The Role of Brand Personality Appeal in AI Subscription Intentions and Brand Advocacy: Mediating Effects of Trust and Emotional Engagement And the Moderating Role of Anthropomorphism Tendency

Student Name: Trung Hieu Dang
Student Number: 733502

Supervisor: Dr. Kyriakos Riskos

Master Media Studies – Media & Business
Erasmus School of History, Culture and Communication
Erasmus University Rotterdam

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ABSTRACT

Artificial Intelligence (AI) Large Language Models (LLMs) such as ChatGPT and Google Gemini are increasingly embedded into users' daily lives, transitioning from functional tools to branded digital companions. While much research in the human-AI interaction field has emphasized functionality, trust, or affect, the role of *Brand Personality Appeal* (BPA) - defined as the degree to which a brand's personality is perceived as favorable, original, and clearly defined—remains underexplored in this domain. This study addresses this gap by investigating how BPA influences two critical user outcomes: AI subscription intentions and brand advocacy, through the mediating roles of user trust and emotional engagement. In addition, the study examines whether anthropomorphism tendency moderates the effects of BPA on these mediators.

Guided by *Consumer–Brand Relationship Theory* (Fournier, 1998), a conceptual model was constructed to test the proposed relationships. A cross-sectional online survey (N = 200) was conducted among users with prior experience using AI LLMs. Validated scales were adapted to measure BPA (favorability and clarity), user trust, emotional engagement, brand advocacy, subscription intentions, and anthropomorphism tendency. The data were analyzed using regression-based mediation and moderation analysis via PROCESS macro in SPSS.

Findings revealed that both BPA dimensions (favorability and clarity) significantly and positively influenced user trust and emotional engagement, which in turn predicted brand advocacy and subscription intentions. Mediation analyses confirmed that these two psychological mechanisms: cognitive and affective serve as parallel mediators linking BPA to the behavioral outcomes. Notably, emotional engagement emerged as the sole significant mediator between BPA clarity and AI subscription intentions. However, anthropomorphism tendency did not moderate any of the hypothesized relationships, suggesting that BPA's impact on trust and engagement may be consistent across varying levels of anthropomorphic perception.

The study offers several theoretical and managerial implications. Theoretically, it contributes to a more nuanced understanding of how relational branding mechanisms operate in AI contexts, reinforcing the dual-process logic of persuasion. Managerially, the results underscore the importance for AI developers and marketers to strategically craft favorable and consistent brand personalities that foster trust and emotional bonds. Overall, this research highlights the emerging significance of brand personality as a central determinant in shaping meaningful human–AI relationships.

KEYWORDS: *Brand Personality Appeal, User Trust, Emotional Engagement, AI Subscription Intentions, Brand Advocacy*

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1. Introduction

The widespread adoption of artificial intelligence (AI) applications has led to profound transformations in how individuals and organizations engage with digital tools. One of the most visible developments is the emergence of large language models (LLMs) such as ChatGPT, Google Gemini, and Meta's LLaMA (Roy et al., 2025, p. 2). These technologies, powered by advanced natural language processing, are designed to understand and generate human-like text across a wide range of tasks, including content creation, problem-solving, and conversational support (Fraiwan & Khasawneh, 2023, p. 2). As they become integrated into everyday life, LLMs are no longer perceived merely as utilitarian systems, but rather as digital agents with distinct identities and, increasingly, personalities (Bommasani et al., 2021, p. 1).

Therefore, due to this integration, AI LLM's branding strategies are constantly evolving to foster not only recognition but also active user advocacy. Unlike traditional technology products, LLMs like ChatGPT or Replika offer interactive, ongoing engagement through their capabilities of adaptive learning and predicting user needs, making their digital experience more personalized (Gnewuch et al., 2022, p. 480; Camilleri, 2023, p. 5). Under a business setting, AI LLMs are also crucial for companies in crafting tailored messages and providing instant and genuine supports that allow users to build familiarity and emotional connection with the AI brand over time. In short, this continuous, personalized interaction creates fertile ground for brand advocacy - a phenomenon where satisfied users voluntarily promote or defend the brand in both online and offline environments (Wilk et al., 2021, p. 1980; Harrison-Walker, 2001, p. 67). For instance, ChatGPT users frequently share their positive experiences on social media, create tutorial content, or encourage others to try the tool, often without any formal incentive from the brand itself (Aldous et al., 2024, p. 377).

As a result, beyond functionality and performance, a user's willingness to financially subscribe to an AI LLM increasingly depends on a complex mix of cognitive and affective factors, including their perceived emotional engagement with the AI and the level of trust in its recommendations (Jo, 2024, p. 1058; Rawool et al., 2024, p. 12). This highlights a shift in how digital users evaluate AI LLMs based on their emotional engagement or trusted interaction with the AI (Chaudhuri & Holbrook, 2001, p. 83). Also, as users' decision-making and creative processes is mainly determined through AI LLMs, their subscription intentions reflect the relationship quality with the AI. Particularly, when AI LLMs exhibit a clearly defined and human-like brand personality, users are more inclined to subscribe (Fernandes & Moreira, 2019, p. 279; Wang, 2024, p. 24).

Therefore, brand personality appeal (BPA) has emerged as a relevant construct to explain user responses to AI. In detail, BPA reflects the degree to which a brand is perceived as favorable, original, and clearly defined (Freling et al., 2011, p. 399). While extensively studied in traditional branding, BPA has only recently begun to receive attention in AI research, where it may serve as a useful predictor of user engagement with intelligent systems (Calderón-Fajardo et al., 2023). However, in contrast to BPA, the roles of emotional engagement and trust remain relatively underexplored within the AI LLM context, particularly as distinct mediators that drive behavioral outcomes like subscription or brand advocacy (Liu et al., 2023, p. 4; Asiabar et al., 2024, p. 5). Likewise, existing studies rarely test these mechanisms in parallel or through an integrated model, leaving a gap in understanding how these psychological processes work together in shaping AI brand relationships (Singh & Kunja, 2024, p. 3; Shen et al., 2024, p. 1077). Thus, this study addresses this gap by examining how BPA influences user subscription intentions and brand advocate behaviors through the roles of emotional engagement and user trust specific to AI LLMs brands rather than other general AI technologies.

To further develop and assist this conceptual model, the Consumer-Brand Relationship Theory by Fournier (1998, p. 344) was utilized as the theoretical framework. This theory highlights the emotional and psychological connections users form with brands, including trust, loyalty, and advocacy. It is particularly suitable for studying AI branding because it provides a framework for understanding how users perceive AI tools not merely as functional products but as interactive, relatable entities (Reimann et al., 2012, p. 130). Trust formation, emotional engagement, and brand advocacy—core tenets of this theory—are essential in AI branding, as users are more likely to adopt and remain loyal to AI tools that exhibit consistent and positive brand experiences (Fournier, 1998, p. 350).

Moreover, to moderate the relationship among the core tenets of this theoretical framework, anthropomorphism tendency - the degree to which individuals attribute human-like traits, emotions, and intentions to non-human entities, such as AI (Epley et al., 2007, p. 865) - plays a crucial role. Specifically, anthropomorphism amplifies the effect of BPA on trust and emotional engagement, as users who assign human-like qualities to AI are more likely to engage with and trust AI brands (Gnewuch et al., 2022, p. 488).

Therefore, the core objective of this study is to investigate the impact of brand personality appeal on AI subscription intentions and brand advocacy, mediated by user trust and emotional engagement, and moderated by anthropomorphism tendency. This leads to the formulation of the following research question: *To what extent does brand personality appeal influence AI subscription intentions and brand advocacy through user trust and emotional engagement?* An additional sub-question addresses the moderating role of anthropomorphism: *To what extent does anthropomorphism tendency affect the strength of these relationships?*

1.1 Scientific Relevance

This research offers several theoretical contributions. First, it extends BPA into a new domain - AI technologies and empirically validates its relevance in shaping user-AI relationships. While Freling et al. (2011, p. 393) developed BPA for traditional branding contexts, its application to LLM-based brands helps refine our understanding of how users engage with non-human yet socially interactive technologies (Wang, 2024, p. 24).

Second, this study strengthens the theoretical understanding of emotional engagement and trust as dual mediators in AI adoption. While traditional models focused on rational factors like usefulness, recent research emphasizes the importance of affective mechanisms in shaping long-term user behavior (Wang, 2024, p. 24; Fernandes & Mena, 2023, p. 18). By positioning trust and emotional engagement as parallel pathways through which BPA drives subscription and advocacy intentions (Freling et al., 2011, p. 393), this study expands current models of human-AI interaction. It also contributes a more nuanced view of how emotionally resonant, personality-driven AI brands foster not just satisfaction, but deep psychological bonds that translate into commitment and loyalty (Cheng, 2024, p. 10; Hollebeek, 2011, p. 565).

Third, by incorporating anthropomorphism tendency as a moderating variable, the study addresses individual-level differences in how users interpret and respond to AI branding. Users high in anthropomorphism tendency are more likely to perceive AI personality cues as authentic, which enhances trust and emotional engagement (Shen et al., 2024, p. 1077; Park et al., 2013, p. 230). Including this factor adds depth to existing models, moving beyond uniform assumptions and enabling a more user-centered perspective. It also aligns with emerging research that calls for more individualized frameworks in AI adoption, accounting for psychological variation in human–AI relationships (Kolomaznik et al., 2024, p. 10).

1.2 Societal Relevance

From a societal perspective, this study underscores the growing role of emotional engagement, trust, and relationship-building in shaping how people interact with artificial intelligence. As AI LLMs become embedded in daily decision-making, creative work, and even companionship, users increasingly evaluate these systems through human-centered lenses, asking not only “what can this do?” but “how does this make me feel?” Emotional attachment to AI is no longer speculative; it is observable in user behavior ranging from personalizing AI responses to defending AI brands in public forums (Singh & Kunja, 2024, p. 3). These evolving relationships raise ethical and psychological questions about user dependency, anthropomorphization, and the social influence of AI agents, especially as they become sources of advice, creativity, or emotional support (Liu et al., 2023, p. 5). Understanding the mechanisms behind emotional engagement and trust in AI brands is therefore vital, not only for product success but for anticipating how AI technologies shape human cognition and relationships on a broader societal scale (Shen et al., 2024, p. 1076).

At the managerial level, this research highlights how intentional brand personality design can be leveraged to secure long-term revenue in subscription-based AI business models. As functional parity increases across AI systems, brand personality becomes a key differentiator influencing not only user satisfaction but also subscription and advocacy behaviors (Waytz et al., 2014, p. 118). However, this is not a matter of simply “humanizing” AI interfaces for novelty’s sake. Personality must be perceived as favorable, original, and consistent - traits that foster trust and emotional engagement (Freling et al., 2011, p. 399; Wang, 2024, p. 24).

In subscription contexts, users are not only paying for access to features but for ongoing relationships with digital agents they find meaningful, trustworthy, and engaging (Jo, 2024, p. 1058). As such, managers should view AI brand personality not as a cosmetic design layer but as a strategic relational asset. When AI personas are aligned with context and user expectations, they enhance perceived authenticity and deepen user retention (Gnewuch et al., 2022, p. 488). In turn, this fosters relational equity that transforms satisfied subscribers into brand advocates and reinforces the freemium-to-premium conversion cycle (Wilk et al., 2021, p. 1980). By managing AI LLMs as relational brands, firms move beyond short-term performance metrics and toward sustainable differentiation in increasingly crowded digital marketplaces (Fournier, 1998, p. 350).

1.3 Chapter Outline

This thesis is organized into five chapters, each contributing to a comprehensive understanding of how Brand Personality Appeal (BPA) influences AI subscription intentions and brand advocacy through trust and emotional engagement.

Chapter One introduces the study's background, highlighting the growing relevance of AI Large Language Models (LLMs) as branded entities in digital environments. It presents the research problem, objectives, questions, and the study's theoretical and societal relevance. This chapter also introduces the core constructs: BPA, trust, emotional engagement, subscription intentions, brand advocacy, and anthropomorphism tendency, and establishes the research's contribution to media and AI branding literature.

Chapter Two provides a detailed theoretical framework supporting the conceptual model. It elaborates on key constructs such as Brand Personality Appeal, user trust, emotional engagement, brand advocacy, subscription intentions, and anthropomorphism tendency. It then justifies the selection of Consumer–Brand Relationship Theory (CBRT) as the study's overarching lens. Building on this, the chapter develops twelve hypotheses and presents the conceptual model that guides the empirical investigation.

Chapter Three outlines the methodological approach. It details the research design, including the rationale for choosing a quantitative, cross-sectional survey. The chapter also explains how each construct was operationalized using validated scales, describes the sampling process and data collection procedure, and discusses steps taken to ensure validity and reliability. Finally, it outlines the statistical techniques used to test the mediation and moderation hypotheses, including the use of the PROCESS macro in SPSS.

Chapter Four presents the empirical findings. It provides the results of the mediation and moderation analyses, testing the proposed hypotheses. Mediation results confirm the roles of user trust and emotional engagement in linking BPA to both subscription intentions and brand advocacy. Moderation results assess whether anthropomorphism tendency influences these effects. The chapter concludes with a summary of key outcomes, including supported and rejected hypotheses.

Chapter Five discusses the findings in light of the theoretical framework and prior literature. It reflects on the implications of the results for theory and practice, emphasizing how BPA fosters AI brand loyalty via trust and emotional engagement. The chapter also examines the limitations of the study such as the cross-sectional design and non-random sampling and suggests directions for future research. The thesis concludes by highlighting the emerging role of brand personality in shaping user behavior within human-AI interactions.

2. Theoretical Framework and Hypotheses Development

2.1 Theoretical Framework

The adoption and sustained use of AI LLMs cannot be adequately understood through technical performance metrics alone. While functional accuracy and usability are undeniably important, these alone cannot explain why some users not only adopt and pay for these tools but also advocate for them publicly (Kim & Sundar, 2012, p. 242). Increasingly, these interactions are mediated by psychological and emotional dimensions such as trust and emotional engagement, with users forming perceptions of AI LLMs not just as tools, but as branded entities with personalities, values, and voices (Sun et al., 2024, p. 3).

Therefore, the goal of this chapter is to review and evaluate the theoretical foundations that inform this thesis, which investigates the role of BPA in AI adoption, mediated by trust and emotional engagement, and moderated by anthropomorphism tendency. Moreover, it also explores how these mechanisms jointly influence subscription intentions and brand advocacy - two critical behavioral outcomes. CBRT will also be justified in this section as the overarching theoretical framework for this study.

2.1.1 Contextual Background: AI LLMs Brand

As LLMs become embedded into users' daily lives - offering real-time text generation, knowledge support, and creative input - they are increasingly perceived as more than functional tools (Siqueira et al., 2024, p. 3). In fact, LLMs like ChatGPT, Gemini, or Replika are often described in human-like terms: friendly, helpful, creative, or empathetic (Camilleri, 2023, p. 5). As users engage in recurring, personalized interactions with these LLMs, they begin to attribute human-like characteristics to them such as friendliness, competence, or empathy based on how the AI communicates (Wang, 2024, p. 24). These perceptions are not incidental; they actively shape trust, emotional responses, and subsequent behaviors such as subscribing to or recommending the AI (Cheng, 2024, p. 10).

Thus, this phenomenon defines the core concept of AI LLM branding - a field exploring how conversational AI agents function as relational brands. A recent bibliometric review highlights branding in AI as one of six primary schools of thought, emphasizing chatbots as emotion-driven brand interfaces and identifying gaps in understanding conversational brand identity (Truong & Ta, 2025, p. 2). Meanwhile, a systematic literature review focused on brand identity in AI chatbots argues that researchers have primarily examined individual design cues but have not yet developed a comprehensive model of AI brand persona and its effects on user-brand outcomes (Dittmar et al., 2024, p. 7).

