More Than Human

The Influence of Interactivity, Anthropomorphism, Parasocial Relationships, and AI Literacy on Consumer Trust in AI Influencers Across Cultures

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ABSTRACT

As artificial intelligence (AI) influencers become more popular across social media channels, their potential for building consumer trust continues to be an unclear and challenging topic. Although AI influencers offer consistency, scalability, and new types of digital connections, their fabricated origin generates societal and ethical issues, and cognitive difficulties amongst consumers. This thesis looks at the psychological and cognitive factors which affect consumer trust in AI influencers, focusing on the contextual predictors of interactivity anthropomorphism, parasocial relationships (PSR), and AI literacy. Cultural environments is further explored as a significant moderating factor. This research, based on theories such as Parasocial Interaction Theory, the CASA paradigm, and Media Equation Theory, addresses the main research question: How do perceptions of and perceived relationships with AI influencers influence consumer trust? To answer this, a quantitative online survey was carried out with *Qualtrics*, focusing on adults that had engaged with influencers on social media platforms. The overall sample (N = 162) included respondents from 34 various nationalities. Respondents were shown images of AI influencers within lifestyle and fashion situations, and they answered pre-existing Likert-scale questions about interactivity, anthropomorphism, parasocial relationships, AI literacy, cultural environments, and consumer trust. Analysis of the data using *IBM SPSS Statistics 29* provided several interesting and significant results. Firstly, PSR appeared as the most significant predictor of trust, emphasizing the emotional and psychological aspect of trust development with AI influencers. Additionally, AI literacy was shown to be positively correlated to trust, revealing that knowledgeable individuals are more assured and carefully aware in their evaluations. Surprisingly, perceived interactivity and anthropomorphism did not significantly predict trust, diminishing the idea that realism or reactivity solely can create trustworthiness. Lastly, the cultural environments had a strong and significant moderating effect on PSR and trust relationship, implying that cultural norms like individualism vs collectivism affect trust in AI influencers. These results have significant implications for marketers, AI developers, and educators. Businesses must focus more on presenting emotionally appealing storylines instead of artificial realism, as well as provide useful information that helps users grasp AI systems. Moreover, this study demonstrates that in an effort to foster genuine consumer trust, AI influencers need to culturally adapt to local consumers rather than being generic to worldwide consumers. As AI blurs the distinction between human and machine, these findings lead to a more ethical, efficient, and inclusive use of AI in digital marketing.

KEYWORDS: *Parasocial Relationships, AI Literacy, Cultural Environments, Consumer Trust, AI Influencers*

1. Introduction

1.1 Artificial Intelligence (AI) Influencers

The rise of artificial intelligence (AI) influencers benchmarks a significant moment in digital marketing and consumer interactions. AI influencers are algorithmically created virtual identities that function on social media channels (Kim & Wang, 2023, p.2). Virtual influencers, for instance, Lil Miquela or Rozy, go beyond conventional influencer types by encapsulating hyperreal, data-driven entities that may simulate human connection instead of the instability or burnout involved with human influencers (Byun & Ahn, 2023, p.5). All of these AI entities are frequently created by inventive design agencies or brand managers, and powered by machine learning and content automation techniques (Li et al., 2024, pp.2-3). They are portrayed as lifestyle professionals, beauty superiors, and fashion idols. They engage, post, empathize, and even campaign for issues, all while remaining completely fabricated and artificial (Díaz-Soloaga & Pelzer-Peinado, 2024, pp. 21-24).

The way AI influencers effortlessly merge into marketing environments unveils important questions, including whether consumers can trust non-human beings or entities. What factors impact trust when the influencer is synthetic or fabricated, detached from emotions, and perhaps unreliable? As AI influencers progress and extend in sectors ranging from fashion, lifestyle, and beauty, they call into question the cognitive, ethical, and social basis that underpin conventional trust in influencers (Jayasingh et al., 2025; Kim & Wang, 2023).

