiousness ("Is reliable, can always be counted on"; α=.75), extraversion ("Is dominant, acts as a leader"; α=.79), neuroticism ("Worries a lot"; α=.81), and openness to experience ("Is fascinated by art, music, or literature"; α=.75). Items were averaged within each subscale to create overall scores for the five personality traits, with higher scores on each subscale indicated higher endorsement of the respective trait.

Pet Attachment. Pet attachment was measured using the 23-item Lexington Attachment to Pets Scale (LAPS; Johnson et al., 1992). The scale consists of three subscale, general attachment (11 items; e.g., "My pet knows when I'm feeling bad", "I often talk to other people about my pet; α=.94), people substitution (seven items; "My pet means more to me than any of my friends", "Quite often I confide in my pet"; α=.83), animal rights (five items; "I believe that pets should have the same rights and privileges as family members", "Pets deserve as much respect as humans do"; α=.85). Items were averaged within each subscale to create scores for each subscale, and the three scores from the subscales were averaged to create an overall pet attachment score, with higher scores indicating higher pet attachment.

Parasocial Attachment. Parasocial attachment was measured using the 20-item Celebrity-Persona Parasocial Interaction Scale (Reynolds et al., 2006). Participants were asked to indicate their agreement to a list of items based on their feelings and experiences regarding a public figure, celebrity or fictional character that they feel most interested in (e.g., "The celebrity/persona makes me feel as if I am with a someone I know well", "If the celebrity/persona appeared on a media program, I would watch that program") on a five-point scale (1=*Strongly disagree*, 5=*Strongly agree*). Items were averaged to create an overall parasocial attachment score (α=.90), with higher scores indicating higher tendency to form parasocial attachments.

Demographics. The demographic measures were similar to Study 3.

Analytic Plan

CFA. Confirmatory factor analysis (CFA) was conducted to evaluate the factor structure of the AI Attachment Scale. The model specified three first-order latent factors as identified in Study 3 (i.e., emotional closeness, social substitution, normative regard), with each of these factors loading onto a single second-order latent construct representing overall attachment to AI. Model fit was evaluated using commonly accepted thresholds: comparative fit index (CFI) and Tucker–Lewis index (TLI) values≥ 90 (Hopwood & Donnellan, 2010; Perry et al., 2015), and root mean square error of approximation (RMSEA) ≤.06 and standardised root mean square residual (SRMR)≤.08 (Hu & Bentler, 1999; Shi & Maydeu-Olivares, 2020). If the initial model does not meet these criteria, theory-driven modifications were considered to improve model fit while preserving conceptual coherence.

Convergent & Divergent Validity. CFA was conducted using the same model previously used during confirmatory factor analysis, with model fits evaluated similarly. To assess construct validity of the AI attachment Scale, both convergent and discriminant validity were tested within a single measurement model. The model specified a second-order latent factor representing overall AI attachment loading onto the first-order latent dimensions identified during confirmatory factor analysis. AI Psychological Anthropomorphism and AI Interaction Positivity were included as observed variables using composite scale means. The Big Five personality traits, as well as pet and parasocial attachment, were also entered as observed variables using scale means.

Convergent validity was examined by assessing the correlation between the second-order AI attachment latent factor and two theoretically related constructs: AI psychological anthropomorphism and AI interaction positivity. A moderate-to-strong positive correlation was expected with AI anthropomorphism, as perceiving AI as capable of humanlike thoughts, feelings, and intentions is a foundational prerequisite for forming emotional bonds. Without attributing internal states to AI, users are unlikely to experience the empathy, comfort, or perceived understanding that characterise attachment processes. A moderate positive correlation was also anticipated with AI interaction positivity, as individuals who are emotionally attached to AI are more likely to appraise their interactions as warm, supportive, or satisfying, reflecting the emotional valence typically associated with attachment relationships. The magnitude of associations were interpreted using effect size guidelines proposed by Funder and Ozer (2019): $|r| < .05$ (no validity), .05−.09 (very small), .10−.19 (small), .20−.29 (medium), .30−.39 (large), and ≥ .40 (very large).

Divergent validity was evaluated using the Fornell–Larcker criterion (Fornell & Larcker, 1981). Specifically, the square root of the average variance extracted (*AVE*) for each divergent validity construct (i.e., Big Five personality traits, pet attachment, parasocial attachment) was compared against their standardised correlations with the second-order AI attachment latent factor. Evidence for discriminant validity is demonstrated when $\sqrt{AVE}$ exceeds the corresponding correlation ($\sqrt{AVE} > |r|$), indicating that each construct shares more variance with its own indicators than with the AI attachment measure.

The Big Five personality traits were included as benchmarks for divergent validity, given their conceptual distinctiveness from context-specific attachment to AI. While some degree of association is plausible, these traits reflect broad dispositional patterns rather than emotionally grounded bonds with artificial agents. Openness to experience, for instance, may relate to exploratory interest in AI due to its novelty and stimulation, yet it reflects cognitive curiosity rather than affective attachment. Conscientiousness, which captures task focus and behavioural regulation, may show weak negative associations if AI attachment interferes with self-discipline, though the trait does not encompass interpersonal bonding. Extraversion involves sociability and external engagement, and lower extraversion may modestly predict AI attachment, given AI's appeal in solitary or less socially demanding contexts. However, extraversion does not reflect the emotional investment that characterises attachment constructs. Agreeableness may also correlate weakly, as more agreeable individuals tend to seek harmony and connection, but its focus on interpersonal cooperation differs from the emotional intimacy assessed by AI attachment. Neuroticism could be modestly linked to attachment insofar as individuals seek comfort, reassurance, or emotion regulation through AI; however, emotional volatility alone does not imply attachment formation. Overall, these traits serve as useful comparators, but attachment to AI is theorised as a distinct, emotionally oriented construct beyond trait-based personality.