Moreover, with LLMs transitioning toward freemium and subscription-based platforms, AI companies must design their systems in ways that go beyond functional performance to emotionally resonate with users, thereby fostering both engagement and advocacy (Rawool et al., 2024, p. 12). However, existing branding literature has not yet sufficiently addressed how users form emotional connections with non-human, conversational AI LLM brands (Leite et al., 2013, p. 291). Therefore, this study conceptualizes LLMs as interactive AI brands, asserting that their success depends not only on usability but also on appearing as social and psychological agents capable of relationship-building (Guerra-Tamez et al., 2024, p. 3).

2.1.2 Consumer–Brand Relationship Theory (CBRT)

To account for the emerging relational dynamics between users and AI, this study draws on Consumer–Brand Relationship Theory (CBRT) (Fournier, 1998, p. 343), which views brand relationships through the same psychological mechanisms as interpersonal ones, namely trust, commitment, and emotional bonding (Fournier, 1998, p. 344). According to this perspective, consumers develop lasting relationships with brands much like they do with people, engaging emotionally and behaviorally over time. This theoretical lens is particularly suitable for AI contexts, where interaction with systems like ChatGPT or Gemini is ongoing, conversational, and emotionally infused. When AI tools respond empathetically, communicate reliably, and exhibit a clear and consistent identity, users begin to perceive them as social partners - increasing their emotional connection, trust, and willingness to engage (Park et al., 2013, p. 230; Ahuvia, 2005, p. 180). In such cases, AI brands become more than just a tool, rather they become a relational entity that fosters loyalty and long-term engagement (Singh & Kunja, 2024, p. 3).

However, CBRT is not without its critics. Some scholars argue that users are not universally inclined to form emotional connections with brands and that certain categories of technological or utilitarian brands may not be inherently "relationship-worthy" (Fournier & Avery, 2011, p. 64). While this critique raises important questions about the boundaries of CBRT, recent research in the AI branding space provides compelling evidence that users are, in fact, capable of forming meaningful, emotion-based relationships with AI systems. For example, Cheng and Jiang (2021, p. 5) applied CBRT to investigate how chatbot marketing efforts such as usefulness, responsiveness, and entertainment further contribute to customer-brand relationships. Their analysis revealed a clear pathway of communication quality leading to trust and commitment, which in turn fosters brand loyalty. This path mirrors classic CBRT mechanisms and further supports the claim that AI agents can activate the same relational processes proposed in CBRT, even when users know they are interacting with machines.

Furthermore, a recent study by Xu et al. (2025, p. 8) provided additional support for applying CBRT in AI contexts by showing how chatbot features like customization and entertainment contribute to brand intimacy and subscription intentions. Particularly, in their research on telecom brands using AI chatbots, they found that emotionally expressive and personalized chatbot interactions increased users' feelings of being understood and valued. These emotional bonds, in turn, significantly predicted behavioral outcomes, including willingness to subscribe. Crucially, their results demonstrated that consumer engagement mediated the relationship between chatbot attributes and behavioral intent which is also following CBRT's emphasis on the relational mechanisms (i.e., trust and affective connection) that link brand perception to behavior.

Taken together, these findings strengthen the theoretical justification for using CBRT to examine user-AI brand relationships. Even though LLMs like ChatGPT are algorithmic and non-human, the way users interact with them resembles relational engagement rather than transactional use. As AI systems are designed with stronger brand personalities, empathic language, and responsive behaviors, users increasingly relate to them in psychologically meaningful ways. Therefore, despite the critique, CBRT remains not only appropriate but necessary for understanding how AI brand personality appeal (BPA) translates into trust, emotional engagement, and downstream behavioral outcomes like brand advocacy and subscription intentions.

2.1.3 Brand Personality Appeal (BPA)

The concept of brand personality stems from the idea that brands, like people, can be perceived to possess human-like characteristics (MacInnis & Folkes, 2017, p. 358). Rooted in symbolic interactionism and relationship marketing, brand personality enables users to form psychological and emotional attachments with brands, assigning them traits such as sincerity, excitement, or competence (Aaker, 1997, p. 351). These humanized brand traits offer users a means of self-expression, allowing them to align with brands that reflect their values, beliefs, and identities (Swaminathan et al., 2009, p. 985). For instance, a user who identifies with innovation may choose a personality-rich AI LLM that projects curiosity and creativity, effectively using the AI as a symbol of their own forward-thinking identity (Kleine et al., 1993, p. 211). As such, brand personality plays a central role in facilitating user-brand relationships, driving trust, affective attachment, and brand loyalty over time (Fournier, 1998, p. 343).

However, traditional brand personality frameworks tend to focus on identifying and categorizing traits by asking, for instance, whether a brand is seen as “competent” or “sincere” rather than evaluating whether these traits are compelling to consumers. For example, Aaker’s (1997, p. 351) Five-factor model classifies traits but does not assess their appeal, and Fournier (1998, p. 343) describes relationship styles without considering user perception of their attractiveness. Therefore, the BPA framework by Freling et al. (2011, p. 393) addresses this gap by shifting the focus from trait presence to evaluative appeal composed of favorability, originality, and clarity. Favorability gauges how positive the personality traits are; originality measures the distinctiveness; clarity reflects well-defined and consistency in communication (Freling et al., 2011, p. 399). These dimensions capture the emotional, aesthetic, and symbolic value of personality from the user's perspective, not just the presence of human-like qualities.

This nuanced shift is highly relevant in contemporary digital brand contexts, particularly where brands are not static symbols but interactive agents (Cheng, 2024, p. 10). In the case of AI LLMs, personality is not a marketing construct imposed from the outside - it is experienced directly by the user through interaction. Users do not merely see or hear the brand, instead, they converse with it, rely on it for tasks, and judge it based on responsiveness, tone, and behavioral consistency (Wang et al., 2024, p. 5). Therefore, this dynamic interaction makes the perceived personality of the AI not just an abstract brand layer but a core part of the user experience.

In such environments, the appeal of that personality becomes a key differentiator. Functional performance among LLMs is becoming increasingly commoditized as most platforms offer competent language generation, retrieval, and summarization (Brand et al., 2023, p. 5). What sets them apart is how they interact with users: whether they feel helpful, approachable, trustworthy, or frustrated. (Wester et al., 2024, p. 3). BPA captures these emotional and symbolic differences more effectively than traditional trait inventories by measuring the extent to which the AI brand’s personality is both attractive and engaging (Freling et al., 2011, p. 399). This is especially pertinent for freemium-to-premium AI LLMs, where user retention and monetization often depend less on features and more on whether users feel connected to the AI brand (Lee et al., 2021, p. 1347). For example, a freemium user might upgrade to ChatGPT Plus not because it can generate text (the free version already does), but because the AI's consistent traits including its helpful and witty tone have established a relational bond (Lee et al., 2021, p. 1347). Thus, personality appeal becomes the emotional hook that transforms interest into subscription.

Critically, a high BPA score implies that users not only notice the AI's personality but also enjoy and value it, suggesting that the brand is not only human-like but worthy of relationship investment (Smit et al., 2007, p. 628). Brands that lack favorability may be seen as cold or transactional; those lacking originality may be perceived as generic or forgettable; and those with unclear personalities may feel inconsistent or disjointed. Particularly, unclear AI personalities pose several risks including inconsistent tone, mixed messaging, or erratic responses, which can erode cognitive trust and emotional engagement (Cate, 2025, p. 5). For instance, if an AI responds warmly one day and coldly the next, users will therefore struggle to predict behavior, creating uncertainty and distrust. This inconsistency disrupts relational dynamics, weakening both user confidence and the emotional bond that drives ongoing interaction. In contrast, brands that score highly on all three BPA dimensions tend to evoke stronger affective responses and greater user commitment (Fernandes & Moreira, 2019, p. 279).

Therefore, BPA is a highly relevant construct within the AI LLM context, offering both conceptual depth and practical explanatory power. It not only enables the measurement of how AI LLMs are perceived but also helps predict meaningful psychological outcomes such as trust, emotional engagement, and ultimately, behavioral intentions such as brand advocacy and subscription intentions (Singh & Kunja, 2024, p. 3). By bridging branding theory with affective and cognitive dimensions of technology use, BPA provides a robust foundation for investigating how users relate to AI not just as tools, but as relational brand agents.

2.1.4 User Trust in AI

As AI LLMs transition from functional tools to relational brand agents, user trust emerges as a foundational element in shaping how these technologies are perceived and adopted. In branding contexts, trust transcends technical functionality – it reflects the degree to which users believe an AI system is competent, ethical, and reliable. Gefen et al. (2003, p. 56) define trust as comprising beliefs in an agent's ability, integrity, and benevolence, offering users a psychological shortcut when direct assessment of complex systems is impractical. This becomes particularly important in the case of LLMs, where users often lack the expertise to verify outputs or system logic, and instead must rely on affective and heuristic cues to judge whether the AI can be depended upon (Tie et al., 2024, p. 7).

From a branding perspective, trust is more than a prerequisite for adoption, it is the linchpin of enduring brand relationships. In line with Consumer-Brand Relationship Theory, trust is one of the earliest and most essential relational markers that signal the formation of a meaningful user-brand bond (Fournier, 1998, p. 344). As LLMs become embedded in daily tasks, from writing and ideation to emotional support and decision-making, the ability of users to trust the AI brand governs their willingness to integrate it into increasingly sensitive aspects of their lives.

Unlike transactional trust in traditional consumer technologies, trust in AI brands is multi-dimensional. It encompasses both cognitive trust, which refers to users' confidence in the system's technical competence and reliability, and affective trust, which captures perceptions of warmth, integrity, and alignment with user values (Hoff & Bashir, 2015, p. 407). The latter is especially significant in AI LLM interactions, where users often anthropomorphize the system and interpret tone, responsiveness, and coherence as relational cues (Wang et al., 2024, p. 5).

Moreover, research in human–AI interaction highlights several antecedents to trust formation that are particularly relevant for branding. These include the consistency of the AI's responses, its transparency in revealing limitations, and the perceived fairness or ethical grounding of its behavior (Rubicondo & Rosato, 2022, p. 8). For instance, when AI LLMs communicate in predictable, empathetic, and respectful ways, users are more likely to form a sense of trust, even in the absence of full system transparency or explainability (Gilpin et al., 2018, p. 2).

Critically, trust also serves as a mechanism of risk reduction. Because LLMs operate through opaque, probabilistic algorithms, users face a degree of uncertainty in interpreting outputs or delegating decisions (Raza et al., 2025, p. 6). Trust, therefore, acts as a compensatory belief structure that enables users to engage with the AI system despite these ambiguities. In this way, trust does not only simply facilitate initial use, it also sustains long-term commitment and enables deeper psychological integration of the AI brand into users' routines and identities (Cheng & Jiang, 2021, p. 5).

Finally, trust has implications for the symbolic positioning of AI brands. As brands increasingly compete not only on functionality but on relational quality, trust becomes a differentiator in crowded markets (Hassan et al., 2025, p. 13). AI LLMs that can demonstrate consistent, reliable, and emotionally attuned behavior are more likely to be perceived as trustworthy brands - worthy of investment, recommendation, and loyalty over time (Sundar et al., 2024, p. 1). Therefore, trust should be understood not only as a technological attribute but as a strategic branding asset that shapes the emotional architecture of user-AI relationships.

2.1.5 Emotional Engagement in AI

Parallel to trust, emotional engagement represents a second key psychological mechanism through which users develop relational ties with AI LLM brands. At its core, emotional engagement refers to the affective intensity of the bond that a user feels toward a brand manifested through enthusiasm, emotional investment, and attachment (Hollebeek, 2011, p. 565). In branding literature, emotional engagement has long been considered a central driver of long-term consumer-brand relationships, as it reflects a user's willingness to internalize and emotionally identify with a brand, beyond surface-level interactions or satisfaction (Brun et al., 2025, p. 3).

In the context of AI LLMs, emotional engagement assumes particular relevance due to the nature of the interaction. Unlike traditional product consumption, LLM-based AI tools such as ChatGPT or Replika operate through conversational, iterative dialogue. Users do not passively consume information; they actively participate in shaping it (Maduku et al., 2024, p. 2854). This interactive format enables the AI to function as a relational partner, rather than a utilitarian tool, thus deepening emotional resonance (Asiabar et al., 2024, p. 5). When the AI responds with warmth, empathy, or humor, users begin to attribute social and affective qualities to it, interpreting it as not merely helpful but companion-like (Singh & Kunja, 2024, p. 3).

Empirical studies affirm that this emotional resonance has meaningful behavioral outcomes. For example, Yun and Park (2022, p. 13) found that when chatbots used emotional expressions during service recovery, customer satisfaction and brand interaction intentions significantly increased. Similarly, Park et al. (2022, p. 28670) demonstrated that AI tools using expressive cues (such as affective tone or visual emoticons) were more likely to elicit perceptions of humanness, thereby enhancing social connection and emotional interest. These studies underscore the potential for emotional engagement to transform the nature of human-AI interaction from functional to affective.

From a branding perspective, emotional engagement offers strategic value. In increasingly saturated AI markets where functional capabilities like text generation or retrieval are becoming commoditized, brands must differentiate themselves through symbolic and emotional cues (Saeedi, 2025, p. 10). Emotional engagement acts as a form of psychological brand equity, reinforcing loyalty, amplifying satisfaction, and motivating word-of-mouth advocacy (Maduku et al., 2024, p. 2854). Moreover, emotional engagement reflects a form of user commitment that is difficult to replicate or displace. Whereas satisfaction may lead to transient approval, emotional engagement signals deeper alignment with the brand's perceived personality and values (Fernandes & Moreira, 2019, p. 279).

Therefore, understanding emotional engagement is crucial for both branding scholars and AI practitioners. It reflects not only how users feel about the AI brand, but how likely they are to return, to invest attention and emotion, and to publicly support it. As the AI ecosystem becomes increasingly relational, emotional engagement emerges as a key variable in understanding how users interpret and sustain human-AI brand relationships.

2.1.6 Brand Advocacy

Under this similar evolving realm of AI, brand advocacy is becoming a central strategic outcome, especially for brands built around interactive, subscription-based AI LLMs. Traditionally understood as users' voluntary endorsement of a brand through behaviors such as recommendations, online praise, and public defense (Brown et al., 2005, p. 125; Wilk et al., 2021, p. 1980), brand advocacy reflects the culmination of a deep consumer-brand relationship - a relationship that in AI branding is mediated through digital dialogue, affective cues, and relational engagement (Harrison-Walker, 2001, p. 67).

Within the scope of this research, brand advocacy is not treated as an isolated outcome, but as an expression of the psychological and emotional ties formed through continuous interaction with AI LLMs (Ahmadi & Ataei, 2022, p. 3). These interactions are fundamentally different from those associated with traditional user goods. Whereas classic brand advocacy may stem from satisfaction with a product's physical utility, brand advocacy in the LLMs context is more intimately tied to perceived relational quality as users' trust in the AI's reliability and alignment with their needs, and the emotional engagement they experience during interactions (Fullerton, 2005, p. 99).

Furthermore, brand advocacy acquires new social significance. Due to the interactive and conversational nature of these systems, brand advocacy focused more on being both rationally justified and emotionally meaningful. Particularly, users who perceive the AI as reliable and engaging are more likely to trust and feel personally connected to it, which significantly increases the likelihood of public endorsement (Wang & Qiu, 2024, p. 3). Furthermore, users are proved to be more likely to promote an AI brand when they perceive it as socially responsive and emotionally intelligent - signals that the technology matters as much for how it makes them feel as for what it can do (Cai et al., 2024, p. 5). Moreover, research also demonstrates that emotional features in chatbots can trigger advocacy behaviors. For instance, Yun and Park (2022, p. 13) found that chatbots equipped with emotional language yielded higher word-of-mouth, which led to an increasing in repurchase intentions.