This research paper analyzes the intricate relationship amongst consumer trust in AI influencers; Perceived interactivity, perceived anthropomorphism, perceived parasocial relationships (PSR), and AI literacy, moderated by cultural environments. Psychological factors rely upon the parasocial interaction theory. Lastly, cognitive knowledge relies upon interactivity, anthropomorphism, parasocial relationships, and AI literacy moderated by the cultural environments one is surrounded by.

1.2 Societal Relevance

The growing number of AI influencers is changing the way consumers interact with online content and businesses, with profound social impacts. AI influencers, as opposed to human influencers, are not impacted by physical constraints or burnouts and are capable of being customized to fit the needs and interests of various consumers, which makes them an essential and reliable resource for businesses wanting versatility and continuous engagement (Karami et al., 2024, p. 6; Karunanayaka et al., 2024, pp. 183-188). This increased dependency on AI entities shows larger developments in consumer culture, which prioritizes customized content, interaction, and engaging experiences.

AI influencers frequently hide their artificial origins, creating concerns for consumers such as deceit, emotional fraud, confidentiality of data, and unawareness of algorithms. Numerous viewers, particularly those in extremely young or extremely old generations, might not be able to discriminate between human and AI influencers. These individuals may form deep connections with AI influencers without completely knowing their artificiality, establishing ample opportunity for misdirected trust and persuasive exploitation (Shil, 2025; Lee & Shen, 2025). This worry is heightened given the fact that AI technologies, regardless of how engaging they appear to be, lack empathy, responsibility, and personal judgment. This shift in AI technologies also emphasizes the role of AI literacy, which refers to consumers' capacity to critically analyze AI technologies, in developing views and trust towards AI entities (Shin et al., 2022, p.1228).

Learning how perceived interactivity, anthropomorphism, and parasocial relationships influence consumer trust may support society in managing the shift in the digital or virtual ecosystem in which AI and human interactions become increasingly obscured. The findings of this study might help marketers, educators, and legislators create digital spaces that encourage well-informed consumer engagement as well as significant and well-aware relationships with AI content (Wang et al., 2022; Ng et al., 2021b). Finally, this aims to prepare society for AI's increasing rise in being involved in marketing strategies and daily AI interactions.

1.3 Academic Relevance

Academic research on AI influencers is growing, but it is still in its early stages. The majority of the current research is concerned with technological advantages, algorithmic structure, or quick marketing effects, instead of the psychological and ethical aspects that influence how consumers engage with and assess AI influencers (Gerlich, 2025; De Cicco et al., 2024). This restricts our knowledge of why AI influencers are effective or complicated from the perspectives of the consumers.

An increasing amount of studies have investigated source reliability and brand efficacy in AI situations, but few have explored to analyze the parameters in which consumers trust AI influencers, or how elements like literacy and cultural environments contribute to, moderate, or break this trust (Hewapathirana & Perera, 2024). Additionally, the emotional aspect of influencer marketing, which is often examined via the perspective of parasocial interaction (PSI), an umbrella term for anthropomorphism and parasocial relationships in this research, has been verified for human influencers, but its significance in AI settings stays unclear (Labrecque, 2014; Feng et al., 2024). Moreover, recent research suggests that AI influencers can evoke powerful emotional reactions when constructed with anthropomorphic signals, challenging the concept that parasocial interactions need human agency (Stein et al., 2022).

Furthermore, while AI literacy has previously been studied in both educational and occupational settings, this topic is hardly investigated in terms of AI-mediated persuasion in consumer situations

(Wang et al., 2022). The subject of whether high literacy promotes or undermines trust in AI influencers stays unanswered and debated. By including AI literacy as a cognitive variable, this paper adds a new perspective to the relationship between communication and marketing studies. Therefore, this research paper fills a cross-industry gap. Despite plenty of AI influencer studies focusing on e-commerce or tech-based providers, the influence of these representatives in visually accelerated areas such as fashion, beauty, and lifestyle on social media has acquired too little academic investigation, especially since those areas are where interpersonal relationships and aesthetics are predominant (Jayasingh et al., 2025).