Pet attachment was examined as a divergent construct given its grounding in human–animal bonding, which, while superficially similar, remains categorically distinct from relationships with AI. Pets elicit affection through tactile presence, reciprocal care, and embodied responsiveness (Borgi & Cirulli, 2016; Prato-Previde et al., 2022), qualities that differ fundamentally from disembodied conversational agents. Although both involve perceived comfort and companionship, attachment to animals reflects biologically ingrained caregiving and affiliative mechanisms that are not activated in the same way by artificial systems. Thus, despite some intuitive overlap, pet attachment and AI attachment represent theoretically distinct domains of emotional connection.

Parasocial attachment was also included for divergent validity, as it reflects one-sided connections with human figures (e.g., celebrities, influencers) rather than with artificial agents. Both parasocial and AI attachments involve imagined reciprocity and feelings of familiarity, but parasocial bonds are rooted in admiration, identification, and perceived intimacy with real yet inaccessible others (Dibble et al., 2016; Xu et al., 2023). In contrast, attachment to AI entails interaction with an artefact capable of simulated responsiveness but lacking human subjectivity. The distinction underscores that attraction to media figures does not necessarily generalise to emotional investment in technological systems, supporting the treatment of parasocial attachment as a divergent construct.

Test-Retest Reliability. Test–retest reliability of the AI Attachment Scale was assessed using both the intra-class correlation coefficient (ICC) and Pearson's zero-order bivariate correlation coefficient (*r*), computed between the two assessment points; initial administration of the AI Attachment Scale (baseline) and the follow-up one week later. ICC was estimated using a two-way mixed-effects model with absolute agreement to capture the extent to which individual scores remain stable across time, reflecting both consistency and agreement in measurement (Bruton et al., 2000). Interpretation of ICC values was based on the 95% confidence interval, following conventional thresholds: values below .50 indicate poor reliability, values between .50 and .75 moderate reliability, between .75 and .90 good reliability, and above .90 excellent reliability (Koo & Li, 2016). Pearson's correlation coefficient (*r*) were also calculated to evaluate the linear association between scores at the two time points. Correlation strength was interpreted in accordance with established guidelines for effect size evaluation in psychological research (Funder & Ozer, 2019).

Results and Discussion

Confirmatory Factor Analysis

The confirmatory factor analysis model evaluating the three-factor structure of the AI Attachment Scale identified in Study 3 indicated good fit to the data ($\chi^2(87)=187.77$, $p<.001$; CFI=.96; TLI=.95; RMSEA=.06; SRMR=.06), with indices meeting or closely approximating established benchmarks for adequate model fit. Although the χ^2 statistic reached significance, this outcome is common in larger samples and is often regarded cautiously given its sensitivity to sample size (Bergh, 2015). However, inspection of parameter estimates revealed a negative error variance for one Emotional Closeness item. Modification indices did not suggest a theoretically meaningful re-specification, and following recommendations in the SEM literature (Farooq, 2022), the error variance was constrained to a small positive value (.05) to yield admissible and interpretable estimates. After this adjustment, the model continued to show good fit ($\chi^2(88)=192.11$, $p<.001$; CFI=.96; TLI=.95; RMSEA=.06; SRMR=.07), and all standardised factor loadings were significant at $p<.001$, with the findings providing evidence in favour of the proposed three-factor solution. The final model is depicted in Figure 2.