From a branding theory perspective, brand advocates act as co-creators of brand value, reinforcing social proof and accelerating diffusion (Schivinski et al., 2016, p. 66). Especially under a tangible, relational domain like AI LLM, where trust is fragile and the technology is often misunderstood, brand advocacy can further function as a signal of legitimacy, helping brands grow through peer-to-peer influence (Hakala et al., 2017, p. 539). Without a robust advocacy base, even high-performing AI brands may struggle to achieve widespread adoption.

In summary, brand advocacy in AI LLMs is not merely an outcome, instead it is a relational endorsement. Particularly, it reflects how deeply users have internalized the AI brand's personality and social role. As such, it becomes a valuable indicator of brand strength and diffusion potential in emotional, symbolic, and social domains.

2.1.7 AI Subscription Intentions

Witnessing the shift of AI LLMs from tools to digital companions, the decision to subscribe to these LLMs becomes more than a simple transactional choice—it reflects a user's long-term commitment to the brand. In freemium-to-premium business models, such as those used by ChatGPT Plus or Google Gemini Advanced, subscription intentions represent a key behavioral milestone. Specifically, this research marks the moment where functional use transforms into relational investment, often driven by factors that extend beyond technical performance alone (Liu et al., 2024, p. 3).

Unlike one-off purchases, subscriptions require sustained belief in the brand's ability to deliver users' pursued value over time. Thus, users are not just paying for features - they are paying to maintain access to a digital partner they've grown to trust and emotionally connect with (Fournier, 1998, p. 362). In this way, subscription intentions becomes an expression of loyalty grounded in emotional and cognitive evaluation, shaped by how users experience and interpret the AI's brand personality (Reimann et al., 2012, p. 131).

From a branding standpoint, this reconceptualization raises managerial and theoretical implications. In AI LLMs, features such as real-time interaction, memory, or conversational style function as relational cues that anchor user expectations. Similar to subscription behavior in media and software-as-a-service (SaaS) industries, the perceived continuity and relevance of value delivery are crucial (Hassan et al., 2025, p. 13). This perception, however, is shaped not only by objective performance but also by symbolic, emotional, and experiential brand attributes (Liu et al., 2024, p. 3).

Empirical findings in adjacent domains reinforce this idea. For example, Ifekanandu et al. (2023, p. 3) found that personalized and emotionally intelligent AI features increased user retention by cultivating a sense of interpersonal involvement. These findings suggest that perceived responsiveness, adaptability, and emotional resonance of AI agents can translate into sustained usage intentions. In freemium-to-premium models, users often upgrade not for additional features, but because of the cumulative value and familiarity they associate with the AI as a digital companion (Lee et al., 2021, p. 1347).

Nevertheless, subscription intentions in AI contexts also face structural challenges. Literature on digital services warns of "subscription fatigue" - a psychological plateau where the perceived novelty of interaction diminishes and commitment wanes (Cate, 2025, p. 5). This effect is particularly pronounced when AI systems fail to evolve or maintain coherent brand expression over time. For instance, inconsistencies in tone or performance can disrupt users' mental models of the AI, leading to disengagement or distrust (Freling et al., 2011, p. 399). Therefore, the sustainability of subscription behavior is inherently tied to the perceived stability and adaptability of the AI’s brand identity.

Despite these developments, the academic literature remains limited in its direct exploration of subscription intentions as an outcome in AI LLM environments. Existing research often generalizes from broader technology adoption models or focuses on satisfaction and usefulness, without sufficiently accounting for the relational and symbolic aspects of AI branding (Liu et al., 2024, p. 4; Bhati & Verma, 2020, p. 11). This conceptual gap necessitates a deeper investigation into the affective and cognitive processes underpinning user commitment. Thus, understanding AI subscription as a relational decision that is deeply influenced by perceptions of brand personality traits, emotional engagement, and symbolic user trust becomes a critical priority for both scholars and practitioners.

2.1.8 Anthropomorphism Tendency

While BPA may offer a compelling foundation for user engagement in AI contexts, the degree to which individuals respond to personality cues is not universal. A critical factor influencing this variability is anthropomorphism tendency - the stable disposition to attribute human-like characteristics, intentions, and emotions to non-human agents, including AI systems (Waytz et al., 2010, p. 226). This construct, grounded in psychological and sociocognitive theory, helps explain why certain users interact with AI brands as if they were human counterparts, while others engage with them in a strictly instrumental manner (Cohn et al., 2024, p. 3).

At its core, anthropomorphism tendency is more than just a perceptual error; it is a psychological mechanism that helps individuals make sense of non-human agents in social and emotional terms. Epley, Waytz, and Cacioppo (2007, p. 865) argue that anthropomorphism emerges from a triadic process: elicited agent knowledge (the recognition of agency), effectance motivation (a desire to predict and understand behavior), and sociality motivation (a drive for social connection). These factors become especially salient in human-AI interaction, where users often lack a full understanding of the AI's logic or transparency. In such contexts, anthropomorphism serves as a psychological shortcut, allowing users to navigate uncertainty by treating the AI as a social actor.

This tendency becomes particularly relevant for AI LLMs, which communicate using natural language and increasingly adopt affective or contextually adaptive cues (Epley et al. (2007, p. 865). When users high in anthropomorphism tendency encounter emotionally resonant behaviors such as humor, empathy, or memory recall, they are more likely to perceive these cues as genuine expressions of agency rather than pre-programmed scripts (Gnewuch et al., 2022, p. 488). As Kim and Sundar (2012, p. 243) note, individuals with higher anthropomorphism tendencies are prone to mindfully processing computer-generated cues, interpreting them through relational frameworks akin to human interaction.

Empirical evidence reinforces the importance of this construct in shaping human–AI perception. Shen et al. (2024, p. 1077) developed and validated a psychological anthropomorphism scale, showing that individuals high on this dimension respond more positively to AI agents with relational behaviors, such as social presence, coherence, and turn-taking responsiveness. Similarly, Zhang and Rau (2022, p. 2) highlight that anthropomorphism tendency can determine whether users interpret AI brand cues as authentic or contrived, thereby influencing the quality of engagement and perceived trustworthiness.

Importantly, anthropomorphism tendency also reflects deeper sociocultural and individual differences. Waytz et al. (2014, p. 116) found that people's prior experiences with technology, emotional needs, and cognitive styles can influence their likelihood to anthropomorphize machines. In branding contexts, this means that identical design elements such as warmth in tone or visual avatars may be perceived differently across users, with some interpreting them as indicators of brand relatability and others as manipulative or artificial.

Furthermore, the implications of anthropomorphism tendency extend beyond immediate perception. As Kolomaznik et al. (2024, p. 10) suggest, socio-emotional attributes in AI can enhance collaboration and user acceptance, but their effects are magnified or diminished depending on users' baseline anthropomorphic sensitivity. This nuance adds complexity to branding strategies in AI: while anthropomorphic cues can enhance relational quality for some, they may remain ineffective or even counterproductive for others if not appropriately calibrated (Chen & Lin, 2022, p. 2177).

Crucially, anthropomorphism tendency also does not override the need for a relational framework like CBRT; rather, it enriches it. While the theory explains how relationships are formed between users and brands, anthropomorphism tendency helps explain why some users are more susceptible to relationship-building cues than others (Fournier, 1998, p. 344; Chen & Lin, 2022, p. 2176). It introduces an important layer of nuance, allowing this model to move beyond one-size-fits-all assumptions and toward a more individualized understanding of user–AI brand relationships (Kolomaznik et al., 2024, p. 10).

2.2 Hypotheses Development

Following the detailed examination of the theoretical constructs in the previous section, this part of the study transitions from conceptual grounding to empirical inquiry. As illustrated in Figure 1, the model positions BPA as the independent variable, influencing both user trust and emotional engagement. These two mediators, in turn, are expected to affect the dependent variables - AI subscription intentions and brand advocacy. Finally, the model incorporates anthropomorphism tendency as a moderator on the paths from BPA to both mediators, accounting for individual-level differences in how users perceive and respond to personality cues in AI systems.

2.2.1 BPA and User Trust

BPA plays a foundational role in trust formation. A favorable personality fosters a sense of approachability and ethical alignment; originality signals innovation and adaptability; and clarity reduces uncertainty, enhancing perceived transparency and consistency (Freling et al., 2011, p. 404; Matzler et al., 2006, p. 428). Also, users are more likely to trust AI LLMs that exhibit a strong and appealing personality (Singh & Kunja, 2024, p. 3). When users interact with AI LLMs that display coherent, favorable, and emotionally appealing personalities, they are more likely to attribute trustworthy intentions and capabilities to them (Guerra-Tamez et al., 2024, p. 3). These BPA dimensions make the AI more relatable and dependable, which aligns with the user's need for consistency and safety in relational exchanges. Therefore, considering the crucial role of the three BPA dimensions and user trust in AI brands, it is logical to posit a positive effect between the two:

H1: (a)BPA (Favorability), (b)BPA (Clarity), (c) BPA (Originality) positively influences user trust.

2.2.2 BPA and Emotional Engagement

Apart from user trust, emotional engagement involves the user's affective investment. Thus, BPA can trigger this investment by making interactions feel more personal, enjoyable, and meaningful (Cheng, 2024, p. 10). While clarity ensures these interactions are smooth and comprehensible, reducing frustration and strengthening user satisfaction (Wang, 2024, p. 24), originality adds excitement and novelty to the interaction, making the AI more engaging and stimulating (Fernandes & Moreira, 2019, p. 279). By reinforcing these emotional connections, the three dimensions of BPA encourage sustained user interaction, deepen engagement, and enhance long-term loyalty to the AI LLMs. Therefore, emotional engagement is not a mere by-product of satisfaction, it is a reciprocal dynamic that strengthens with continued interaction. The more users feel emotionally connected to the AI, the more they use it; and the more they use it, the deeper the emotional bond becomes (Cheng, 2024, p. 10). As such, it is expected that these three BPA dimensions would have a positive impact on emotional engagement in AI:

H2: (a)BPA (Favorability), (b)BPA (Clarity), (c) BPA (Originality) positively influences emotional engagement.

2.2.3 User Trust and Emotional Engagement as Drivers of Brand Advocacy

Trust and emotional engagement are both theorized to directly influence brand advocacy. Trust provides the psychological security users need to publicly endorse the brand, while emotional engagement amplifies attachment and enthusiasm, leading to a higher likelihood of advocacy behaviors such as recommending and defending the AI brand (Fatma & Khan, 2023; Wilk et al., 2021). In AI LLM contexts where the technology often remains opaque and its capabilities not easily evaluated by the average user, trust becomes particularly central to advocacy behavior. Moreover, users must feel confident that the system is not only competent, but also reliable, benevolent, and aligned with their best interests (Fatma & Khan, 2023, p. 4). This confidence lowers perceived risk in sharing and recommending the brand to others, especially in public or professional settings (Hakala et al., 2017, p. 539).

Emotional engagement, meanwhile, offers an affective pathway to brand advocacy. When users feel emotionally invested in an AI brand such as experiencing warmth, enjoyment, or empathy during interaction, they are more inclined to share these positive experiences with peers (Wang & Qiu, 2024, p. 3). This behavior is not transactional but relational, rooted in a desire to support a brand that reflects the user's identity or values. Previous studies in digital branding have shown that emotionally engaged users are more likely to generate user-generated content, participate in brand communities, and actively defend the brand in online discussions (Hollebeek et al., 2014, p. 154). Therefore, the following hypotheses are presented:

H3: User trust positively influences brand advocacy.

H4: Emotional engagement positively influences brand advocacy.

2.2.4 User Trust and Emotional Engagement as Drivers of AI Subscription Intentions

User trust and emotional engagement also play a pivotal role in shaping users' intentions to subscribe to AI LLMs. Trust alleviates concerns about reliability and long-term value, while emotional engagement creates a sense of ongoing relational fulfillment (Rawool et al., 2024, p. 12). Particularly, Rawool et al. (2024, p. 12) demonstrated that trust mediates the relationship between perceived usefulness and willingness to subscribe to AI LLM, whereas Asiabar et al. (2024, p. 5) showed that trust in AI is a stronger predictor of continued use than even objective system performance. These findings emphasize that trust is not solely built on rational evaluation, it is equally shaped by users' emotional and symbolic interpretations of the AI's behavior. Together, they increase users' willingness to move from casual to committed use (Blasco-Arcas et al., 2016, p. 574), leading to these hypotheses:

H7: User trust positively influences AI subscription intentions.

H8: Emotional engagement positively influences AI subscription intentions.

2.2.5 The Mediating Role of User Trust and Emotional Engagement towards the relationship between BPA and Brand Advocacy

In addition to their direct effects, both trust and emotional engagement are expected to mediate the relationship between the three dimensions of BPA and brand advocacy. Additionally, BPA and its three dimensions facilitate these relational experiences, which then drive users to act as brand advocates (Wang & Qiu, 2024, p. 3).

This relational pathway is activated through the AI's BPA where a favorable, original, and clearly defined personality makes the AI feel authentic and differentiated (Wang, 2024, p. 24). In detail, users are more likely to perceive such brands as capable of understanding their needs and aligning with their communication preferences (Freling et al., 2011, p. 393). This, in turn, strengthens user trust by providing a sense of assurance in promoting the brand and fosters emotional engagement, further creating affection that motivates users to share their experiences and recommendations (Fatma & Khan, 2023, p. 4).

In essence, BPA does not lead directly to advocacy; instead, it initiates a chain of responses that make advocacy both rationally justified and emotionally meaningful. Users who perceive the AI as reliable and engaging are more likely to trust and feel personally connected to it, which significantly increases the likelihood of public endorsement (Wang & Qiu, 2024, p. 3). Especially under AI LLM, where trust is fragile and the technology is often misunderstood, advocacy can function as a signal of legitimacy, helping brands grow through peer-to-peer influence (Hakala et al., 2017, p. 539).

This understanding is closely aligned with the principles of CBRT, which emphasizes trust as a central relational outcome that emerges from emotionally meaningful brand interactions (Fournier, 1998, p. 344). In the context of AI LLMs, trust functions not merely as an evaluative belief but as a psychological mechanism that reinforces long-term user commitment (Kim & Sundar, 2012, p. 34). It acts as a bridge between users' interpretations of the AI's brand personality and their willingness to engage in deeper loyalty behaviors and most notably, brand advocacy expressed through recommendation, defense, and public endorsement. Thereby, the relationship between BPA and brand advocacy is mediated by consumer trust and emotional engagement, leading to the following hypotheses:

H5: User trust mediates the relationship between (a)BPA (Favorability), (b)BPA (Clarity), (c)BPA (Originality) and brand advocacy.

H6: Emotional engagement mediates the relationship between (a)BPA (Favorability), (b)BPA (Clarity), (c)BPA (Originality) and brand advocacy.

2.2.6 The Mediating Role of User Trust and Emotional Engagement towards the relationship between BPA and AI Subscription Intentions

User trust and emotional engagement are also theorized to mediate the relationship between the three dimensions of BPA and AI subscription intentions, acting as psychological bridges that convert personality perception into subscription behavior (Kim & Sundar, 2012, p. 34).

Central to this experience is the perception of the AI LLMs as trustworthy. Studies show that trust significantly influences users' willingness to commit financially, especially when they cannot fully evaluate the internal logic or transparency of the technology (Bhati & Verma, 2020, p. 11). In AI LLMs, where algorithmic opacity is the norm, trust is not derived solely from output accuracy, it is formed through patterns of interaction, tone, and responsiveness (Sun & Wang, 2025, p. 1). Therefore, AI that exhibits clarity and reliability is more likely to be perceived as trustworthy and, as a result, worthy of a subscription relationship (Rawool et al., 2024, p. 12).

Yet trust alone is insufficient. The decision to subscribe is also significantly influenced by the emotional engagement users have with the brand. In detail, it fosters not just attention but immersion, strengthening users' personal identification with the AI (Blasco-Arcas et al., 2016, p. 574). An emotionally engaging AI LLM does more than solve problems, it rather creates a space where users feel understood, supported, and even inspired. This emotional resonance transforms the LLM from a task-oriented tool into a relational presence in the user's digital life, deepening their motivation to continue and pay for the interaction (Ratican & Hutson, 2023, p. 45).