1.4 Research Gap and Research Question

AI Literacy as a cognitive variable is again important as most marketing, media, and communications research studies make the implicit assumption that consumers are aware of what AI is and how it operates. This represents an incorrect assumption because AI literacy levels differ greatly, impacting how consumers understand and trust AI-generated information and in this case social media content (Ng et al., 2021b). High literacy may reduce trust by revealing that consumers are aware of the methods of persuasion by AI. Moreover, cultural moderation of consumer trust. Cultural environments influence how consumers react to digitalization and virtual entities. However, few researchers have looked at how on an individual basis the cultural environment one is surrounded by influences the consequences of perceived parasocial interactions in AI influencer relationships (Cleveland & Laroche, 2007; Omeish et al., 2025).

This study will combine these formerly neglected concepts into a unified framework that examines how and why trust is established, or not, with AI influencers. Therefore, this research will investigate how perceived interactivity, perceived anthropomorphism, perceived parasocial relationships, and perceived AI literacy with AI influencers influence consumer trust, with cultural environments as a moderating factor. Based on the existing literature and established research gaps, this thesis addresses the following research question:

How do perceptions of and perceived relationships with AI influencers influence consumer trust?

2. Theoretical Framework

2.1 AI Influencers and Consumer Trust

2.1.1 The Rise of AI Influencers and the Trust Framework

The combination of digital advertising and AI has resulted in AI influencers who are self-governing and algorithmically controlled identities that mimic human characteristics on social media channels. These identities, which range from hyper-realistic avatars such as Lil Miquela to animated or brand-conceptualized avatars, call into question traditional ideas about influence, credibility, and trust. Consumer trust regarding such AI influencers is developing as an important predictor of advertising efficacy, especially in cases when AI influencers are considered to advocate, endorse, or speak for businesses (Kim & Wang, 2024).

In digital consumption settings, trust indicates the idea that the influencer is harmless, capable, and operates with authenticity (Kim & Kim, 2021). Although past studies have focused on consumer trust in human influencers (Belanche et al., 2024), trust in AI influencers poses an original challenge. Such influencers do not have genuine human motives, emotions, or responsibility to continue to encourage interpersonal relationships and purchasing decisions (Looi & Kahlor, 2024). The psychological reasons underlying this appear multilayered and influenced by consumer perceptions of interactivity, anthropomorphism, parasocial relationships, and AI literacy, all of which will be discussed in depth throughout this theoretical framework.

2.1.2 Conceptualizing Consumer Trust in AI Influencers

Consumer trust in AI influencers is determined by cognitive and emotional measurements of the influencer's perceived authenticity and relationship connection, rather than only perceived capability or communication reliability (Feng et al., 2024). As AI influencers become more human-like in terms of reactivity, compassion, and identity (Go & Sundar, 2019), consumers start to develop opinions that are similar to human influencers. Nevertheless, the lack of human control driving these virtual influencers raises concerns about if anything non-human can genuinely be responsible or authentic.

According to previous studies, trust in AI influencers may appear paradoxical. Whilst many consumers are intrigued by advancements in technology and accuracy, many others are concerned about manipulation or an absence of realness in AI development (Curry & Curry, 2023). Therefore, recognizing how particular perceptions impact an increase in trust is critical. Kim and Kim (2021) present a more complex framework for trust in influencer marketing on social media, differentiating between affective trust (emotional connection) and cognitive trust (trust in capability and authenticity). In AI settings, such constructs are mediated by the influencer's anthropomorphic appearance (Stein et al., 2022), perceived interactivity and reactivity (Li & Peng, 2021), and overall AI literacy among consumers (Wang et al., 2022).

This analysis operates under the idea that consumer trust is dynamic reasoning impacted by interaction competence, perceptions of relevant context, and knowledge about AI technologies. Developing on this theoretical framework, the next subsections will investigate the independent variables which are interactivity, anthropomorphism, parasocial relationships, AI literacy, and moderating variable which is cultural environments that are hypothesized to influence consumer trust in AI influencers, the dependent variable.