Figure 2

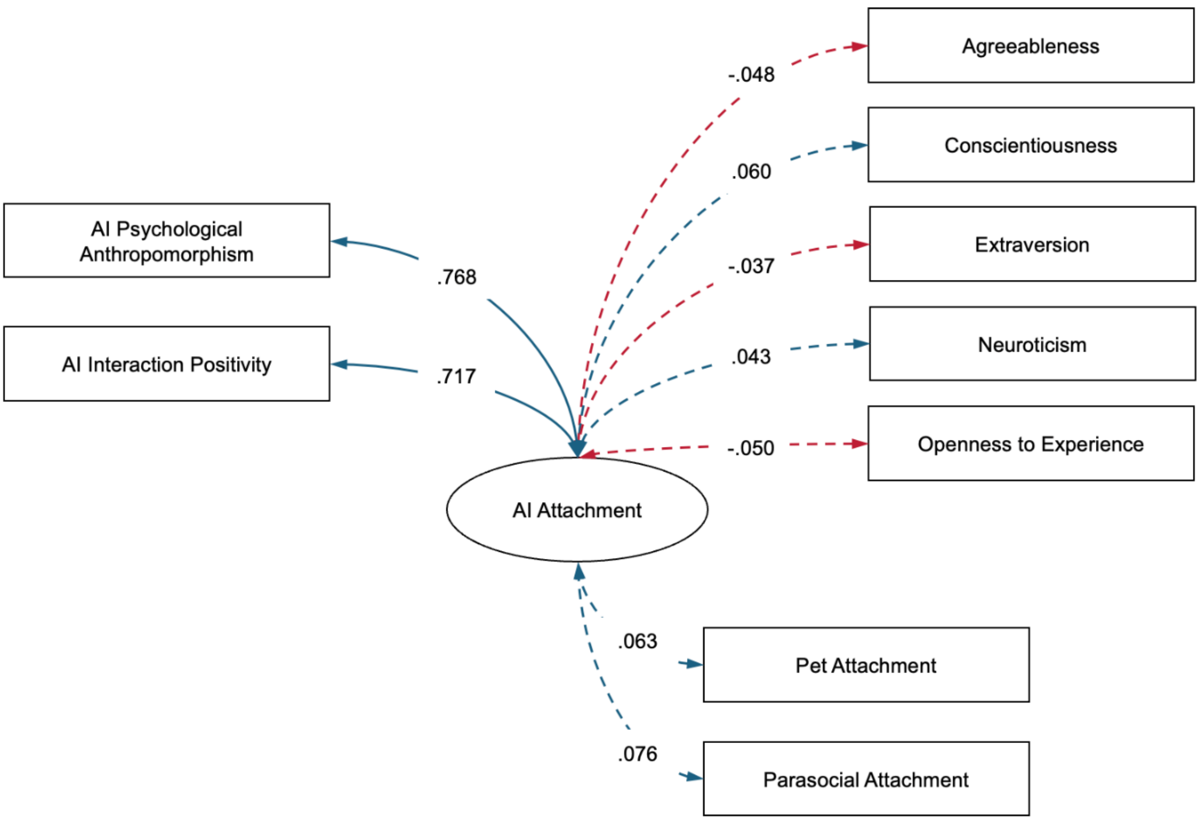
CFA Model of the AI Attachment Scale

Convergent and Divergent Validity

The model for convergent and divergent validity adjusted the model established using confirmatory factor analysis, and demonstrated good fit to the data ($\chi^2(214)=373.98$, $p<.001$, CFI=.95, TLI=.93, RMSEA=.05, SRMR=.06). For convergent validity, the results revealed a significant and strong positive correlations between attachment to AI and AI anthropomorphism ($r=.77$, $p<.001$), as well as AI interaction positivity ($r=.72$, $p<.001$). For divergent validity, associations between AI attachment and all tested constructs (i.e., Big Five personality, pet attachment, and parasocial attachment) were small and non-significant (rs≤.|08|, ps>.05), consistent with expectations. In addition, the Fornell–Larcker criterion was satisfied for all comparisons, with the *AVE* for the AI Attachment Scale exceeding |r| values between attachment to AI and the Big Five personality traits (agreeableness: .58>.05, conscientiousness: .61>.06, extraversion: .63>.04, neuroticism: .65>.04, openness to experience: .59>.05), as well as pet attachment (.72>.06) and parasocial attachment (.58>.08). These findings support both convergent and divergent validity of the AI Attachment Scale. All standardised covariances between AI attachment and constructs included in the convergent and divergent validity model are indicated in Figure 3 (refer to Supplement 7 for the corresponding zero-order correlation matrix).

Figure 3

Standardised Covariances Between AI Attachment and Constructs Included for Convergent and Divergent Validity



Note. *N*=255. All values represent standardised covariances. Solid lines indicate significant associations, while dotted lines represent non-significant associations. Blue and red lines indicate positive and negative associations respectively.

Test-Retest Reliability

When evaluating intra-class correlations (ICC) derived from a two-way mixed effects model with absolute agreement, the scale as a whole showed strong temporal consistency (ICC=.89) when modelled with a single fixed rater. A Pearson correlation of .89 (p<.001) between total scores at the two time points further confirmed a large association and high stability over time. At the level of individual items, ICC values ranged from .56 to .85, reflecting moderate to good reliability. Average scores were highly similar across sessions (Time 1: M=2.77, SD=0.82; Time 2: M=2.76, SD=0.84) as well. The item-level ICC results are available in Supplement 8.

Study 5: Measurement Invariance & Correlates

Study 5 was conducted to examine whether the AI Attachment Scale demonstrated measurement invariance across participants in Singapore and the United States. In addition, this study explored a range of correlates of attachment to AI in order to situate the construct within broader psychological contexts. Specifically, we investigated associations with AI-related variables, motivational factors, psychological characteristics, and relational outcomes.

Method

Participants & Procedure

Study 5 was conducted to explore potential psychological antecedents and consequences of attachment to AI. We aimed to recruit a minimum target sample size of 250 to ensure stable parameter estimates and sufficient statistical power for correlational analyses (Boateng et al., 2018). Accordingly, 301 participants (M_{age}=44.20, SD_{age}=12.76, $\text{range}_{\text{age}}$=[19-77]; refer to Supplement 9 for participant demographics) were recruited via Prolific for Study 5. To ensure participants had sufficient familiarity with AI, only individuals who reported using generative AI at least once a week were eligible to take part. All questionnaires were administered online via Qualtrics. Upon providing informed consent electronically, participants completed a battery of measures including demographic questions, the AI Attachment Scale, and a series of validated scales selected to assess constructs relevant to potential correlates. Participants received either 3.05 USD as compensation.

Measures

Attachment to AI. Attachment to AI was measured using the same scale as Study 4.

Demographics. Demographics were measured using the same items as Studies 3-4.

AI Use. A single item was included to measure how often participants use AI. Participants rated the item on a five-point scale (1=*Never*, 2=*Once a week*, 3=*2-6 times a* week, 4=*Everyday*, 5=*Multiple times a day*). Additionally, a second question was added to ask if participants use an AI companion with romantic or emotionally intimate features (e.g., Replika with romantic mode enabled, EVA AI, Anima, or similar apps).

Motivations for AI Use. Motivations for AI Use was measured using two items. One item assessed instrumental motivations ("I use AI tools mainly to get tasks done more efficiently") and the other measures socioemotional motivations ("I turn to AI tools when I want to feel understood or supported") on a five-point scale (1=*Strongly disagree*, 5=*Strongly agree*). Each item was taken as a standalone score to indicate instrumental motivations of AI use and socioemotional motivations of AI use, with higher scores indicating higher endorsement.

Loneliness. Loneliness was measured using the UCLA-8 Loneliness Scale (Hays & DiMatteo, 1987). Participants were asked to indicate their agreement on statements related to how lonely they are (e.g., "I lack companionship", "There is no one I can turn to") on a four-point scale (1=*Never*, 4=*Often*). Items were averaged to create an overall loneliness score (α=.89), with higher scores indicating higher loneliness.