In this relational model, BPA is also positioned as the initiating force. A favorable, original, and clearly defined personality invites trust by conveying dependability and credibility, while simultaneously fostering emotional engagement (Freling et al., 2011, p.

399; Kim & Sundar, 2012, p. 34). Together, these responses create the psychological conditions under which users are not only satisfied with the service but motivated to sustain and deepen the relationship through subscription.

This process also follows CBRT, which posits that trust is a core relational output of emotionally resonant brand interactions (Fournier, 1998, p. 344). Thus, under AI LLM contexts, trust, therefore acts as a key psychological mediator, linking users' perceptions of brand personality with deeper commitment behaviors such as paid subscriptions:

H9: User trust mediates the relationship between (a)BPA (Favorability), (b)BPA (Clarity), (c) BPA (Originality) and AI subscription intentions.

H10: Emotional engagement mediates the relationship between (a)BPA (Favorability), (b)BPA (Clarity), (c) BPA (Originality) and AI subscription intentions.

2.2.7 The Moderating Role of Anthropomorphism Tendency

Not all users respond to BPA in the same way. Specifically, anthropomorphism tendency - a user's predisposition to attribute human-like traits to non-human entities - is expected to moderate the strength of BPA three dimensions' influence on trust and emotional engagement (Hill & Troshani, 2024, p. 5).

In this research, BPA comprises favorable, original, and clear brand personality traits that shape perceptions of trust and emotional engagement (Freling et al., 2011, p. 393). However, these traits only resonate if they are interpreted as socially meaningful. For users high in anthropomorphism tendency, the originality of an AI LLM may be experienced as evidence of intentionality or empathy, prompting stronger affective responses (Epley et al., 2007, p. 865). Similarly, clarity may be seen not just as communicative efficiency but as a reflection of the AI's reliability and coherence as a "social partner." This perspective is supported by Shen et al. (2024, p. 1077), who found that users with higher anthropomorphism tendencies were significantly more responsive to AI systems exhibiting relational behaviors, including social presence and conversational consistency.

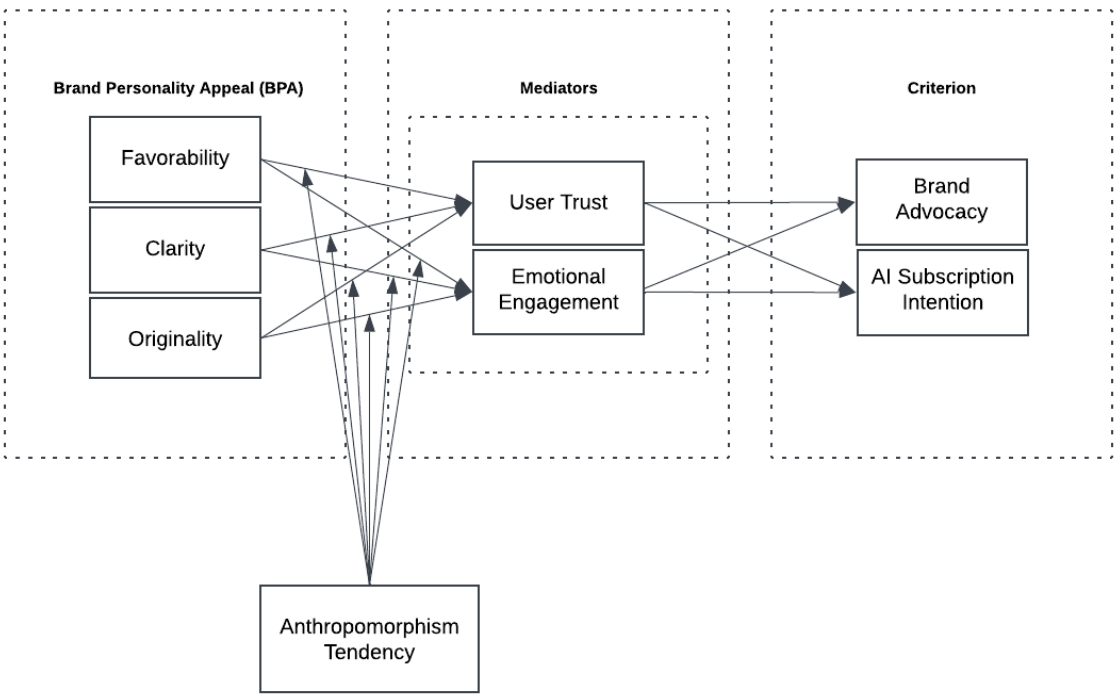
Conversely, for users low in anthropomorphism tendency, the very same BPA cues may hold less relational value. A humorous tone might be seen as functional design rather than social signaling. Without the tendency to project human qualities onto the AI, these users are less likely to develop trust or form emotional bonds, thus dampening the relational effects of BPA (Troshani et al., 2020, p. 9). In this way, anthropomorphism tendency acts as a moderating variable, shaping the intensity of the relationships between BPA and its downstream outcomes (Hill & Troshani, 2024, p. 5). Therefore, the following hypotheses are presented:

H11: Anthropomorphism tendency moderates the relationship between (a)BPA (Favorability), (b)BPA (Clarity), (c) BPA (Originality) and user trust.

H12a: Anthropomorphism tendency moderates the relationship between (a)BPA (Favorability), (b)BPA (Clarity), (c) BPA (Originality) and emotional engagement.

2.3 Conceptual Model

Figure 1. Conceptual Model



3. Methodology

This chapter presents a comprehensive outlook on the research design, operationalization of the proposed concepts, procedure, sampling methods, and data collection. Finally, this chapter concludes with a detailed description of data analysis, as well as the steps taken to ensure the validity and reliability of the research findings. By providing a comprehensive overview of the methodology used, the precision and credibility of this research are more apparent.

3.1 Research Design

This study employs a quantitative, survey-based research design to examine how perceptions of brand personality appeal (BPA) in AI large language models (LLMs), mediated by user trust and emotional engagement, influence AI subscription intentions and brand advocacy. In addition, the role of anthropomorphism tendency is further investigated in moderating these relationships.

A quantitative approach was deemed most appropriate for several interrelated reasons. First, the study aims to test a theory-driven conceptual model that includes mediating and moderating variables. Such models require not only descriptive data but also statistical inference, which is best facilitated through quantitative analysis (Groves et al., 2011, p. 31). Moreover, quantitative methods are well-suited to investigating causal mechanisms and hypothesized relationships among latent psychological constructs, especially when rooted in established frameworks such as the CBRT (Fournier, 1998) and BPA model (Freling et al., 2011).

Compared to qualitative approaches such as interviews and ethnographies which are valuable for generating exploratory insights, quantitative surveys allow for hypothesis testing across a larger and more diverse respondent base (Harvey & Dijkers, 2020, p. 257). This enhances the external validity and generalizability of findings, ensuring that the conclusions drawn are not bound to a small or idiosyncratic sample. In particular, the goal of identifying patterns of engagement with AI brands across varying degrees of anthropomorphism tendency necessitates a larger sample size, which is more efficiently achieved via surveys (Hair et al., 2021, p. 48).

Surveys are also particularly well-suited for this research because the study investigates subjective user experiences such as trust, emotional engagement, and brand perceptions that are not directly observable (Jhingan, 2023, p. 5). By using validated psychometric scales, the survey method enables systematic measurement of latent constructs, providing both reliability and comparability across respondents (DeVellis, 2017, p. 25). Furthermore, the standardized format of surveys reduces interviewer bias and supports consistent data collection, which is critical when evaluating mediation and moderation effects through statistical techniques such as structural equation modeling (SEM) or hierarchical regression analysis (Fowler, 2014, p. 83)

Importantly, the survey instrument also supports multivariate statistical techniques necessary to test the complex conceptual model proposed in this study. It enables the assessment of direct, indirect, and interaction effects - for instance, how BPA indirectly influences subscription intentions through trust, or how anthropomorphism tendency conditions these effects (Klein & Moosbrugger, 2000, p. 457). Such layered analysis would be impractical using purely qualitative methods, where general patterns are more difficult to isolate due to the interpretative nature of data (Bryman, 2016, p. 160).

3.2 Sampling and Data Collection

For the mass respondents to fully understand and ensure the seamless continuity and flow of the survey, the questionnaire was fully drafted in English, adapted from all English-written scales. Furthermore, to successfully conduct the research, a pilot test was carried out to test out the validity and clarity of its instruments. This research drew on the author's related academic and professional network to voluntarily recruit 10 participants ranging from master students to office workers from IT companies. In short, minor wording issues and order alignments were conducted based on the collected feedback to improve the quality of the questionnaire.

The theoretical framework was empirically tested using data collected through an online survey administered via Qualtrics. The survey was distributed between late April and mid-May 2025 and targeted individuals who had prior experience with at least one AI Large Language Model (LLM) brand, including ChatGPT, Gemini, Copilot, Claude, and others. Initially, the research aimed to distribute the questionnaire via professional survey platforms such as Prolific or Amazon MTurk, or through partnerships with AI companies, technology organizations, and academic communities to ensure access to participants with prior experience using AI Large Language Models (LLMs). However, due to financial and time constraints, recruitment was ultimately carried out through social media outreach. The survey link was disseminated across various online communities and forums, particularly through WhatsApp and Facebook groups dedicated to AI, technology, and university student networks.

WhatsApp, in particular, played a central role in the recruitment strategy due to its widespread use and cultural integration within the Netherlands. National statistics confirm that WhatsApp is the most dominant messaging platform in the country, with over 84% of Dutch individuals aged 12 and above using it to exchange messages, making it a deeply embedded tool for digital communication (CBS, 2020, p. 18). Its ubiquity among various age groups and social segments made it a strategic channel for disseminating the survey to a broad and demographically diverse population.

Furthermore, WhatsApp has been increasingly utilized in academic and applied research for quota-based survey sampling, particularly because it allows direct, conversational-style engagement with respondents. Research conducted by the Immigration Policy Lab has demonstrated that WhatsApp surveys can be designed to emulate real-time interactions and can yield high response rates with minimal friction (IPL, 2023, p. 2). These characteristics make it particularly well-suited for capturing responses from digitally literate populations, such as AI users, with relatively low cost and high accessibility.

Regarding reach and diversity, the questionnaire was conducted in the Netherlands, which ranks third globally in technological readiness, recognized for its advanced digital infrastructure and high technological readiness (International Trade Administration, 2024; Martinetti et al., 2024, p. 3). Thus, it provides an ideal context for studying the adoption of advanced AI tools like LLMs. The country has made significant investments in AI research and development, with initiatives such as the AiNED National Growth Fund Investment Programme aiming to bolster AI capabilities across sectors (Rathenau Instituut, 2021, p. 3). Furthermore, Dutch higher education institutions are actively integrating AI into their curricula and research agendas, fostering a technologically adept population well-suited for examining AI LLM usage across various demographic groups (Abdelwahab et al., 2022, p. 5). This environment enhances the likelihood of engaging participants who utilize AI LLMs for academic and research purposes, thereby enriching the study's insights into user experiences and subscription intentions.

A total of 214 responses were collected. After filtering out incomplete entries based on progress and consistency, 200 fully completed and valid responses were retained for analysis. In detail, age was disproportionately distributed, resulting in 3% between 18-19 years old (6 respondents), 92.5% between 20-29 years old (179 respondents), 3.5 % between 30-39 (13 respondents) and only 1% between 40-59 (2 respondents).

While this study did not impose strict age-based sampling restrictions, it primarily focuses on the 20 to 40-year-old cohort, as this demographic is particularly engaged with AI technologies, especially large language models (LLMs). Individuals in this age range represent a digitally active segment of the population, often integrating advanced AI tools into both professional workflows and academic contexts (Morris & Venkatesh, 2000, p. 390). Their prominent role in the digital economy and educational environments makes them especially relevant for exploring behavioral responses to AI LLMs.

Notably, this cohort includes a significant number of academic users, such as university students and postgraduate researchers, who frequently rely on LLMs for tasks like literature reviews, academic writing, and research design (Deng et al., 2025, p. 2; Wang et al., 2024, p. 7). While respondents from other age groups were also included in the broader sample, the emphasis on this digitally immersed segment provides a focused lens through which to analyze patterns of AI engagement. Thus, although the sample is not age-representative in the strictest sense, its composition aligns with the study's goal of understanding AI LLM use among highly involved and experienced user segments.

In terms of brand familiarity and usage, the most frequently mentioned AI LLM was ChatGPT (OpenAI), selected by 95% of respondents (204 choices), reaffirming its position as the most widely adopted conversational AI platform among digitally active users. Gemini (Google) followed with 53% (115 choices), Copilot (Microsoft) with 37% (79 choices), and Claude (Anthropic) with 23% (50 choices). Additionally, a smaller segment of participants (7%, or 16 choices each) reported familiarity with emerging or niche models such as Grok, LLaMA, DeepSeek, Cohere, Perplexity, Elicit, and GitHub Copilot. Although these platforms were less prominent in the dataset, their mention suggests a growing awareness of alternative LLM ecosystems and demonstrates the increasingly diverse AI landscape in which users are operating.

3.3 Procedure

In this research, the survey comprised three main structured sections designed to assess key variables of interest in this research, with the full questionnaire provided in Appendix B.

The survey first began with an introductory section that explained the purpose of the study and emphasized the voluntary and confidential nature of participation. A screening question was included at the outset, requiring respondents to explicitly consent to the research terms before continuing. Those who declined were automatically exited from the survey. Next, a second screening question ensured that only participants who had used an AI large language model (LLM) in the past six months could proceed. Respondents who answered “no” to this question were routed to the end of the survey and excluded from further participation. This filter was crucial for targeting individuals with relevant experience, ensuring the validity of subsequent responses.

In the next section, participants were first asked to indicate the AI LLM brand they used most frequently in the past six months (e.g., ChatGPT, Claude, Gemini, Copilot). This step ensured that subsequent responses were grounded in a specific, personally relevant user experience. Immediately following this question, respondents were instructed to keep this selected brand in mind while completing the remainder of the survey. A brief instruction emphasized that all subsequent items should be answered concerning their interactions with this particular AI brand. This framing was essential for ensuring contextual consistency across measures, allowing for a more accurate assessment of participants’ psychological and behavioral responses toward a single AI LLM entity. Following this, participants were presented with six separate blocks of items measuring the key variables outlined in the theoretical framework: BPA, user trust, emotional engagement, brand advocacy, AI subscription intentions, and anthropomorphism tendency. Each construct was measured using a validated multi-item scale adapted from prior academic literature. All items were rated using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

The third section gathered demographic information, including age, gender, nationality, education level, and employment status. At the end of the survey, the final screen presented a thank-you message expressing appreciation for their time and contribution. On average, the questionnaire took approximately 7–10 minutes to complete.

3.4 Measurements and Operationalization

In this research, a structured online survey was designed to capture and measure the core constructs. Since it is based around different constructs, the following subsections below offer a detailed description of how each key construct was operationalized. Each scale has been selected based on prior validation in the relevant literature and theoretical framework section above. All results are further displayed in Table 1.

3.4.1 Brand Personality Appeal

To operationalize Brand Personality Appeal (BPA), this study initially adopted the full 16-item scale proposed by Freling et al. (2011), encompassing the dimensions of Favorability, Originality, and Clarity. As shown in Table A1 under Appendix A, the scale consists of three subdimensions with each item scored using a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). In detail, all 16 items under three BPA dimensions were grouped as favorability includes BPA3, BPA5, BPA7, BPA9-10, BPA12-13, originality consists of BPA6, BPA8, BPA14-15, and clarity has BPA1-2, BPA4, BPA11, BPA16. However, due to a low internal consistency score (Cronbach's $\alpha = .65$) observed for the Originality subscale, it was excluded from subsequent factor analyses. Exploratory factor analysis (EFA) was therefore conducted separately for the Favorability and Clarity dimensions to validate their factorial structure and reliability within the current sample.