2.2 Interactivity

According to research on digital marketing, interactivity is defined as the extent of bilateral communication between the consumer and the influencer that the consumer perceives (Li & Peng, 2021). Contrary to traditional marketing or stagnant media sources, social media content supports dynamic, adaptable, and interactive communication. In the context of AI influencers, interactivity allows artificial entities to emulate reactivity, attention, and relational engagement, all of which are important elements for trust development (Rungruangjit et al., 2024, pp. 6-8).

Go and Sundar (2019) differentiate functional and relational interaction. Functional interactivity is defined as basic interface-based answers, but relational interactivity includes greater engagement indicators like customized answers, hilarious or emotional messages, and appreciation of followers who support the influencers. Given their artificial persona, AI influencers that participate in relational interactivity, via algorithmically powered DMs, story polls, and comment replies on *Instagram*, are frequently considered as more "authentic" (Go & Sundar, 2019). Rungruangjit et al. (2024) provide more empirical evidence, discovering that AI influencers who are extremely engaging, generated higher emotional connections and followers on social media platforms, resulting in enhanced trust and purchasing intentions. Particularly, the perceived anthropomorphism of these interactions was a strong predictor for interpersonal connections.

The human-machine communication (HMC) framework theoretically supports the latter, stating that when technology and AI systems display anthropomorphic behavior, people attach social norms and standards to them (Guzman & Lewis, 2020). Thus, interactivity is more than just a technological function, it is a psychological modifier of trust and parasocial interactions. In influencer marketing, where trust can be an affective and cognitive construct, the influencer's perceived reaction increases the relationship's connection and credibility. Therefore, the following hypothesis is proposed:

H1: Perceived interactivity with AI influencers is positively associated with consumer trust.

2.3 Parasocial Interactions and Anthropomorphism

2.3.1 The Role of Anthropomorphism in Building Emotional Connections

Anthropomorphism, or the attribution of human qualities to non-human entities (Cambridge University Press, 2025), is a critical facilitator of parasocial connection in AI-mediated settings. When AI influencers seem and behave like humans, they evoke higher emotional reactions from consumers, such as perceived comfort, capability, and reliability (Maeda & Quan-Haase, 2024).

Feng et al. (2024) underline that anthropomorphism has both perceptual and behavioral effects. AI influencers appear like humans because of accurate facial expressions, fashion, and physical movements. They exhibit human interaction behaviors like humor, empathy, and cultural references. These traits diminish emotional separation and promote perceived relational genuineness, resulting in increased trust. Stein et al. (2022) determined that perceived similarity and human likeness strongly predicted parasocial involvement for actual and AI influences. Respondents who saw AI influencers look more human-like had higher PSI scores and were more inclined to trust their recommendations. This conclusion is consistent with Cialdini et al.'s (1991) research on social impact, which implies that perceived similarity is an effective predictor of trust and convincing others, despite influencers not being reciprocative. Moreover, anthropomorphism has a utilitarian purpose in addition to its aesthetic appeal. AI influencers who demonstrate persistent emotional reactivity, social signals, and coherent narration evoke the same social patterns as humans in interpersonal relationships (Go & Sundar, 2019). As an outcome, the artificial appearance of the influencer is not as important as the authenticity of the connection.

Nonetheless, the positive effects of anthropomorphism are not endless. Though human-like features might raise a sense of relatability and realistic thinking, excessive use of anthropomorphic AI influencers could cause distress, a phenomenon known as the "uncanny valley" (Mara, 2012, pp. 34-35), in which fake human portrayals trigger mixed feelings or skepticism Thus, the efficacy of anthropomorphism can be determined by complementing variables like interactivity and consistency of the AI's actions. For example, when an AI influencer acts in a socially interactive and appropriate manner, anthropomorphic signals can be received positively. On the other hand, when interaction is restricted or seems out of sync with normal human standards, excessive anthropomorphism can fail, which can lead to decreasing trust instead of increasing it. Therefore, the following hypothesis is proposed:

H2: Perceived anthropomorphism with AI influencers is positively associated with consumer trust.