Life Satisfaction. Life satisfaction was measured using the Satisfaction with Life Scale (Diener et al., 1985). Participants were asked to indicate how satisfied they are with their life (e.g., "In most ways my life is close to my ideal", "So far I have gotten the most important things I want in life") on a seven-point scale (1=*Strongly disagree*, 7=*Strongly agree*). Items were averaged to create an overall life satisfaction score (α=.92), with higher scores indicating higher life satisfaction.

Positive & Negative Affect. Positive and negative affect was measured using the Positive and Negative Affect – Short Form Scale (Watson et al., 1988). The scale consists of two subscales, each with ten items for positive (e.g., "Excited", "Inspired"; α=.93) and negative affect (e.g., "Distressed", "Upset"; α=.92) rated on a five-point scale (1=*Never*, 5=*Always*). Items were averaged within each subscale to create an overall positive affect score and an overall negative affect score, with higher scores indicating higher levels of positive and negative affect.

Social Anxiety. Social anxiety were measured using the Social Interaction Anxiety Scale – Short Form (Peters et al., 2012). Participants were asked to indicated how similar they are to six-items (e.g., “I tense up if I meet an acquaintance on the street”, “I have difficulty talking with other people”) rated on a five-point scale (0=*Not at all true of me*, 5=*Very true of me*). Items were averaged to create an overall social anxiety score (α=.89), with higher scores indicating higher levels of social anxiety.

Self-Esteem. Self-esteem was measured using the Rosenburg Self-Esteem Scale (Rosenburg, 1979). Participants were asked to indicate their agreement on 10 items (e.g., “On the whole, I am satisfied with myself.”, “I feel that I have a number of good qualities”) on a four-point scale (1=*Strongly agree*, 4=*Strongly disagree*). Items were averaged to create an overall self-esteem score (α=.92), with higher scores indicating higher self-esteem.

Needs Satisfaction. Need for autonomy, competence, and relatedness were assessed using the 21-item Psychological Needs scale (Deci & Ryan, 2014). Each subscale consisted of 7 items; autonomy (e.g., “I feel pressured in my life.”, “I feel like I can pretty much be myself in my daily situations.”; α=.74), relatedness (e.g., “I consider the people I regularly interact with to be my friends.”, “People in my life care about me.”; α=.83), and competence (e.g., “Often, I do not feel very competent.”, “People I know tell me I am good at what I do.”; α=.83). Responses were measured on a 7-point scale (1=*Not at all true*, 7=*Very true*). Items were averaged within each subscale to create overall scores, with higher scores indicating higher need for autonomy, relatedness, and competence.

Need for Closure. Need for closure was assessed using the Need for Closure Scale – Short Form (Roets & Van Hiel, 2011). Participants were asked to indicate their agreement on 15 items (e.g., “I don't like situations that are uncertain”, “When I have made a decision, I feel relieved”) on a six-point scale (1=*Strongly disagree*, 6=*Strongly agree*). Items were averaged to create an overall need for closure score (α=.88), with higher scores indicating higher need for closure.

Social Connectedness. Social connectedness was measured using the Social Connectedness Scale – Revised (Lee & Robbins, 1995). Participants were asked to indicate how connected they feel to the people around them on 20 items (e.g., “I feel so distant from people”, “I don’t feel related to anyone”) on a six-point scale (1=*Strongly disagree*, 6=*Strongly agree*). Items were averaged to create an overall social connectedness score (α=.96), with higher scores indicating lower social connectedness.

Attachment Style. Attachment styles were measured using the Experiences in Close Relationship Scale-Short Form Scale (Wei et al., 2007). The scale consists of two subscales, each with six items for anxious attachment (e.g., “I need a lot of reassurance that I am loved by my partner”, “I find that my partner(s) don’t want to get close as I like”; α=.81) and avoidance attachment (e.g., “I want to get close to my partner, but I keep pulling back”, “I am nervous when my partners get too close to me ”; α=.86) rated on a seven-point scale (1=*Strongly disagree*, 7=*Strongly agree*). Items were averaged within each subscale to create an overall anxious attachment score and an overall avoidant attachment score, with higher scores indicating higher levels of anxious and avoidant attachment.

Conflict Avoidance. Conflict avoidance was measured using five items adapted from the Conflict Avoidance Scale (Goldstein, 1999). Participants rated their agreement to each item (e.g., “I hate arguments”, “I feel upset after an argument”) on a 5-point Likert scale (1=*Strongly disagree*, 5=*Strongly agree*). Items were averaged to create an overall conflict avoidance score (α=.73), with higher scores reflecting greater avoidance of interpersonal conflict.

Analytic Plan

Measurement Invariance. Measurement invariance across sex (male and female) and culture (U.S. and Singapore) was tested using the same analytic approach utilised during Study 3 to analyse measurement invariance. For comparisons across cultures, the sample of the current study (from the US) was compared to the sample of Study 4 (from Singapore).

Correlates. To examine associations between AI attachment and a range of theoretically relevant correlates, CFA was conducted following the same structural approach from Study 4. Model fit indices (χ^2, CFI, TLI, RMSEA, SRMR) was assessed using the same thresholds. A second-order latent factor representing AI attachment was specified, comprising of three first-order dimensions. This latent factor was freely correlated with the observed and latent variables representing the correlates. Covariances among all correlates was also freely estimated to account for shared variance and yield a more accurate structural representation. In addition, separate CFA models were conducted for each subdimension of the AI Attachment Scale to estimate their individual associations with each correlate. This approach allowed for clearer interpretation and improved model convergence, as estimating all relationships in a single model would result in oversaturation and reduced model fit.