For the BPA Favorability dimension, a Principal Component Analysis (PCA) method with direct oblimin rotation was employed, based on an eigenvalue threshold of >1.00. The Kaiser-Meyer-Olkin (KMO) measure verified sampling adequacy (KMO = .840), exceeding the minimum acceptable value of .60 (Kaiser, 1970, p. 32). Bartlett's Test of Sphericity was significant, $\chi^2(21) = 380.65$, $p < .001$, indicating that the correlations between items were sufficiently large for factor analysis (Bartlett, 1954, p. 297). A single factor emerged from the analysis, accounting for 38.46% of the total variance. All seven items loaded strongly on this factor, with loadings ranging from .481 to .774. The factor demonstrated high internal consistency, with a Cronbach's alpha of .82.

Similarly, BPA Clarity was subjected to the same PCA procedure with direct oblimin rotation. The KMO value of .72 confirmed adequate sampling adequacy, and Bartlett's Test of Sphericity was again significant, $\chi^2(10) = 204.24$, $p < .001$. One factor was extracted, explaining 36.26% of the variance. Four of the five items showed strong factor loadings between .478 and .798. The resulting factor demonstrated acceptable internal reliability that exceeded the minimum criterion of .70 (Cronbach's $\alpha = .72$) (Nunnally & Bernstein, 1994, p. 265).

3.4.2 User Trust

To measure this construct, a validated user trust in AI LLM branding scale comprising eleven items was adapted from Rawool et al. (2024, p. 12), designed to assess perceived competence, benevolence, and integrity in AI LLM interactions. Particularly, detailed items can be seen in Table A1 under Appendix A. For this scale, participants responded to each item using a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

To assess the factor structure, an EFA was also conducted using PCA. The KMO value of .932 verified the sampling adequacy for this analysis, exceeding the recommended threshold of .60 (Kaiser, 1970, p. 32). Bartlett's Test of Sphericity was significant, $\chi^2(55) =$

1324.16, $p < .001$, confirming the suitability of the data for factor analysis (Bartlett, 1954, p. 297). Results indicated a unidimensional structure, with a single factor explaining 54.04% of the variance. All items loaded strongly on this factor, with factor loadings ranging from .611 to .782, and communalities ranging from .373 to .611. The internal consistency of the scale was excellent (Cronbach's $\alpha = .93$), exceeding the minimum criterion of .70 and supporting its reliability for further analysis (Nunnally & Bernstein, 1994, p. 265).

3.4.3 Emotional Engagement

Emotional engagement was assessed using a five-item scale developed by Fernandes and Moreira (2019, p. 279), capturing users' affective attachment and enthusiasm toward AI LLM usage (table 1, appendix A). As with the other scales, responses were collected on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

Similarly, PCA was also applied for EFA. Thus, the KMO value of .871 and a significant Bartlett's Test of Sphericity, $\chi^2(10) = 473.69$, $p < .001$, indicated adequate sampling and sufficient correlations among items (Kaiser, 1970, p. 32; Bartlett, 1954, p. 297). Additionally, a single factor emerged, explaining 58.87% of the total variance. Five items presented qualified factor loadings ranging from .657 to .811. Lastly, Cronbach's alpha for the scale was .87, exceeding the minimum criterion of .70 and confirming high internal consistency (Nunnally & Bernstein, 1994, p. 265).

3.4.4 Brand Advocacy

To assess brand advocacy within the context of AI LLMs, this study utilized a nine-item scale originally developed by Wilder (2015, p. 78). The scale captures two critical advocacy dimensions: defending the brand in the face of criticism and promoting it to others (table 1, appendix A). All items were rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

To evaluate the construct validity and internal consistency of the scale, an EFA was conducted using PCA. The KMO value confirmed the sampling adequacy (KMO = 0.91), exceeding the recommended threshold of 0.60 (Kaiser, 1970, p. 32). Bartlett's Test of Sphericity was significant, $\chi^2(36) = 979.65$, $p < .001$, indicating the data were suitable for factor analysis (Bartlett, 1954, p. 297).

The EFA results further revealed a single-factor structure explaining 53.42% of the total variance, thereby justifying the unidimensional treatment of the construct. All nine items demonstrated satisfactory factor loadings, ranging from .496 to .830. The Cronbach's alpha for the scale was .91, exceeding the minimum criterion of .70 and further indicating excellent internal reliability (Nunnally & Bernstein, 1994, p. 265).

3.4.5 AI Subscription Intentions

AI subscription intentions were measured using a three-item scale adapted from Jo (2024, p. 1058), designed to capture respondents' future-oriented behavioral commitment to paid access to AI LLM services. As shown in Table A1 under Appendix A, responses were collected on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree).

An EFA was conducted using PCA as the main method to validate the construct's dimensionality. Thus, the KMO value was 0.77, confirming sampling adequacy, and Bartlett's Test of Sphericity yielded a significant result, $\chi^2(3) = 292.15$, $p < .001$, validating the use of factor analysis (Kaiser, 1970, p. 32; Bartlett, 1954, p. 297). Additionally, a single factor emerged, explaining 83.52% of the variance. Furthermore, factor loadings for the three items ranged from .909 to .920, indicating strong coherence among the items. The Cronbach's alpha coefficient was .94, exceeding the minimum criterion of .70 and suggesting excellent internal consistency (Nunnally & Bernstein, 1994, p. 265).

3.4.6 Anthropomorphism Tendency

To assess anthropomorphism tendency in the context of AI LLMs, this study employed the Artificial Intelligence Psychological Anthropomorphism Scale developed by Shen et al. (2024, p. 1077). The scale comprises 16 items designed to capture individuals' tendencies to attribute human-like qualities to AI systems across three conceptual domains: affective warmth, empathy, and mind. Specifically, affective warmth reflects perceptions of the AI as socially appealing or emotionally expressive; empathy captures beliefs that the AI can understand and share human emotions; and mind assesses the extent to which individuals perceive AI systems as possessing cognitive abilities. Participants rated their agreement with each item on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Full-scale items are presented in Appendix A, Table A1.

To evaluate the scale's dimensional structure and reliability, an EFA was conducted using PCA with oblimin rotation. The KMO value verified sampling adequacy (KMO = .92), well above the recommended threshold of .60 (Kaiser, 1970, p. 32), and Bartlett's Test of Sphericity was significant ($\chi^2(120) = 2390.43$, $p < .001$), confirming that the correlation matrix was factorable (Bartlett, 1954, p. 297). The EFA revealed a three-factor solution, which is consistent with the theoretical structure proposed by Shen et al. (2024), accounting for 67.3% of the total variance.

Despite this multidimensional structure, the inter-factor correlations were moderately high ($r = .41$ to $.63$), indicating substantial overlap and shared variance across the three sub-dimensions. Therefore, in line with prior research on generalized anthropomorphizing tendencies (Waytz et al., 2010, p. 226), and given the conceptual coherence of the items, this study retains anthropomorphism tendency as a higher-order unidimensional construct. This treatment is theoretically justified, as the focus of this study is not on the individual roles of affective warmth, empathy, or mind, but rather on users' overall predisposition to perceive AI LLMs as socially and psychologically human-like.

Furthermore, the scale exhibited excellent internal consistency, with a Cronbach's alpha of .94, exceeding the minimum criterion of .70 and further confirming the reliability of the construct in this research context (Nunnally & Bernstein, 1994, p. 265).

Table 1.

Validity and reliability test result

Construct	No. of Items	Cronbach's α	KMO
BPA Favorability	7	0.82	0.84
BPA Clarity	5	0.72	0.72
User trust	11	0.93	0.93
Emotional engagement	5	0.87	0.87
Brand advocacy	9	0.91	0.92
AI subscription intentions	3	0.94	0.78
Anthropomorphism tendency	16	0.94	0.92

3.4.7 Demographics

This study collected several demographic variables to better characterize the sample and contextualize the findings. Key demographic data included age, gender, nationality, educational level, and employment status. Age was measured as a continuous variable and ranged from 18 to 50 years (M = 25.87, SD = 3.59), reflecting a predominantly young adult cohort highly familiar with digital tools and emerging AI technologies.

Gender distribution in the sample was slightly uneven, with 53.0% female (n = 106), 44.5% male (n = 89), and 2.5% identifying as non-binary, third gender, or preferring not to disclose (n = 5). Participants were also asked to indicate their nationality from a dropdown menu comprising 197 recognized sovereign states. The four most frequently represented nationalities were Vietnam (n = 85), the Netherlands (n = 14), Australia (n = 13), and China (n = 7), reflecting a diverse yet digitally immersed respondent pool.

Education level was assessed using a 7-point Likert-type scale, where 1 represented "secondary school or equivalent" and 7 denoted "other." Employment status was similarly coded from 1 ("employed full-time") to 7 ("other"). Gender categories included 1 for male, 2 for female, 3 for non-binary/third gender, 4 for prefer not to say, and 5 for other. These variables help capture the diversity and socio-demographic backgrounds of respondents while controlling for potential confounding effects in later analyses.

All construct measurements, questionnaire items, and their corresponding academic sources are detailed in Table A1 under Appendix A, while the demographic features of respondents are presented in Table 2.

Table 2.

Demographic features of respondents

Subject: N=200

Demographics	Item	Frequency	Percentage
Gender	Male	89	44.5%
	Female	106	53.0%
	Non-Binary/Third Gender	3	1.5%
	Prefer not to say	2	1%
Age	18-19	6	3.0%
	20-29	179	92.5%
	30-39	13	3.5%
	40-49	1	0.5%
	50-59	1	0.5%

3.5 Ethical Concerns

In detail, the survey instrument first included an introductory consent section informing participants about the study's purpose, the voluntary nature of participation, the absence of financial compensation, and strict measures to ensure anonymity and data confidentiality. Moreover, participation required respondents to explicitly agree to four consent statements related to data usage and GDPR compliance. Additionally, participants were also informed that their personal data would be anonymized and used solely for research purposes. This research adhered fully to the ethical guidelines of Erasmus University Rotterdam and was conducted with explicit consent from all participants.

3.6 Data Analysis

The data analysis was conducted in a series of structured stages using IBM SPSS Statistics (version 29) and the PROCESS macro (version 5.0). First, preliminary data screening was carried out to handle missing values, check for outliers, and ensure that all items were properly coded. Descriptive statistics were generated to examine the distribution and central tendency of each variable.

Following this, the core hypotheses were tested through mediation and moderation analyses using the PROCESS macro for SPSS. Specifically, Model 4 was employed to examine whether user trust and emotional engagement mediate the relationships between the BPA subdimensions (favorability and clarity) and the two outcome variables: brand advocacy and AI subscription intentions. These analyses also simultaneously provided estimates of direct and indirect effects, allowing for an assessment of mediation strength.

To examine the potential moderating role of anthropomorphism tendency, separate analyses were conducted using PROCESS Model 1. These tested whether anthropomorphism tendency moderated the influence of each BPA subdimension on user trust and emotional engagement. Before data analysis, to conveniently facilitate regression-based analysis, composite scores were computed for each latent construct by averaging the responses to their respective scale items. This approach aligns with standard practice in quantitative behavioral research and allows each theoretical construct to be represented as a single continuous variable (Hayes, 2022, p. 492). However, since BPA was explicitly conceptualized as a multi-dimensional construct comprising three second-order dimensions: favorability, originality, and clarity (Freling et al., 2011, p. 399), mean scores of BPA were calculated per dimension.

This analytical approach enabled a comprehensive examination of the proposed conceptual model by identifying both the mediating mechanisms through which BPA exerts its influence on user outcomes and the moderating conditions under which these effects may vary.

4. Results

4.1 Testing the Direct Effects

This section outlines the direct relationships hypothesized between variables in the model, prior to introducing any mediation or moderation mechanisms. While these direct effects are statistically tested within the subsequent mediation models using the PROCESS macro (Model 4), they are reported here independently for clarity and logical coherence in line with the hypothesis structure.

4.1.1 Testing the Direct Effects of BPA Favorability and Clarity on User Trust

The first set of analyses explored the direct relationships between two dimensions of BPA (favorability and clarity) and user trust as a key psychological construct.

To begin, the influence of BPA favorability on user trust was tested. The result showed that BPA favorability had a positive significant influence on user trust ($\beta = .88$, $p < .001$), indicating that when users perceive an AI LLM as favorable in personality, their trust in the brand significantly increases. Therefore, H1a is supported.

The effect of BPA clarity on user trust was also examined. Based on the result, BPA clarity significantly predicted user trust ($\beta = .61$, $p < .001$), showing that when an AI brand is perceived as clearly defined, users report greater trust in the system. Thus, H1b is accepted.

4.1.2 Testing the Direct Effects of BPA Favorability and Clarity on Emotional Engagement

The second set of analyses evaluated the direct impacts of BPA favorability and clarity on emotional engagement.

Next, the influence of BPA favorability on emotional engagement was tested. BPA favorability was found to be positively influencing emotional engagement ($\beta = .98$, $p < .001$), suggesting that favorable brand personality traits elicit stronger emotional responses. As a result, H2a is supported.

The role of BPA favorability in predicting emotional engagement was also examined. The results demonstrated BPA clarity positively influencing emotional engagement ($\beta = .54$, $p < .001$). This indicates that clearly defined personality traits enhance emotional connection with the AI LLM, confirming H2b.

4.1.3 Testing the Direct Effects of User Trust and Emotional Engagement on Brand Advocacy

Further analyses investigated the direct impact of user trust and emotional engagement on brand advocacy.

First, user trust was examined as a predictor of brand advocacy. The result showed that trust was positively associated with brand advocacy ($\beta = .50$, $p < .001$), confirming that users who trust the AI brand are more likely to recommend or defend it publicly. Therefore, H3 is supported.

Second, the effect of emotional engagement on brand advocacy was also assessed. After analyzing, emotional engagement was concluded to significantly predict brand advocacy ($\beta = .38$, $p < .001$), indicating that emotionally invested users are more likely to advocate for their preferred AI brand. As a result, H4 is accepted.

4.1.3 Testing the Direct Effects of User Trust and Emotional Engagement on AI Subscription Intentions

Furthermore, the relationship between user trust and emotional engagement as mediators and AI subscription intentions was examined.

The result proved that user trust strongly predicted AI subscription intentions ($\beta = .70$, $p < .001$). This further confirms that cognitive trust is critical in prompting financial commitment to AI LLM services, thereby supporting H7.

Lastly, emotional engagement was found to have a positive and significant effect on AI subscription intentions ($\beta = .39$, $p = .001$), suggesting that affective bonds also contribute meaningfully to users' willingness to subscribe. Thus, H8 is accepted.

4.2 Testing the Mediating Effects

4.2.1 The Mediating Effect of User Trust towards the relationship between BPA Favorability and Clarity and Brand Advocacy

The first mediation analysis explored the extent to which user trust mediated the relationship between BPA favorability and brand advocacy. The model set brand advocacy as criterion, BPA favorability as predictor and user trust as mediator. In addition, no control variables were included. Overall, the complete model was found to be significant ($F(2, 197) = 51.73$, p <.001, $R^2 = .34$). Moreover, in the absence of the mediator, the results from the analysis displayed that the relationship between BPA favorability and brand advocacy was significant ($\beta = .78$, $p < .001$).

When considering the effects of user trust as a mediator, the direct relationship between BPA favorability and brand advocacy was still significant, despite slightly decreased ($\beta = .34$, $p = .005$). Additionally, the indirect relationship through user trust remained significant, ($\beta = .44$, Cl 95% [.30, .61]). This suggests partial mediation, where BPA favorability still exerts a direct influence on brand advocacy but also operates significantly through user trust. Therefore, H5a is supported.