2.3.2 Understanding Parasocial Relationships in the Context of AI Influencers

The theory of parasocial interaction (PSI) is based on the original research of Horton and Wohl (1956), who described it as an unbalanced, emotionally loaded connection that media consumers develop with personality-driven entities regardless of the lack of genuine interpersonal reciprocity. In digital settings, particularly on social media, parasocial relationships are widely regarded as a key method for influencers to create trust, loyalty, and interaction with their followers (Labrecque, 2014, p.135).

Given the rise of AI influencers, parasocial interaction has become more intricate. As opposed to normal influencers, AI individuals are entirely synthetic, they are created, programmed, and managed by organizations and algorithms (Sharma et al., 2025, pp.2-8). However, other studies reveal that parasocial interactions may continue to develop with these entities, as long as they properly replicate emotions and social signals (Feng et al., 2024). These replicas feature personalized messages, anthropomorphic facial expressions, interactive responses, and content-based narrations (Feng et al., 2024). Feng et al. (2024) used PSI and anthropomorphism measures to experimentally evaluate the relationship between consumers and AI influencers. Feng et al.'s (2024) results indicate that higher levels of perceived anthropomorphism strengthen parasocial connections, which in turn increases consumer trust. The Parasocial Relationship Scale (PRS) utilized in this research, obtained emotional connection, perceived familiarity, and envisioned comfort, all of which Labrecque (2014) had previously verified. This observation is consistent with Media Equation Theory (Reeves & Nass, 1996), which presents that people unintentionally regard devices, media, and artificial entities as though they are humans. According to the theory, social signals in controlled systems may provoke human social reactions like courtesy, trust, and emotional connection, even if consumers know that their interactions are fake (Reeves & Nass, 1996). In terms of AI influencers, this theory offers an important explanatory perspective, it explains why parasocial interactions occur despite the lack of real human interaction.

From a critical position, mentioning Media Equation Theory in this situation is more than simply a theoretical addition. It validates the whole psychological credibility of trusting non-human beings (Reeves & Nass, 1996). Without this kind of theoretical foundation, one may wonder if consumers have the ability to emotionally commit to a thing they know as fake. Media Equation Theory tackles that by demonstrating how structure overcomes an ontological framework. As long as AI influencers are intended to have anthropomorphic interaction, expression, and reaction, consumers will spread ethical and social frameworks, such as trust, to artificial entities (Reeves & Nass, 1996).

Hence, in this theoretical framework, trusting an AI influencer is about more than simply determining if their content appears credible, it is also about how consumers automatically approach them as if they are actual people, despite the fact they are not. This emphasizes the importance of interpersonal behaviors (e.g., interaction), which contribute to the perception of social status created by the Media

Equation Theory (Reeves & Nass, 1996). Thus, the Media Equation Theory establishes a theoretical relationship between interface design, emotional perception, and cognitive trust processes in AI influencer settings (Reeves & Nass, 1996). Therefore, the following hypothesis is proposed:

H3: Perceived parasocial relationship with AI influencers is positively associated with consumer trust.

2.3.3 Parasocial Interaction in AI vs. Human Influencers

Recent literature is progressively comparing the relationship dynamics between AI and human influencers. Belanche et al. (2024) and De Cicco et al. (2024) discovered that, though human influencers remain to be seen as more real, AI influencers could generate equal amounts of parasocial connection if they are perceived as interactive, engaged, persistent, and trustworthy. Surprisingly, AI influencers are frequently perceived as less problematic and more controlled, particularly in collectivist cultural situations in which uniformity and avoiding risk are valued (Omeish et al., 2025). The finding suggests an overlapping process; parasocial relationships with AI influencers may be conceptually rationalized as "safe" while still being successfully fulfilling because of their programmed compassion and consistently pleasant appearance (Shil, 2025). Compared to human influencers, who can be inconsistent, inappropriate, or stressed out, AI influencers provide dependability and consistency which improve consumer trust when combined with personal interaction.