Results and Discussion

Measurement Invariance

Sex. The unconstrained configural model demonstrated an acceptable fit to the data ($\chi^2(176)=445.82$, $p<.001$, CFI=.96, TLI=.95, RMSEA=.07, SRMR=.06), indicating that the three-factor solution was comparable across male and female participants. When factor loadings were constrained to be equal, the model retained its fit, with only negligible changes in model fit indices (ΔCFI<.001) and improved BIC, supporting metric invariance. Adding equality constraints to intercepts (scalar invariance) also produced a well-fitting solution (ΔCFI=.004), with further decreases in BIC, confirming scalar invariance. Residual variances were then constrained, and model fit remained adequate (ΔCFI=.001), with lower BIC values. Collectively, these results demonstrate that scalar invariance was achieved, enabling meaningful cross-sex comparisons (Table 3).

Culture. The configural model showed good fit ($\chi^2(176)=438.54$, $p<.001$, CFI=.96, TLI=.95, RMSEA=.07, SRMR=.06), indicating that the proposed three-factor structure was consistent across cultures. Metric invariance was supported as the metric model resulted in only a small change in fit (ΔCFI=.001) and lower BIC values. Scalar invariance for the full model was not supported (ΔCFI=.014) with a higher BIC value. Modification indices suggested intercept non-invariance in one item ("I feel a sense of closeness and comfort in my interactions with AI"). Freeing the intercept of the item lead to partial scalar invariance, with minimal change in fit (ΔCFI=.007) and a lower BIC value. Residual invariance was also supported for the partial model, with only a small change in fit (ΔCFI=.003) and a smaller BIC value. Overall, these results provide evidence for partial scalar invariance across cultures (Table 3).

Table 3

Summary of Model Fit Statistics for Measurement Invariance (Study 5)

Model	Sex				Culture			
	CFI	ΔCFI	AIC	BIC	CFI	ΔCFI	AIC	BIC
Configural	.958		20948.50	21354.60	.957		20747.31	21153.47
Metric (vs Configural)	.957	<.001	20937.54	21283.20	.956	.001	20741.70	21087.36
Scalar (vs Metric)[1]	.953	.004	20953.90	21252.04	.949	.007	20772.82	21075.27
Residual (vs Scalar)[1]	.952	.001	20943.96	21177.28	.940	.003	20821.72	21059.36

Note. ΔCFI=change in CFI relative to the previous model. Lower AIC and BIC values indicate better model fit. All ΔCFI values are below the recommended cutoff of .01 (Cheung & Rensvold, 2002). [1]For cultural invariance, both scalar and residual invariance model fits reported are from the partial models after freeing the intercept of one item.

Correlates

The model estimating the associating between the second-order latent factor of AI attachment and various correlates showed acceptable fit to the observed data (χ^2(354)= 717.72, p<.001, CFI=.95, TLI=.92, RMSEA=.06, SRMR=.06).

AI-Related Correlates. Attachment to AI was positively associated with time spent on AI to a very large extent (r=.54, p<.001). Attachment to AI was also positively associated with the use of romantic AI companions to a large extent (r=.41, p<.001). In addition, using AI for socioemotional motives was also significantly and positively associated with attachment to AI to a very large extent (r=.85, p<.001). However, using AI for instrumental motives was not significantly associated with attachment to AI (Figure 4).

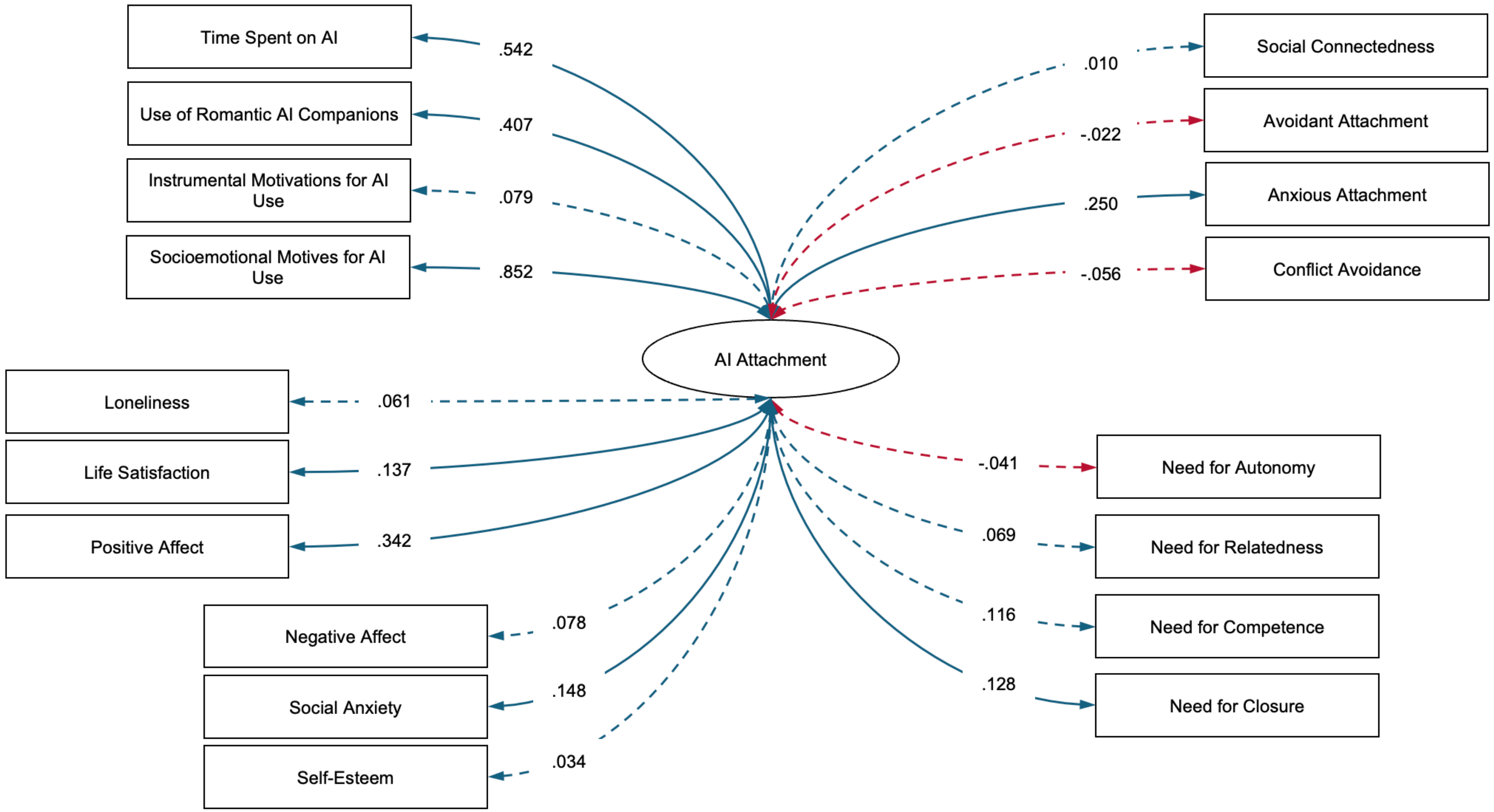
Motivational Correlates. Out of the motivational needs, only need for closure was significantly associated with attachment to AI to a positive and small extent (r=.13, p=.037). Need for autonomy, need for relatedness, and need for competence did not show significant associations with attachment to AI (Figure 4).