The second mediation analysis aimed to examine whether user trust mediates the relationship between BPA clarity and brand advocacy. For this model, BPA clarity was defined as the predictor variable, brand advocacy as the criterion variable, and user trust as the mediator. Moreover, no covariates were added. The overall model was statistically significant, ($F(2, 197) = 52.30$, $p < .001$, $R^2 = .35$). The results from the analysis proved that there was a significant positive relationship between BPA clarity and brand advocacy, without a mediator ($\beta = .59$, $p < .001$).

However, upon controlling for the effects of user trust, the direct relationship between BPA clarity and brand advocacy decreased substantially but remained significant ($\beta = .27$, $p = .003$). Furthermore, the indirect relationship through user trust was also found to be significant ($\beta = .31$, CI 95% [.19, .44]). Since the confidence interval did not include zero, the mediation effect was statistically confirmed. This suggested a moderately strong indirect pathway from BPA clarity to brand Advocacy via user trust. Considering these results, H5b is supported.

4.2.2 The Mediating Effect of Emotional Engagement towards the relationship between BPA Favorability and Clarity and Brand Advocacy

The third mediation analysis was conducted to comprehend the extent to which emotional engagement mediated the relationship between BPA favorability and brand advocacy. In this model, BPA favorability was treated as the predictor, brand advocacy as the criterion, and emotional engagement as the mediator. Also, there were no covariates included in the conducted process.

In general, the overall model was statistically significant ($F(2, 197) = 42.18$, $p < .001$, $R^2 = .30$). The relationship between BPA favorability and brand advocacy, without the mediator in the model, was significant ($\beta = .78, p < .001$). Although, regarding the impacts of emotional engagement, the model remained significant, and partially dropped to ($\beta = .40$, $p = .001$). Moreover, the indirect effect through emotional engagement statistically stayed significant at ($\beta = .38$, CI 95% [.23, .55]). This indicates that emotional engagement partially mediates the relationship between BPA favorability and brand advocacy. As a result, H6a is supported.

The fourth mediation analysis was conducted regarding the examination of the mediating effect of emotional engagement in the relationship between BPA clarity and brand advocacy. Specifically, for this model, BPA clarity was defined as the predictor variable, brand advocacy as the criterion variable, emotional engagement as the mediator, and no control variables. The comprehensive model was found to be significant ($F(2, 197) = 46.14$, $p < .001$, $R^2 = .32$). Within the model, the relationship between BPA clarity and brand advocacy was found to be significant, which observed in the absence of the mediator ($\beta = .59$, $p < .001$).

When controlling for the mediating effect of emotional engagement, the relationship between BPA clarity and brand advocacy decreased substantially but remained statistically significant ($\beta = .36$, $p < .001$). This reduction in magnitude indicates the presence of a partial mediation effect. Furthermore, the indirect effect of BPA clarity on brand advocacy through emotional engagement was also statistically significant ($\beta = .23$, CI 95% [.13, .34]). The confidence interval did not include zero, which confirms the presence of a meaningful mediation effect. Taken together, these results further accepted H6b, demonstrating that emotional engagement partially mediates the relationship between BPA clarity and brand advocacy.

4.2.3 The Mediating Effect of User Trust towards the relationship between BPA Favorability and Clarity and AI Subscription Intentions

The fifth mediation analysis was conducted to inspect the mediating effect of user trust in the relationship between BPA favorability and AI subscription intentions. Given that the subscription intentions items were only shown to a subset of participants who had prior interaction with AI LLMs, the sample size was reduced to $N = 114$. The overall mediation model evaluating user trust as a mediator between BPA favorability as the predictor and AI subscription intentions as the criterion was found to be significant ($F(2, 111) = 10.79$, $p < .001$, $R^2 = .163$). Notably, the relationship between BPA favorability and AI subscription intentions, in the absence of the mediator, was small and non-significant ($\beta = .19$, $p = .338$).

In contrast, when controlling for the impacts of user trust, the results demonstrated by the model displaying the relationship between BPA favorability and AI subscription intentions was negative and marginally non-significant (β = –.44, p = .053). This indicates that the presence of trust substantially altered the pathway, implying a suppression effect, where the direct and indirect effects move in opposite directions. Most critically, the indirect effect of BPA favorability on AI subscription intentions via user trust was significant (β = .63, CI 95% [.32, .97]).

Since the confidence interval did not include zero, this mediation pathway was statistically supported. Taken together, H9a is still supported, demonstrating that user trust fully mediates the relationship between BPA favorability and AI subscription intentions. While BPA favorability on its own was not a significant direct predictor of AI subscription intentions, it significantly contributed to the outcome indirectly through enhanced user trust.

The sixth mediation analysis examined whether user trust mediates the relationship between BPA clarity and AI subscription intentions. With the intention of testing this premise, a mediation analysis was run by placing BPA clarity as predictor and AI subscription intentions as criterion. The comprehensive model predicting AI subscription intentions from BPA clarity and user trust was statistically significant ($F(2, 111) = 8.87$, $p < .001$, $R^2 = .138$). The results from the analysis clarified that in the absence of the mediator, the relationship between BPA clarity on subscription intentions was positive but non-significant (β = .27, p = .090).

However, the direct relationship between BPA clarity and AI subscription intentions, after controlling for user trust's effects, was negative and non-significant (β = –.13, p = .476). This reversal in direction suggests the presence of a suppression effect, where the mediator accounts for the true mechanism of influence and suppresses the inconsistent direct pathway. Furthermore, the indirect relationship via user trust was statistically significant (β = .41, CI 95% [.17, .67]), which does not include zero. These results confirm that user trust partially mediates the effect of BPA clarity on AI subscription intention. Therefore, H9b is accepted, as user trust significantly mediates the effect of BPA clarity on subscription intention.

4.2.4 The Mediating Effect of Emotional Engagement towards the relationship between BPA Favorability and Clarity and AI Subscription Intention

The next mediation analysis was conducted to investigate the mediating effect of emotional engagement in the relationship between BPA favorability and AI subscription intentions. The mediation model was performed with BPA favorability as the predictor, emotional engagement as the mediator, and AI subscription intentions as the criterion. The overall model was statistically significant ($F(2, 111) = 6.25$, $p = .002$, $R^2 = .10$). However, in the absence of mediating effect, the statistical analysis revealed that the direct relationship between BPA favorability and AI subscription intentions was non-significant ($\beta = .19$, $p = .338$). As part of this pathway, support was found for H8, which predicted that emotional engagement would positively influence AI subscription intentions.

Interestingly, the model also uncovered that the direct link between BPA favorability and AI subscription intentions became negative and remained statistically non-significant, after accounting for controlling emotional engagement effects ($\beta = -.32$, $p = .183$). Furthermore, the indirect relationship between BPA favorability and AI subscription intentions through emotional engagement was statistically significant ($\beta = .50$, CI 95% [.17, .84]). Since the confidence interval did not include zero, the mediation effect was statistically supported.

In total, these findings suggest that emotional engagement fully mediates the relationship between BPA favorability and AI subscription intentions. Although BPA favorability alone did not significantly predict AI subscription intentions, its influence was channeled effectively through heightened emotional engagement, thereby supporting H10a.

The final mediation analysis examined whether emotional engagement mediates the relationship between BPA clarity and AI subscription intentions. The analysis was conducted proposing BPA clarity as the predictor, emotional engagement as the mediator, AI subscription intentions as the criterion, and no covariates were included in the model. The total model predicting emotional engagement from BPA clarity was statistically significant, ($F(1, 112) = 34.36$, $p < .001$, $R^2 = .235$). The results from the analysis demonstrated that in the absence of a mediator, the relationship between BPA clarity and AI subscription intentions was marginal and non-significant ($\beta = .16$, $p = .090$). Conversely, the direct relationship of BPA clarity on AI subscription intentions became non-significant once emotional engagement's impacts were controlled in the model ($\beta = .03$, $p = .83$).

However, the indirect relationship of BPA clarity on AI subscription intentions through emotional engagement was found to be statistically significant, excluding zero ($\beta = .23$, CI 95% [.05, .45]). Therefore, these results provide support for H10b, suggesting that emotional engagement partially mediates the relationship between BPA clarity and AI subscription intentions.

4.3 Testing the Moderating Effect

4.3.1 The Moderating Effect of Anthropomorphism Tendency towards the relationship between BPA Favorability and Clarity and User Trust

To acknowledge whether anthropomorphism tendency moderates the relationship between BPA favorability and user trust, a moderation analysis was conducted with BPA favorability as the predictor, user trust as the criterion, and anthropomorphism tendency as the moderator. The analysis was performed using PROCESS Macro for SPSS model 1 (Hayes, 2022, p. 492) and resulted in a significant model ($F(3, 196) = 50.00$, $R^2 = .43$, $p < .001$). Furthermore, both BPA favorability and anthropomorphism tendency was found to be significant predictors of user trust ($p < .001$). However, the interaction term was clarified as not significant ($p = .859$), which reveals that anthropomorphism tendency does not function as a moderator. Therefore, H11a is rejected.

The second moderation was conducted to test if anthropomorphism tendency moderates the relationship between BPA clarity and user trust. The analysis considered BPA clarity as the predictor, user trust as the criterion, and anthropomorphism tendency as the moderator. The model was found to be significant ($F(3, 196) = 43.38$, $R^2 = .39$, $p < .001$). Moreover, BPA clarity was proved to be a significant predictor of user trust ($p < .001$). Additionally, anthropomorphism tendency was also found to be a significant predictor of user trust ($p = .0002$). Nonetheless, the interaction term was determined as not significant ($p = .989$). This indicates that anthropomorphism tendency does not qualify to be a moderator and thus, H11b is not accepted.

4.3.2 The Moderating Effect of Anthropomorphism Tendency towards the relationship between BPA Favorability and Clarity and Emotional Engagement

The following moderation analysis was carried out using the same process as the previous moderation analysis to examine whether anthropomorphism tendency moderates the relationship between BPA favorability and emotional engagement. In this model, BPA favorability was entered as the predictor, emotional engagement as the criterion, and anthropomorphism tendency as the moderator. The analysis resulted in a significant model ($F(3, 196) = 46.16$, $R^2 = .41$, $p < .001$). Furthermore, both BPA favorability and anthropomorphism tendency were validated as significant predictors of emotional engagement ($p < .001$). However, similar to previous analyses, the interaction term was still deemed as not significant (p = .645). This shows that anthropomorphism tendency does not certify to be a moderator. Due to the result from this analysis, it concludes that H12a is rejected.

The final moderation analysis was conducted to test if anthropomorphism tendency moderates the relationship between BPA clarity and user trust, following the same procedure as the previous analysis. The model was carried out by placing BPA clarity as the predictor, emotional engagement as the criterion, and anthropomorphism tendency as the moderator. It was found to be a significant model ($F(3, 196) = 31.73$, $R^2 = .32$, $p < .001$). Moreover, BPA favorability was found to be a statistically significant predictor of emotional engagement (p = .0105). Additionally, anthropomorphism tendency was also proved to be a positive significant predictor of emotional engagement ($p < .001$). Nevertheless, the interaction term for this analysis was also not significant (p = .538). Thereby, H12b was also not accepted.

Table 3. Summary of hypothesis and testing results (Direct, Mediating and Moderating effects)

Hypothesis	Relationship	P-value/ confidence intervals	Result
H1a	BPA favorability positively influences user trust.	<.001	Supported
H1b	BPA clarity positively influences user trust.	<.001	Supported
H2a	BPA favorability positively influences emotional engagement.	<.001	Supported
H2b	BPA clarity positively influences emotional engagement.	<.001	Supported
H3	User trust positively influences brand advocacy.	<.001	Supported
H4	Emotional engagement positively influences brand advocacy.	<.001	Supported
H5a	User trust mediates the relationship between BPA favorability and brand advocacy.	between .30 and .61	Supported
H5b	User trust mediates the relationship between BPA clarity and brand advocacy.	between .19 and .44	Supported

H6a	Emotional engagement mediates the relationship between BPA favorability and brand advocacy.	between .23 and .55	Supported
H6b	Emotional engagement mediates the relationship between BPA Clarity and brand advocacy.	between .13 and .34	Supported
H7	User trust positively influences AI subscription intentions.	<.001	Supported
H8	Emotional engagement positively influences AI subscription intentions.	= .001	Supported
H9a	User trust mediates the relationship between BPA favorability and AI subscription intentions.	between .32 and .97	Supported
H9b	User trust mediates the relationship between BPA clarity and AI subscription intentions.	between .17 and .67	Supported
H10a	Emotional engagement mediates the relationship between BPA favorability and AI subscription intentions.	between .17 and .84	Supported
H10b	Emotional engagement mediates the relationship between BPA clarity and AI subscription intentions.	between .05 and .45	Supported
H11a	Anthropomorphism tendency moderates the relationship between BPA favorability and user trust.	.859	Not supported
H11b	Anthropomorphism tendency moderates the relationship between BPA clarity and user trust.	.989	Not supported
H12a	Anthropomorphism tendency moderates the relationship between BPA favorability and emotional engagement.	.645	Not supported
H12b	Anthropomorphism tendency moderates the relationship between BPA clarity and emotional engagement.	.538	Not supported

5. Conclusion and Discussion

The primary focus of this research was to examine and assess users' AI subscription intentions and brand advocacy as influenced by brand personality appeal (BPA). It also explored the roles of user trust and emotional engagement as the fundamental mechanism, as well as anthropomorphism tendency as the refinement of users' AI subscription intentions and brand advocacy indicators. The first research question referred to the extent to which BPA influenced AI subscription intentions and brand advocacy, through the mediating roles of emotional engagement and user trust. The second research question considered the investigation of anthropomorphism as a moderator of the direct links between BPA and AI subscription intentions and brand advocacy indicators. Consequently, the sections outline a thorough clarification of the hypothesis outcomes, seeking to provide explanations and answers to the research questions.

5.1 Brand Personality Appeal (BPA) as antecedents of Emotional Engagement and User Trust

Based on previous literature, three main dimensions of BPA were identified. These three theoretically supported dimensions are proven to serve as relevant constructs to further examine users' response to AI LLM, as originally proposed by Freling et al. (2011, p. 393). Thus, favorability, clarity and originality were decided and analyzed as corresponding independent variables in this research. However, since the originality dimension was excluded due to an unsatisfactory Cronbach's alpha value ($\alpha = .065$) and fallen below the reliability threshold of 0.70 (Nunnally & Bernstein, 1994, p. 265), a two-dimensional conceptualization of BPA (favorability and clarity) was proposed and adopted instead. This decision is further consistent with prior adjustments in personality scale applications when subdimensions fail to meet validity requirements (Hair et al., 2019, p. 140).

Previous findings conclude user trust and emotional engagement as relevant variables in the context influencing users' perceptions of AI technology in general and AI LLM usage in specific (Chaudhuri & Holbrook, 2001, p. 83). Thus, both BPA favorability and BPA clarity were hypothesized to influence user trust and emotional engagement. Central to the Consumer–Brand Relationship Theory (CBRT), these psychological constructs reflect users' affective and cognitive responses to brand stimuli (Fournier, 1998, p. 344). Furthermore, CBRT also suggests that users do not merely consume functional outputs but actively form relationships with brands that exhibit emotionally resonant characteristics. In the context of

AI LLMs, where interaction is dynamic and interpersonal in nature, BPA offers a compelling explanation for how these perceptions translate into trust and emotional bonding. Several hypotheses were developed to answer the research questions. Results were as expected, showing positive relationships between BPA favorability and both user trust and emotional engagements. These findings affirm the view that when AI LLMs are perceived as warm, ethical, and likable which are all hallmarks of favorability, users are more likely to perceive them as trustworthy entities (Matzler et al., 2006, p. 428). This outcome is further substantiated by previous research indicating that favorable personality cues foster approachability and psychological safety, even in human-AI interactions (Wang et al., 2024, p. 5). Simultaneously, the emotional resonance induced by favorability appears to deepen the user-AI bond, aligning with studies that emphasize warmth and comfort as precursors to emotional engagement (Cheng, 2024, p. 10).