Therefore, parasocial interactions in AI settings are not just feasible, but also progressively successful in influencing consumer trust and behavior when it comes to purchasing decisions. When AI influencers reveal human or anthropomorphic characteristics and interactive actions, they provide sufficient social and emotional signals to cause parasocial connections. This connection, consequently, represents an effective predictor of consumer trust.

2.4 AI Literacy and Its Role in Consumer Trust

2.4.1 Defining AI Literacy

AI literacy can be defined as the set of skills that allow people to comprehend, analyze, and utilize artificial intelligence systems ethically and successfully. Although it theoretically started as digital literacy, AI literacy includes analytical thinking, being ethically aware, and effective engagement with autonomous technologies (Long & Magerko, 2020; Ng et al., 2021b).

Wang et al. (2022) describe AI literacy through four interrelated constructs: Awareness refers to identifying the existence and performance of AI technologies in everyday situations. Usage refers to the capability to utilize AI technologies and networks successfully. Evaluation refers to the ability to objectively analyze the trustworthiness, results, and opinions of AI. Lastly, ethics refers to comprehending the moral concerns regarding AI systems. Wang et al.'s (2022) Artificial Intelligence Literacy Scale (AILS) was successfully and scientifically verified across a broad spectrum of populations, demonstrating how AI literacy is versatile and influences a diverse number of behavioral and ideological results. This framework serves as a basis for how AI literacy is implemented in this research. According to Cengiz and Peker (2025), AI literacy impacts emotional reactions, like AI anxiety and AI enthusiasm, that modify consumer trust. The integration of ethical thinking has received significant attention in current academic studies, highlighting its importance in comprehending trust factors in intricate AI technologies like AI influencers (Wang et al., 2025).

2.4.2 From Acceptance to Skepticism in Literacy

Although digital literacy is frequently associated with increased technological acceptance (Börekci & Çelik, 2024, p.229), the purpose of AI literacy remains somewhat uncertain (Gerlich, 2023, pp.16-17; Schiavo et al., 2024, pp.2-3). Consumers with an adequate amount of AI literacy can better understand the algorithmic design, tactical objectives, and commercial interests of AI influencers, which could lower their trust (Kim & Wang, 2023).

Consumers who have greater AI literacy are better able to recognize when content on social media is generated by an automated system, which might make AI influencers appear like advertising tools rather than authentic, trustworthy individuals (Guzman & Lewis, 2020). According to Kim and Kim (2021), perceived authenticity and genuine compassion are critical to consumer trust in influencer marketing. However, AI literacy provides consumers with cognitive skills to unravel the false sense of authenticity, possibly provoking skepticism, disconnectedness, or perhaps rejection. This is consistent with the results of Curry and Curry (2023), who claim that compassionate AI entities could struggle to win trust if consumers become aware of their lack of actual emotional abilities. Based on the Computers as Social Actors (CASA) model, people frequently interact with AI as if it were a real person by responding to its social signals (Gu et al., 2024, p. 3). However, people with a greater AI literacy can detect these signals as algorithmic instead of legitimate, lowering the trust they generally believe in (Gu et al., 2024, p. 8).

Therefore, while AI literacy improves consumers' knowledge, it can also weaken the emotional trust of consumers. This happens when feelings of artificiality and risk are raised, and they become aware of the manipulative purpose behind AI influencers. In this setting, AI literacy is not only a predictor of knowledge but also of skepticism or disconnectedness. Therefore, the following hypothesis is proposed:

H4: AI literacy is negatively associated with consumer trust.