Psychological Correlates. With respect to psychological correlates, attachment to AI was significantly and positively associated with life satisfaction to a small extent (r=.14, p=.025 Similarly, attachment to AI was also significantly and positively associated with positive affect to a medium extent (r=.34, p<.001). In addition, social anxiety was also significantly and positively associated attachment to AI to a small extent as well (r=.15, p=.016). However, attachment to AI was not significantly associated with loneliness, negatively affect, or self-esteem (Figure 4).

Relational Correlates. From the relational correlates, attachment to AI was significantly and positively associated with attachment anxiety to a medium extent (r=.25, p<.001). In contrast, social connectedness, attachment avoidance, and conflict avoidance was not significantly associated with attachment to AI (Figure 4; refer to Supplement 10 for the corresponding zero-order correlations table).

Figure 4

Correlations Between Attachment to AI and Other Measures



Note. N=301. All values represent standardised covariances. Solid lines indicate significant associations, while dotted lines represent non-significant associations. Blue and red lines indicate positive and negative associations respectively.

Subscale Analysis

The model estimating the associating between the three first-order factors of AI attachment and various correlates showed acceptable fit to the observed data (χ^2(315)= 567.56, *p*<.001, CFI=.97, TLI=.94, RMSEA=.05, SRMR=.03).

AI-Related Correlates. Consistent significant and positive associations were observed between AI-related correlates and the subdimensions of attachment to AI. Specifically, time spent on AI was significantly and positively associated to a large extent with emotional closeness (*r*=56, *p*<.001) and social substitution (*r*=45, *p*<.001), and to a medium extent with normative regard (*r*=39, *p*<.001). The use of romantic AI companions was also similarly consistent in its association with the subdimensions of AI attachment, being significantly and positive associated to a medium extent with emotional closeness (*r*=.39, *p*<.001) and social substitution (*r*=.40, *p*<.001), and to a small extent with normative regard (*r*=.20, *p*<.001). Using AI for socioemotional reasons was consistently associated with all three subdimensions, emotional closeness (*r*=79, *p*<.001), social substitution (*r*=.86, *p*<.001), and normative regard (*r*=.50, *p*<.001), to a large extent. In contrast, using AI for instrumental needs was not significantly associated with any of the subdimensions of AI attachment (Table 4).

Motivational Correlates. From the motivational correlates, need for competence was significantly associated to a positive and small extent with both emotional closeness (*r*=.15, *p*=.014) and normative regard (*r*=.21, *p*=.001), but not social substitution. Need for relatedness was only significantly associated with normative regard out of the three subdimensions, to a positive and medium extent (*r*=.20, *p*=.002). Need for closure was only significantly associated with emotional closeness, to a positive and small extent (*r*=.14, *p*=.022). Need for autonomy was not significantly associated with any of the subdimensions of AI attachment (Table 4).

Psychological Correlates. In terms of psychological correlates, loneliness was only significantly associated with the social substitution subscale, to a positive and small extent (r=.16, p=.010). Life satisfaction was associated significantly to a positive and small extent with both emotional closeness (r=.14, p=.020) and normative regard (r=.18, p=.004). Positive affect was consistently associated significantly with all three subscales; to a positive and medium extent with emotional closeness (r=.37, p<.001) and social substitution (r=.23, p<.001), and to a positive and large extent with normative regard (r=.36, p<.001). Negative affect was significantly associated to a positive and small extent with only the social substitution dimension (r=.13, p=.027). Similarly, social anxiety was also significantly associated to a positive and medium extent with only the social substitution dimension (r=.21, p=.001). Self-esteem was significantly associated to a positive and small extent with only the normative regard dimension (r=.14, p=.028; Table 4).

Relational Correlates. Out of the relational correlates, attachment avoidance showed a significant and negative correlation to a small extent only with the normative regard subscale (r=-.20, p=.002). Attachment anxiety was significantly and positively associated with both the emotional closeness subscale (r=.24, p<.001) and the social substitution subscale (r=.26, p<.001) to a medium extent. Social connectedness and conflict avoidance was not significantly associated with any of the subscales of AI attachment (Table 4).