Moreover, BPA clarity also demonstrated significant predictive power for both outcomes. The results suggest that clearly defined and consistently communicated AI personalities contribute not only to higher trust through perceived reliability and coherence but also enhance emotional engagement by reducing friction in interaction (Fernandes & Moreira, 2019, p. 279; Matzler et al., 2006, p. 428). This reinforces recent scholarship in AI branding, which highlights the importance of clarity in building relational stability, especially when users navigate ambiguous or evolving technological environments (Freling et al., 2011, p. 404). Interestingly, contrary to Freling's (2013, p. 403) initial ranking of favorability as the dominant dimension, the current findings suggest a more balanced influence of clarity and favorability in shaping user perceptions of AI LLMs. This reorientation calls attention to clarity as not merely a supporting dimension, but a central mechanism that reduces uncertainty and fosters sustained affective connection.

Collectively, these findings reinforce the theoretical value of BPA in AI LLM research and highlight its empirical utility in predicting both cognitive trust and emotional engagement responses. They also contribute to extending the CBRT framework by illustrating how digital brand cues in which simulate social presence and intentionality can initiate human-like relational processes even in interactions with non-human agents.

5.2 User Trust and Emotional Engagement as Antecedents of AI Subscription Intentions and Brand Advocacy

Building upon the foundational role of trust and emotional engagement, this study examined their downstream effects on brand advocacy and AI subscription intentions. The results confirmed that both constructs play essential roles in shaping users’ behavioral intentions toward AI brands.

User trust demonstrated a strong and significant relationship with brand advocacy. This aligns with prior research positioning trust as a necessary antecedent to public endorsement, particularly in digital environments where technical opacity and risk perception are high (Ahmadi & Ataei, 2022, p. 3; Wang & Qiu, 2024, p. 3). Trust, in this case, functions not only as confidence in system performance but also as an emotional commitment to the perceived integrity and reliability of the AI brand (Tie et al., 2024, p. 7). These findings underscore the value of trust as a reputational currency in demonstrating to users their likelihood to promote and defend brands they deem dependable.

Similarly, emotional engagement also emerged as a significant predictor of brand advocacy. Emotional bonds reflect a higher-order relationship between users and AI, which goes beyond satisfaction with outputs to encompass personal relevance and symbolic alignment (Fullerton, 2005, p. 99). Users who feel emotionally understood or supported by an AI system are more likely to recommend it, not out of obligation, but from a sense of affinity and belonging (Asiabar et al., 2024, p. 5). These results are in line with the perspective that emotionally engaged users act as brand ambassadors, co-constructing value through word-of-mouth and social influence (Schivinski et al., 2016, p. 66).

When examining AI subscription intentions, both trust and emotional engagement were found to significantly influence users' willingness to engage in long-term paid usage. However, the effect of trust was more pronounced, suggesting that financial commitment in AI environments may require stronger cognitive assurance of performance and reliability (Bhati & Verma, 2020, p. 11). Trust, particularly in contexts characterized by algorithmic opacity, becomes the foundation upon which subscription behavior is built (Oyekunle et al., 2024, p. 75). The emotional aspect, while still impactful, appears to play a more complementary role - supporting but not substituting cognitive evaluations.

This distinction is important. Subscription behavior in AI is not solely a utilitarian decision since it reflects a blend of trust-based risk mitigation and emotional alignment with the AI's brand identity (Sun & Wang, 2025, p. 1; Blasco-Arcas et al., 2016, p. 574). Therefore, AI brands must simultaneously earn users’ trust through consistency and transparency while cultivating emotional resonance through engaging, humanized interaction.

5.3 Mediating Effect of User Trust and Emotional Engagement

To further disentangle the psychological mechanisms underlying users' responses to AI brands, mediation analyses were conducted. These analyses tested the roles of user trust and emotional engagement in mediating the relationships between BPA (favorability and clarity) and the two behavioral outcomes: brand advocacy and AI subscription intentions.

The results provided robust evidence for the mediating roles of both trust and emotional engagement. Specifically, both constructs significantly mediated the relationship between BPA favorability and brand advocacy. This suggests that favorability does not lead directly to advocacy, but rather initiates a chain of affective and cognitive responses that culminate in behavioral endorsement. In other words, favorability establishes emotional warmth and credibility, which then fosters trust and engagement - both of which drive advocacy (Wang & Qiu, 2024, p. 3).

Similarly, both trust and engagement mediated the link between BPA clarity and brand advocacy. The clarity dimension helped users interpret the AI's identity and behavior as stable and coherent, thereby increasing the psychological safety necessary for advocacy (Villagra et al., 2021, p. 1157). These findings highlight how relational cues embedded in personality design such as consistency and originality can translate into loyalist behavior through internalized psychological mechanisms.

When assessing the mediation pathways toward subscription intentions, the analysis revealed partial mediation for BPA favorability and full mediation for BPA clarity. In the former case, favorability influenced subscription intentions both directly and through the mediators. In the latter, clarity's effect on subscription was exclusively indirect, functioning through emotional engagement. This distinction is noteworthy because while users may be drawn to favorable AI brands on the basis of surface-level warmth or approachability, it is the perceived clarity and coherence of those brands that fosters enduring emotional investment and long-term subscription behavior (Freling et al., 2011, p. 399; Ratican & Hutson, 2023, p. 45).

These findings extend the explanatory power of CBRT by demonstrating that emotional engagement and trust do not merely accompany user-brand relationships in AI, instead, they operationalize them. They are the bridges through which personality perceptions are transformed into meaningful behavioral commitments (Kim & Sundar, 2012, p. 34). By incorporating mediation analysis, this study provides empirical confirmation that trust and emotional engagement are not just outcomes, but active mechanisms linking personality cues with behavioral loyalty.

5.4 Moderating Effect of Anthropomorphism Tendency

To address the second research question, this study investigated whether anthropomorphism tendency moderates the relationship between the two dimensions of BPA (favorability and clarity) and the psychological mechanisms of user trust and emotional engagement. Contrary to expectations drawn from previous research, moderation analyses yielded no significant interaction effects. All four hypotheses related to moderation were rejected, indicating that anthropomorphism tendency did not alter the strength of the relationships between BPA dimensions and the outcome variables.

This finding diverges from earlier work by Shen et al. (2024, p. 1077), who found that individuals high in anthropomorphism tendency were more responsive to AI systems exhibiting relational cues such as coherence, empathy, and turn-taking responsiveness. According to their research, users with elevated anthropomorphism tendencies are more likely to interpret emotionally intelligent behaviors as authentic expressions of agency, thereby deepening engagement. However, the present findings suggest that in the context of text-based AI LLMs where human-like cues may be more subtle or less visually embodied, such dispositional traits may have diminished influence.

Additionally, the results provide nuance to the findings by Troshani et al. (2020, p. 9), who cautioned that excessive anthropomorphism could reduce users' trust in AI, particularly when the agent fails to meet human-like expectations. In particular, the neutral moderation effect implies that BPA-based branding cues are perceived as equally persuasive by users regardless of their predisposition to anthropomorphize. This outcome aligns with prior discussions in the thesis suggesting that brand-driven cues, such as consistency and favorability, may function as universally effective signals in fostering user–AI relationships, especially when cognitive evaluation and affective resonance operate independently of individual tendencies to humanize machines (Park et al., 2013, p. 230).

These findings hold important theoretical implications. While the CBRT posits that users form trust and engagement through relational brand cues (Fournier, 1998, p. 344), anthropomorphism tendency was anticipated to amplify this process by enhancing the perceived social presence of the AI. The absence of such a moderation effect invites further inquiry into the boundary conditions of anthropomorphism as a psychological amplifier. One possible explanation is that in purely text-based interactions such as those common to LLMs, users rely more on functional and semantic cues embedded in personality design (tone consistency and clarity of communication) than on anthropomorphic projection per se (Waytz et al., 2010, p. 226).

In summary, the data suggest that BPA favorability and clarity exert a robust influence on trust and emotional engagement across user types, regardless of individual differences in anthropomorphism tendency. This reinforces the strategic relevance of brand personality in AI design and provides empirical support for universal branding approaches in LLM-based environments. While anthropomorphism tendency remains a theoretically valuable construct, its role in this research appears limited, underscoring the need for future research to distinguish between visual, embodied AI contexts and text-based LLMs in assessing dispositional moderators.

5.5 Theoretical Implications

This research advances the literature at the intersection of branding and human-AI interaction by empirically validating a mediation model that links BPA to key psychological mechanisms and behavioral outcomes in the context of AI LLMs. While trust and emotional engagement have been widely studied in consumer-brand literature, their role as parallel mediators in AI contexts particularly in response to personality cues embedded in conversational interfaces remains underexplored (Longoni et al., 2019, p. 630; Manzo et al., 2024, p. 5).

The findings contribute to this emerging field in three main ways. First, by isolating the favorability and clarity dimensions of BPA, the results offer a more nuanced view of which personality traits most strongly influence user perceptions. Although prior research often treats brand personality as a global construct, this approach reveals how specific attributes such as warmth, dependability, and coherence activate relational pathways, resulting in higher trust and emotional attachment. This confirms earlier conceptualizations by Freling et al. (2011, p. 400) but contextualizes them within AI interactions, where brand personality is not just seen but experienced through dialogue.

Second, the inclusion of both trust and emotional engagement as mediating variables sheds light on the dual psychological routes by which BPA influences user behavior. This finding aligns with the principles of dual-process theories, particularly the Elaboration Likelihood Model (Petty & Cacioppo, 1986, p. 133), which distinguishes between central and peripheral processing routes in persuasion. Trust functions as a cognitive response to perceived competence, stability, and ethical alignment, suggesting that users engage in deliberate evaluation of the AI's capabilities and reliability. Emotional engagement, on the other hand, operates as an affective response to the AI's expressive cues - how warm, engaging, or relatable it feels in the interaction. These two processes are not mutually exclusive; rather, they complement each other, jointly explaining how users move from personality perception to behavioral commitment. In AI branding contexts, where users often face informational asymmetries or algorithmic opacity, this dual-route activation becomes especially salient (Sun & Wang, 2025, p. 1).

Third, the results challenge assumptions drawn from the broader literature on anthropomorphism and human–machine interaction. Contrary to expectations, anthropomorphism tendency did not moderate the effect of BPA on trust or emotional engagement (Epley et al., 2007, p. 865). This suggests that in LLM-based interactions, unlike in social robotics or embodied agents, dispositional tendencies to anthropomorphize may be less predictive of user response. Instead, relational perceptions appear to be driven more by design factors, such as the AI's perceived warmth and clarity, than by individual differences in anthropomorphism (Cohn et al., 2024, p. 3). This insight is valuable for AI branding strategies: it implies that personality-driven cues may resonate broadly across user segments, regardless of their anthropomorphic predispositions.

Taken together, these contributions offer a more comprehensive theoretical framework for understanding how users form relationships with AI brands. By bridging consumer–brand relationship theory, BPA literature, and dual-process models, the findings support an integrated approach to studying AI adoption, not merely as a functional choice but as a relational and symbolic act.

5.6 Managerial Implications

One of the key contributions of this study is to emphasize the importance of cultivating a strong and coherent brand personality, particularly attributes linked to favorability (e.g., pleasantness, likability) and clarity (e.g., consistency, distinctiveness). The study was able to determine the connection between the two dimensions of BPA and brand advocacy and AI subscription intentions while examining the mediating effect of user trust and emotional engagement. These two dimensions were shown to positively influence both user trust and emotional engagement, which in turn predict key behavioral outcomes such as brand advocacy and subscription intentions. For companies such as OpenAI, Google, or other LLM-based service providers, this underscores the importance of crafting a personality for their AI systems that is not only likable but also clearly defined and consistently presented across user touchpoints. This includes consistent linguistic tone, visual identity, navigational simplicity, and communication style - elements that together reflect the AI's personality and enhance ease of use (Freling et al., 2011, p. 400; Kim & Sundar, 2012, p. 96).

Moreover, the study further identifies user trust and emotional engagement as mediators, underscoring the dual responsibility of AI LLM brands to address both rational and emotional user needs. In detail, to foster trust and strengthen user confidence in technology, AI brands can invest in transparent data practices and explainable AI functionalities (Schoorman et al., 2007, p. 346). Additionally, to promote emotional engagement, AI brands should leverage personalized features, interactive design elements, and immersive interfaces that increase user enjoyment and emotional resonance (Bagozzi & Dholakia, 2006, p. 48).

Another important finding regards emotional engagement, rather than trust, as the sole significant mediator linking BPA clarity to AI subscription intentions. This finding suggests that when an AI LLM is perceived as coherent and well-defined, it triggers an emotional engagement strong enough to enhance users' willingness to subscribe. Therefore, this insight is also essential for LLM developers and marketers in assisting their design of user experiences to enhance accuracy and directness can translate into higher AI subscription rates.

Third, the non-significant role of anthropomorphism tendency as a moderator implies that BPA strategies may be broadly effective, irrespective of individual psychological predispositions toward anthropomorphizing machines. This simplifies marketing and design strategies, allowing AI companies to focus on universal branding principles rather than tailoring interfaces based on user traits. Such findings echo broader literature in human-AI interaction, where consistent brand signals often override dispositional moderators in predicting user behavior (Waytz et al., 2010, p. 220).

Nonetheless, the observed suppression effects present an important caution for AI brand strategists. The study revealed that while BPA favorability increased trust and emotional engagement, its direct effect on AI subscription intentions turned negative when user trust was controlled. This finding results in a suppression effect, where user trust must be concurrently developed to translate positive personality perceptions into concrete outcomes. Thus, cultivating trust is not optional but foundational.

5.7 Limitations and Future Research

Despite its contributions, this study is not without limitations. First, due to the selection of a non-random sampling method, the results from this research cannot be generalized as the collected sample might not precisely represent the population under investigation. One specific limitation considering the study's sample involves the age group of respondents. Particularly, 95.5% of participants are aged between 20 to 30, primarily comprising digitally literate students and professionals. While this aligns with the demographic most likely to engage with AI LLMs, it limits the generalizability of the findings to older or less tech-savvy populations. Also, ethical concerns further restricted the research's population and removed under-aged users. This could also raise an issue as there were 77.1 % of the younger population who have been in contact with AI LLM before (Department for education, 2025). Future research should take into consideration replicating this study with random sampling methods and expanding the overall responding population for a more generalized result.

Secondly, the method choice for analysis must also be considered as a limitation since the cross-sectional design restricts the ability to infer causality (Maxwell & Cole, 2007, p. 23). Although cross-section design is widely acceptable for examination, other methods could also be utilized to test if the results are replicated (Rindfleisch et al., 2008, p. 263). While mediation paths were statistically tested, longitudinal or laboratory experimental designs would provide stronger evidence for the causal mechanisms proposed (Hayes, 2022, p. 492).

Thirdly, this research is further limited because of the exclusion of the BPA originality dimension. In detail, BPA originality low internal consistency ($\alpha = .065$) limits the comprehensiveness of the analysis. Therefore, if future researchers would like to conduct comparative studies or replicate this study, they should aim to refine and validate this dimension to ensure a comprehensive assessment of BPA and its three dimensions.

Finally, the study also identified the null findings for moderation analysis of anthropomorphism tendency towards the relationship between BPA favorability and clarity and user trust and emotional engagement. However, while this finding is informative, it also may result from measurement limitations or the nature of the AI interface (text-based vs. embodied). Therefore, future research should explore whether these findings hold in other AI modalities, such as voice assistants, chatbots or humanoid robots.

In conclusion, this study provides robust evidence that BPA significantly shapes AI subscription intentions and brand advocacy behaviors through user trust and emotional engagement. It highlights the pivotal role of BPA in human-AI interaction and lays the groundwork for further theoretical and practical advancements in AI branding and user behavioral and psychological study.