2.4.3 Cultural Variation in AI Literacy and Trust Perceptions

The influence of AI literacy on consumer trust can vary between societies. Chien et al. (2018) discovered that cultural aspects including power distance and individualism have a crucial impact on how individuals perceive and assess automated technology. According to Hofstede (1991) in Chien et al.'s (2018, p.6) study, Power Distance (PD) refers to "the fact that all individuals in societies are not equal, and it expresses the attitude of the culture toward these power inequalities amongst us". In societies with strong power dynamics, less powerful individuals must follow directions from the higher ups of the organization. This element may influence the extent to which in a high-PD culture, individuals view automation as authoritative, leading them to quickly trust automated perspectives. In high-PD settings, individuals may take longer to rebuild trust after any breaches (Brockner et al., 1992; Chien et al., 2018, p.6). Therefore, higher levels of AI literacy can occur with trust in collectivist societies since calm and positive attitude towards technology are prioritized (Omeish et al., 2025). On the other hand, according to Hofstede (1991), Individualism against Collectivism (IDV) refers to "the extent to which people from birth onwards are integrated into strong, cohesive in-groups, which throughout people's lifetimes continue to protect them in exchange for unquestioning loyalty" (Chien et al., 2018, p.6). It depicts a person's identity as "I" or "We" in an environment. Individualistic cultures prefer to focus on oneself and their immediate family members, whereas collectivist societies focus on outsiders in return for unwavering devotion. In simple terms, in a society with a high IDV, individuals prioritize their own successes over common aspirations (Chien et al., 2018, p.6). Therefore, in individualist societies, the similar understanding can lead to mistrust and skeptical disconnection (Omeish et al., 2025).

Therefore, the concept of cultural environments plays a key role in determining how AI literacy resonates with consumers' opinions. Cleveland and Laroche's (2007) Acculturation to Global Consumer Culture (AGCC) explains how consumers acquire global consumer culture. Acculturation is the process by which people adopt and use the customs and ideals of a culture other than their own (Cleveland & Laroche, 2007, p.250). This global consumer culture model (Cleveland & Laroche's, 2007) adds theoretical depth, proposing that cultural background, personal orientation, and value orientation impact how consumers perceive AI-based content. A consumer in Japan, for example, might regard AI empathy as an indication of technical progress, but a consumer in the United Kingdom might regard it as an unconventional marketing technique (Chien et al., 2018; Cleveland & Laroche's, 2007; Hofstede, 2001).

Thus, whilst AI literacy consistently allows consumers to identify fundamental patterns of AI interaction, its impact on trust is influenced by cultural values, expectations, and past engagement to AI in daily life (Hofstede, 2001; Singelis et al., 1995).

2.4.4 Integrating AI Literacy with Broader Consumer Psychology

AI literacy could additionally be interpreted in terms of consumer involvement. Consumers who are highly literate process AI content proactively. Those people are more prone to examine statements made by AI, doubt reliability, and reject emotional or persuasive appeals which are not supported by perceived truthfulness (Shin et al., 2022, p.1228). Consumers do not automatically trust an AI influencer just because of superficial appearances such as openness, realism, or aesthetic (Feng et al., 2024, p.40). It is a careful judgment depending on how well the consumer knows how the AI operates and what its behaviors imply.

According to Cialdini et al. (1991), persuasion is less successful when consumers are proactively involved. When consumers grasp the way AI operates, they are more effectively able to identify when algorithms attempt to influence them. This prevents consumers from becoming too deeply invested in AI influencers that appear to be authentic but are not really (Pinski & Benlian, 2024). Although, it is important to remember that the kind of AI literacy can differ. Ethical reflection, for instance, can stimulate close examination and skepticism, but functional literacy, like usage, can increase consumer trust and decrease uncertainty. This aligns with Carolus et al. (2023, pp.7-8) who discovered that specific kinds of AI literacy, like self-efficacy and ethical awareness, had a greater impact on behavioral consequences versus the overall understanding or familiarity of consumers.

2.5 Cultural Environments as a Moderation Effect

2.5.1 Culture as an Influencing Factor in Human and AI Interaction

Culture has a significant impact on the psychological mechanisms which consumers use to figure out technology, particularly AI influencers. Hofstede (2001) and Singelis et al. (1995) established that aspects like individualism vs. collectivism, power distance, and uncertainty avoidance influence how consumers react to new ideas, social signals, and risk perception. These qualities are especially important in AI settings, as the line between human beings and technology blurs and trust has to be established even when human authenticity is lacking.