Table 4

Associations Between the Subscales of AI Attachment and Correlates

Variable	Emotional Closeness		Social Substitution		Normative Regard	
	r	*p*	*r*	*p*	*r*	*p*
AI-Related Correlates						
Time Spent on AI	.56	<.001	.45	<.001	.39	<.001
Use of Romantic AI Companions	.39	<.001	.40	<.001	.20	.002
Instrumental Motivations of AI Use	.12	.061	.01	.866	.11	.085
Socioemotional Motivations of AI Use	.79	<.001	.86	<.001	.50	<.001
Motivational Correlates						
Need for Autonomy	-.01	.893	-.10	.084	.05	.382
Need for Relatedness	.10	.098	-.02	.701	.20	.002
Need for Competence	.15	.014	.02	.764	.21	.001
Need for Closure	.14	.022	.09	.134	.11	.075
Psychological Correlates						
Loneliness	.01	.832	.16	.010	-.09	.168
Life Satisfaction	.14	.020	.08	.139	.18	.004

Positive Affect	.37	<.001	.23	<.001	.36	<.001
Negative Affect	.05	.426	.13	.027	-.03	.609
Social Anxiety	.12	.060	.21	.001	-.02	.690
Self-Esteem	.07	.273	-.05	.422	.14	.028
Relational Correlates						
Social Connectedness	-.03	.612	.10	.103	-.10	.099
Attachment Avoidance	-.06	.292	.09	.143	-.20	.002
Attachment Anxiety	.24	<.001	.26	<.001	.03	.622
Conflict Avoidance	-.04	.509	-.06	.287	-.07	.284

Note. N=301. All values represent standardised covariances.

General Discussion

With artificial intelligence (AI) becoming increasingly embedded in everyday life, growing attention has been directed to the possibility that individuals may form emotional attachments to AI (Boine, 2023; Cherelus, 2024; Samuel, 2024). Anecdotal reports suggest that some people experience strong bonds with AI, ranging from perceiving AI as a confidant to considering it a romantic partner (Kim et al., 2023; Willoughby et al., 2025). Attention has also been drawn to the consequences of such attachments, with individuals sometimes reporting greater life satisfaction and perceived social support (Heritage, 2025; Saga et al., 2025), but also potential downsides such as reduced investment in offline relationships (Roose, 2023). Given the potential implications for human psychology and social functioning, it is important to measure attachment to AI in a systematic way to better understand its antecedents and consequences. To this end, the present research developed and validated the AI Attachment Scale, a novel measure designed to capture individual differences in the extent to which people form attachments to AI tools. Across multiple studies, the scale demonstrated sound psychometric properties, a stable factor structure, good construct validity, evidence of measurement invariance across sex and cultural groups, and strong test–retest reliability. These findings establish the scale as a reliable and valid tool for advancing research on AI attachment in diverse populations and for clarifying its broader psychological and relational consequences.

Psychometric Properties

The AI Attachment Scale was developed through a systematic, theory-driven process. In Study 1, an initial item pool was generated and refined through expert review for clarity, redundancy, and theoretical alignment, yielding 30 items. Content validity was further established by independent raters unfamiliar with the construct, who confirmed that items mapped onto their intended dimensions. Readability analyses verified that the items were easily comprehensible for both native and non-native English speakers. In Study 2, the refined pool was administered to samples in Singapore and the United States to evaluate item performance. Descriptive analyses indicated well-distributed responses with no floor or ceiling effects. This step-by-step process resulted in a theoretically grounded and linguistically accessible measure for attachment to AI for subsequent psychometrics validation.

Study 3 used exploratory factor analysis with Singaporean and U.S. samples to identify the scale's structure, revealing a three-factor solution: emotional closeness, social substitution, and normative regard. The final 15-item version (five items per factor) reflected both the theoretical foundations of the scale and empirical evidence, aligning with dimensions found in pet attachment research (Johnson et al., 1992). Emotional closeness captures intimacy and comfort in interactions with AI; social substitution reflects the use of AI in place of human contact; and normative regard represents respectful or moral consideration toward AI. Emotional closeness reflects the sense of intimacy, connection, and comfort that individuals may experience in their interactions with AI. Social substitution represents the extent to which AI is used in place of human interaction, capturing both compensatory use (in response to social isolation or rejection) and preferential use (choosing AI over available human alternatives). Normative regard encompasses the tendency to treat AI with a level of respect and consideration typically reserved for sentient others, reflecting the moral or personal regard that can arise from perceived attachment.

Studies 4 and 5 confirmed this structure and established the scale's validity and reliability. Confirmatory factor analysis supported a higher-order factor model. Convergent validity was demonstrated through large, significant associations with AI anthropomorphism and AI interaction positivity, while discriminant validity was shown through weaker links with broad personality traits and related constructs such as pet and parasocial attachment.

Test–retest reliability indicated that attachment to AI reflects a stable individual difference, not a transient state. Invariance testing demonstrated strict invariance across sex and partial scalar invariance across culture (Singapore, United States), supporting the scale's use across different cultural groups and longitudinal research designs.

Correlates of Attachment to AI

Beyond psychometric validation, the present research also examined correlates of attachment to AI. Findings indicated that simply being exposed to AI frequently was associated with forming relational bonds with AI, as time spent interacting with AI consistently predicted attachment across the overall construct and all subscales. This pattern resonates with the mere exposure effect, which posits that familiarity breeds affinity (Young et al., 2016; Zajonc, 1968), and with social surrogacy theory, which suggests that repeated interaction with an available and responsive agent can substitute for human connection (Derrick et al., 2009; Schäfer & Eerola, 2020). While the use of romantic AI companions was also associated with stronger attachment, effect sizes were smaller than for time spent using AI, indicating that the accumulation of everyday interactions may exert a stronger influence on attachment formation than explicitly relational framings. Motivations for AI use reinforced this pattern: socioemotional motives for AI use (e.g., seeking comfort or companionship) were strongly predictive of attachment, whereas instrumental motives (e.g., using AI for tasks) were unrelated. This distinction parallels compensatory Internet use theory (Kardefelt-Winther, 2014), which emphasises that individuals turn to mediated technologies to meet unmet socioemotional needs, and suggests that attachment to AI is more likely to develop when engagement is driven by affective rather than utilitarian goals.