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Appendix

Table A1

Construct	Code	Item	References
Brand Personality Appeal (BPA)	BPA1-16	This AI LLM's personality is unapparent/apparent. This AI LLM's personality is indistinct/distinct. This AI LLM's personality is unsatisfactory/satisfactory. This AI LLM's personality is obvious/not obvious. This AI LLM's personality is unpleasant/pleasant. This AI LLM's personality is common/distinctive. This AI LLM's personality is unattractive/attractive. This AI LLM's personality is ordinary/novel. This AI LLM's personality is negative/positive. This AI LLM's personality is bad/good. This AI LLM's personality is vague/well-defined. This AI LLM's personality is poor/excellent. This AI LLM's personality is undesirable/desirable. This AI LLM's personality is predictable/surprising. This AI LLM's personality is routine/fresh.	Freling et al. (2011, p. 399)

		This AI LLM's personality is unclear/clear.	
Emotional Engagement	EME1-5	This AI LLM inspires me. I am proud of using this AI LLM. I use this AI LLM with total dedication. Using this AI LLM makes me happy. I feel enthusiastic about this AI LLM.	Rawool et al. (2024, p. 12)
User Trust	UTR1-11	This AI LLM makes truthful claims and recommendations. This AI LLM is trustworthy. I believe what this AI LLM tells me/suggests. This AI LLM is honest with me. I can rely on this AI LLM to do what it is supposed to do. This AI LLM provides accurate information. This AI LLM performs all of its roles very well. This AI LLM is proficient. This AI LLM would act in thisbest interests. This AI LLM is sincere and genuine. This AI LLM will do its best to assist me.	Fernandes & Moreira (2019, p. 279)
Brand Advocacy	BAD1-9	If a friend or acquaintance said something negative about this AI LLM, I would speak up to defend it.	Wilder (2015, p. 78)

		If a friend or acquaintance said that a competing AI LLM was superior to it, I would tell them why I disagree. If a friend or acquaintance made fun of this AI LLM, I would stick up for it. If a friend or acquaintance questioned the quality of this AI LLM, I would try to set them straight. If a friend or acquaintance said they disliked this AI LLM, I would try to prove to them why it is good. If I think you should be using this AI LLM, I will actively work to get you to try it. I have convinced others to try this AI LLM. I would be an excellent salesperson for this AI LLM. I have actively worked to get someone to try this AI LLM.	
AI Subscription Intentions	ASI1-3	I intend to subscribe to this AI LLM in the future. I will likely pay for a subscription to this AI LLM. I am considering subscribing to this AI LLM as a paid service.	Jo (2024, p. 1058)
Anthropomorphism Tendency	ATE1-16	I feel this AI LLM humorous. I feel this AI LLM very cute. I feel this AI LLM very warm. I feel this AI LLM can actively understand my needs.	Shen et al. (2024, p. 1077)

		I feel this AI LLM always considers issues from my perspective.
		I feel this AI LLM can provide more targeted information based on my needs.
		I feel this AI LLM can give more tailored suggestions based on the questions I ask.
		I feel this AI LLM can offer personalized recommendations based on my preferences.
		I feel this AI LLM has creativity and imagination like a human.
		I feel this AI LLM has the ability to think like a human.
		I feel this AI LLM has reasoning abilities like a human.
		I feel this AI LLM has memory like a human.
		I feel this AI LLM can experience my emotions.
		I feel this AI LLM can respond appropriately based on my emotional state.
		I feel this AI LLM has its own emotions like a human.
		I feel this AI LLM also has its own mood like a human.
Demographic Variables	Gender	What is your gender?
	Age	Please enter your age as a whole number.

Educational level	What is your highest level of education?
Employment Status	What is your current employment status?
Nationality	What is your nationality?

Online Survey

Artificial Intelligence Large Language Models as Brands

Dear participant,

Welcome to this survey! My name is Trung Hieu Dang and currently enrolled at Erasmus University of Rotterdam. To support my research, this survey was created to discover how users perceive, interact with, as well as intend to subscribe to brands of Large Language Models (LLMs) like ChatGPT, Google Gemini, CoPilot, Meta Llama, Claude and others.

The study's findings will contribute to understanding how these technologies influence users' personal and professional development. Your contribution to the research is crucial because since you can help provide me valuable insights into how users connect with brands of Large Language Models (LLMs). Moreover, your input will help shape the future of Al technologies and ensure they align with the expectations and values of their users.

WHY HAVE I BEEN INVITED TO PARTICIPATE?
You have been invited to participate in this research because your experience and insights as a user of Large Language Models are valuable for understanding how these tools are perceived, used, and experienced.

WHAT WILL BE REQUIRED OF ME TO DO?
To participate in the research, you will be asked to complete an online questionnaire that includes questions about your experiences, perceptions, and interactions with brands of AI Large Language Models (LLMs). The questionnaire may take

approximately 6-8 minutes to complete, and your responses will be collected anonymously to ensure your privacy and confidentiality.

ARE THERE ANY RISKS OR BURDENS REGARDING MY PARTICIPATION IN THE RESEARCH?
Your participation in the research does not imply any risk or financial burden on you.

AM I OBLIGED TO PARTICIPATE IN THE RESEARCH?
Your participation in the research is completely voluntary. You can refuse to participate without justification. You can leave the research at any time without justification, and without consequences. In this case you can request that the collected data and information to be deleted.

WILL I RECEIVE REMUNERATION?
Participants will not receive remuneration for their participation in the survey.

HOW WILL MY PERSONAL DATA BE PROTECTED?
Erasmus University of Rotterdam acts as the Controller of your data. Your data will be processed exclusively for research, scientific, and statistical purposes, based on your explicit consent provided through this form. Your personal data will be anonymized to ensure confidentiality and security. Your identity will not be revealed in publications, public presentations, or scientific reports. To proceed with the survey, please click on all four text boxes below. With this you indicate that you are at least 18 years of age; you have read this consent form; and you voluntarily agree that you will participate in this research study.

To proceed with the survey, please click on all four text boxes below. With this you indicate that you are at least 18 years of age; you have read this consent form; and you voluntarily agree that you will participate in this research study.

- Yes, I consent to participate in this study
- Yes, I consent to collect personal data as listed above
- Yes, I consent to the storage of my anonymized data for research purposes
- Yes, I consent that my data will be anonymized and used for further research

Thank you for participating in my study on Al Large Language Model (LLM) brands!

AI LLMs are advanced artificial intelligence systems that generate human-like text and respond to user input in a conversational way. They are used for a variety of tasks, including answering questions, writing content, assisting with everyday tasks in both personal and professional settings, providing companionship, and even for recreational purposes.

Some popular examples of Al LLM brands include ChatGPT by OpenAl, Google's Gemini, Microsoft's Copilot, and Anthropic's Claude.

1. Please start by indicating which of the following Al LLM brands you are familiar with (Select all that apply).

- ChatGPT (OpenAl)
- Gemini (Google)
- Claude (Anthropic)
- Copilot (Microsoft)
- Others (please specify):
- I am not familiar with any Al LLM brands

2. Please inform me which AI LLM brand you use most often (Please enter only one brand) .

Some popular examples of AI LLM brands include ChatGPT by OpenAI, Google’s Gemini, Microsoft’s Copilot and Anthropic’s Claude.

3. Have you used ${q://QID4/ChoiceTextEntryValue} in the past six months?

- Yes
- No

4. How often do you use ${q://QID4/ChoiceTextEntryValue}?

- Less than once a week
- 1 to 2 times a week
- 3 to 5 times a week
- Once every day
- Several times a day

5. Why do you primarily use ${q://QID4/ChoiceTextEntryValue}?

- For personal use
- For professional use/my job
- For both personal and professional use

6. Now, for each of the following statements, consider the kind of personality you think ${q://QID4/ChoiceTextEntryValue} brand would have by selecting a point on the scale between the two opposing adjectives.

* If I wanted to describe ${q://QID4/ChoiceTextEntryValue} as a person, I would suggest that it has a personality that is:

	1	2	3	4	5	
unapparent	○	○	○	○	○	apparent
indistinct	○	○	○	○	○	distinct
unsatisfactory	○	○	○	○	○	satisfactory
not obvious	○	○	○	○	○	obvious
unpleasant	○	○	○	○	○	pleasant
common	○	○	○	○	○	distinctive
unattractive	○	○	○	○	○	attractive
ordinary	○	○	○	○	○	novel
negative	○	○	○	○	○	positive
bad	○	○	○	○	○	good
vague	○	○	○	○	○	well-defined
poor	○	○	○	○	○	excellent
undesirable	○	○	○	○	○	desirable
predictable	○	○	○	○	○	surprising
routine	○	○	○	○	○	fresh
unclear	○	○	○	○	○	clear

7. For these statements, please consider your emotional engagement when you interact with ${q://QID4/ChoiceTextEntryValue} as a brand.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
${q://QID4/ChoiceTextEntryValue} inspires me.	○	○	○	○	○	○	○
I am proud of using ${q://QID4/ChoiceTextEntryValue}.	○	○	○	○	○	○	○
I use ${q://QID4/ChoiceTextEntryValue} with total dedication.	○	○	○	○	○	○	○
Using ${q://QID4/ChoiceTextEntryValue} makes me happy.	○	○	○	○	○	○	○
I feel enthusiastic about ${q://QID4/ChoiceTextEntryValue}.	○	○	○	○	○	○	○

8. Next, please evaluate the confidence and trust you associate with ${q://QID4/ChoiceTextEntryValue} brand as you respond to the following statements.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
${q://QID4/ChoiceTextEntryValue} makes truthful claims and recommendations.							
${q://QID4/ChoiceTextEntryValue} is trustworthy.							
I believe what ${q://QID4/ChoiceTextEntryValue} tells me/suggests.							
${q://QID4/ChoiceTextEntryValue} is honest with me.							
I can rely on ${q://QID4/ChoiceTextEntryValue} to do what it is supposed to do.							
${q://QID4/ChoiceTextEntryValue} provides accurate information.							
${q://QID4/ChoiceTextEntryValue} performs all of its roles very well.							
${q://QID4/ChoiceTextEntryValue} is proficient.							
I believe ${q://QID4/ChoiceTextEntryValue} would act in my best interests.							
${q://QID4/ChoiceTextEntryValue} is sincere and genuine.							
If I ask for help, ${q://QID4/ChoiceTextEntryValue} will do its best to assist me.							

9. For this next set of questions, please take into account your support for ${q://QID4/ChoiceTextEntryValue} as a brand.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
If a friend or acquaintance said something negative about ${q://QID4/ChoiceTextEntryValue}, I would speak up to defend it.	○	○	○	○	○	○	○
If a friend or acquaintance said that a competing brand was superior to ${q://QID4/ChoiceTextEntryValue}, I would tell them why I disagree.	○	○	○	○	○	○	○
If a friend or acquaintance made fun of ${q://QID4/ChoiceTextEntryValue}, I would stick up for it.	○	○	○	○	○	○	○
If a friend or acquaintance questioned the quality of ${q://QID4/ChoiceTextEntryValue}, I would try to set them straight.	○	○	○	○	○	○	○
If a friend or acquaintance said they disliked ${q://QID4/ChoiceTextEntryValue}, I would try to prove to them why it is a good brand.	○	○	○	○	○	○	○
If I think you should be using ${q://QID4/ChoiceTextEntryValue}, I will actively work to get you to try it.	○	○	○	○	○	○	○
I have convinced others to try ${q://QID4/ChoiceTextEntryValue}.	○	○	○	○	○	○	○
I would be an excellent salesperson for ${q://QID4/ChoiceTextEntryValue}.	○	○	○	○	○	○	○
I have actively worked to get someone to try	○	○	○	○	○	○	○

10. Have you already subscribed to the paid ${q://QID4/ChoiceTextEntryValue} version?

- o Yes
- o No

11. For each of the following statements, consider your subscription intentions towards ${q://QID4/ChoiceTextEntryValue} as a brand.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I intend to subscribe to ${q://QID4/ChoiceTextEntryValue} in the future.	○	○	○	○	○	○	○
I will likely pay for a subscription to ${q://QID4/ChoiceTextEntryValue}.	○	○	○	○	○	○	○
I am considering subscribing to ${q://QID4/ChoiceTextEntryValue} as a paid service.	○	○	○	○	○	○	○

12. The next sets of statements evaluates your human-traits attribution towards ${q://QID4/ChoiceTextEntryValue} as a brand.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I feel ${q://QID4/ChoiceTextEntryValue} humorous.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} very cute.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} very warm.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} can actively understand my needs.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} always considers issues from my perspective.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} can provide more targeted information based on my needs.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} can give more tailored suggestions based on the questions I ask.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} can offer personalized recommendations based on my preferences.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} has creativity and imagination like a human.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} has the ability to think like a human.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} has reasoning abilities like a human.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} has memory like a human.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} can experience my emotions.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} can respond appropriately based on my emotional state.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} has its own emotions like a human.	○	○	○	○	○	○	○
I feel ${q://QID4/ChoiceTextEntryValue} also has its own mood like a human.	○	○	○	○	○	○	○

13. Before concluding, I would like to ask a few demographic questions.

Age

Please enter your age as a whole number: ____________

14. Gender

What is your gender?

- o Male
- o Female
- o Non-binary / third gender
- o Prefer not to say
- o Other

15. Educational Level

What is your highest level of education?

- o Secondary school or equivalent
- o High school or equivalent
- o Some college or equivalent
- o Bachelor's degree
- o Master's degree
- o PhD
- o Other

16. Employment Status

What is your current employment status?

- o Employed full-time
- o Employed part-time
- o Self-employed

- Unemployed
- Student
- Retired
- Other

17. Nationality

What is your nationality?

We thank you for your time spent taking this survey.

Your response has been recorded.

Erasmus School of
History, Culture and
Communication

Declaration Page: Use of Generative AI Tools in Thesis

Student Information
Name: Trung Hieu Dang
Student ID: 733502
Course Name: Master Thesis CM5000
Supervisor Name: Dr. Kyriakos Riskos
Date: 22/06/2025

Declaration:

Acknowledgment of Generative AI Tools
I acknowledge that I am aware of the existence and functionality of generative artificial intelligence (AI) tools, which are capable of producing content such as text, images, and other creative works autonomously.

GenAI use would include, but not limited to:
- Generated content (e.g., ChatGPT, Quillbot) limited strictly to content that is not assessed (e.g., thesis title).
- ~~Writing improvements, including~~ grammar and spelling corrections (e.g., Grammarly)
- Language translation (e.g., DeepL), without generative AI alterations/improvements.
- Research task assistance (e.g., finding survey scales, qualitative coding verification, debugging code)
- Using GenAI as a search engine tool to find academic articles or books (e.g.,

☒ I declare that I have used generative AI tools, specifically Grammarly, in the process of creating parts or components of my thesis. The purpose of using these tools was to aid in generating content or assisting with specific aspects of thesis work.

Extent of AI Usage
☒ I confirm that while I utilized generative AI tools to aid in content creation, the majority of the intellectual effort, creative input, and decision-making involved in completing the thesis were undertaken by me. I have enclosed the prompts/logging of the GenAI tool use in an appendix.

Ethical and Academic Integrity
☒ I understand the ethical implications and academic integrity concerns related to the use of AI tools in coursework. I assure that the AI-generated content was

☐ I declare that I have NOT used any generative AI tools and that the assignment concerned is my original work.

Signature:
Date of Signature:

used responsibly, and any content derived from these tools has been appropriately cited and attributed according to the guidelines provided by the instructor and the course. I have taken necessary steps to distinguish between my original work and the AI-generated contributions. Any direct quotations, paraphrased content, or other forms of AI-generated material have been properly referenced in accordance with academic conventions.

By signing this declaration, I affirm that this declaration is accurate and truthful. I take full responsibility for the integrity of my assignment and am prepared to discuss and explain the role of generative AI tools in my creative process if required by the instructor or the Examination Board. I further affirm that I have used generative AI tools in accordance with ethical standards and academic integrity expectations.

Signature:

Date of Signature: 22/06/2025