Furthermore, the current work also found that dispositional needs shaped attachment patterns to AI as well. Need for closure was robustly associated with overall AI attachment, particularly emotional closeness. Individuals high in need for closure typically prefer clear, predictable, and consistent partners, and show heightened discomfort with ambiguity or relational uncertainty (Gendi et al., 2023; Roets & Van Hiel, 2011). Human relationships are often characterised by miscommunication and the risk of rejection without closure (Johnson et al., 2022; Richter et al., 2024), but AI systems provide stable, immediate, and non-contingent feedback (Ventura et al., 2025; Wu et al., 2025; Zhang & Li, 2025). In this sense, AI can fulfil the relational certainty sought by high need for closure individuals. By contrast, the three basic psychological needs, autonomy, competence, and relatedness, did not predict overall AI attachment, though subscale analyses revealed more specific links. Competence needs were modestly associated with both emotional closeness and normative regard. As competence involves a drive to feel capable and effective (Deci & Ryan, 2000; White, 1959), individuals high in this need may respond favourably to AI's tendency to affirm and validate inputs. Relatedness needs predicted only normative regard, consistent with self-determination theory's proposition that relatedness drives the extension of social norms of care and reciprocity (Van den Broeck et al., 2010). Overall, these findings suggest that while broad psychological needs do not uniformly explain AI attachment, specific dispositional tendencies, such as the desire for certainty, competence, and relatedness, shape the ways in which individuals form and express attachments to AI.

Another set of findings highlighted how vulnerabilities in social relationships can shape attachment to AI. High social anxiety was significantly associated with high AI attachment, driven mainly by the social substitution dimension. This is consistent with compensatory Internet use theory (Kardefelt-Winther, 2014), which suggests that individuals who find face-to-face interactions threatening may turn to digital or mediated partners to reduce the risk of negative evaluation. Similarly, anxious attachment was also associated significantly with higher AI attachment, driven both by the emotional closeness and social substitution dimensions. Attachment theory emphasises the need for reassurance and fear of abandonment among anxiously attached individuals (Li & Chan, 2012; Mikulincer & Shaver, 2005; Shaver et al., 2005). AI systems, being continuously available and predictably responsive (Yang & Oshio, 2025), may be particularly attractive to such individuals because they reduce relational uncertainty and deliver steady validation without the unpredictability inherent in human partners. Collectively, these patterns suggest that whether through the avoidance of social threat due to social anxiety or the amplification of relational needs due to anxious attachment, individuals facing interpersonal vulnerability may gravitate toward AI as a safer, more predictable surrogate for human relationships.

Interestingly, the current study showed that being attached to AI was also associated with wellbeing benefits. Positive affect was the most consistent wellbeing correlate, significant both at the overall scale and across each subdimension, suggesting that attachment bonds with AI may serve a mood-enhancing function. This aligns with attachment theory, which emphasises the role of close figures in providing emotional regulation and affective uplift (Messina et al., 2024; Mikulincer et al., 2003). In this case, AI appears capable of fulfilling the safe-haven role by offering reliable responsiveness and a sense of comfort, which in turn has been shown to sustain positive emotional states (Collins & Feeney, 2000). Beyond positive affect, life satisfaction was also significantly associated with attachment to AI. Research on subjective wellbeing highlights that the presence of supportive, stable bonds is one of the strongest predictors of life satisfaction (Gustavson et al., 2016; McCamish-Svensson et al., 1999). In this sense, attachment to AI may not only shape immediate affective experience but also contribute to broader evaluations of life quality by providing a consistent relational anchor.

Limitations and Future Directions

While the current work followed rigorous and multi-step psychometric procedures (Graziotin et al., 2021; Kline, 2015), it is not without limitations. First, the correlational design prevents conclusions about causality. Future research should look towards conducting longitudinal research are to determine whether AI attachment precedes or results from associated psychological and relational factors. Second, as the current work fully utilised self-report measures, responses may be influenced by social desirability or impression management. This concern may be especially salient in the context of AI attachment, as the phenomenon is relatively new and often portrayed negatively in public discourse (Cherelus, 2024; Walther, 2025), which may discourage candid reporting. As AI use becomes more widespread and socially normalised, measurement of this construct may become more reliable and less affected by stigma. Third, although cultural invariance was tested, this was limited to Singapore and the U.S., and future work should examine whether the scale generalises to other cultural contexts.

Conclusion

Taken together, across five studies the present research developed and validated the AI Attachment Scale as a theoretically grounded and empirically supported instrument for assessing individual differences in attachment to AI. The scale demonstrated a multidimensional structure, strong reliability, and acceptable psychometric properties, with measurement invariance established across sex and partial invariance across culture. Using this tool, patterns of associations suggested that individuals higher in social anxiety, loneliness, and anxious attachment may be more likely to engage with AI as a compensatory resource and social surrogate, while those who report stronger attachment also tend to experience greater positive affect and life satisfaction. Importantly, results further indicate that attachment is more likely to form when AI use is socioemotional in nature, rather than purely instrumental. As AI systems become increasingly embedded in daily routines, the scale provides a rigorous framework for understanding the psychological dynamics of human–AI attachment and its implications for social and emotional functioning.

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