With influencer marketing, culture influences one's content preference, as well as perceived trustworthiness and expectations regarding interactions. Consumers in collectivist countries, for instance, might prioritize peace, coherence, and societal hierarchy, making them more tolerant of filtered or programmed influencer content, particularly AI-generated content, if it conforms to social standards (Cleveland & Laroche, 2007; Hofstede, 2001). In contrast, in individualist societies where authenticity and self-expression are valued, the identification of artificiality can more easily destroy trust in AI entities (Cleveland & Laroche, 2007; Hofstede, 2001).

This cultural upbringing affects how consumers perceive parasocial interactions with AI influencers. Although the cognitive process of parasocial interaction can be common, consumers' trust and value for these interactions is influenced by cultural factors (Chien et al., 2018).

2.5.2 Cultural Environment as a Moderator of Parasocial Interaction and Trust

The effectiveness of parasocial interactions in establishing consumer trust remains unsecured, it varies depending on how social signals are read, which is greatly impacted by cultural environments (Omeish et al., 2025, pp.3-5). Parasocial connections, for example, can be viewed to be more genuine or credible in cultures that value intimacy, group relations, and personal connections (Omeish et al., 2025, pp.3-5). In these kinds of societies, any AI-generated entity can satisfy emotional and social requirements provided that they are compassionate and attentive.

On the contrary, in cultures that emphasize autonomy, skepticism, and self-worth, similar signals can be perceived as manipulative or deceptive (Soares et al., 2007). Consumers in these situations might respond poorly if they believe that these relationship signals are intentionally generated or algorithmically controlled from the influencers' side to the consumers. This perspective is consistent with the cultural coherence framework, that states that people are more inclined to listen to persuasive advertisements that reflect their cultural beliefs and standards (Soares et al., 2007).

According to Feng et al. (2024), anthropomorphic creations and parasocial connections make people believe AI influencers more and increase trust in most situations, yet the extent of this effect changes depending on cultural factors. Orlando (2024) says that AI influences are typically regarded as trustworthy and are approved in Asian societies, in which collective norms and trust in technology come together. Whereas in Western societies, individuality such as being cautious could result in more scrutiny (Izea, 2024).

The above studies imply that cultural environments act as an obstruction for developing trust from parasocial interactions. In the marketing and endorsing world, neglecting to consider diverse cultural environments could result in wrong usage of global AI techniques. As well as misinterpretations of the collected data for consumer activity. Therefore, the following hypothesis is proposed:

H5: Cultural environments moderate the relationship between parasocial relationships and consumer trust in AI influencers.

2.5.3 Operationalizing Culture in Consumer Research

The cultural environments could be implemented in consumer trust research using Hofstede's (2001) cultural dimensions and personal opinions like Acculturation to Global Consumer Culture

(Cleveland & Laroche, 2007). The combined approach of the above reflects that every single person in a country follows the stereotypical dimensions, especially in such a globalized, digitally intertwined society.

Cleveland and Laroche (2007) established the Self-identification with Global Consumer Culture scale within the acculturation to global consumer culture (AGCC) theory, which evaluates how closely people interact with global consumption trends such as media, goods, services, and forms of communication. Highly acculturated people can be more accepting of AI influencers because they see them as part of a multinational or global lifestyle trend (Cleveland & Laroche, 2007, pp.251-252). For example, people who cherish other nations' lifestyles are more inclined to want to buy their consumption representations, such as goods (certain products) or services (Cleveland & Laroche, 2007, p.253). People who are less acculturated can be more impacted by local customs, which influence their perceptions of trust in AI influencers, authenticity regarding parasocial interactions, and ethical standards for AI (Cleveland & Laroche, 2007, pp.251-252).

Through a theoretical perspective, incorporating cultural moderators within the model enhances the ability to explain and validate cross cultural data. It allows for the discovery of distinct consumer groups that react differently to AI influencers. Because both their cognitive and emotional perceptions are shaped by fundamental cultural norms rather than the design of the marketing strategy.

2.5.4 Bridging Culture, Trust, and AI Literacy

Cultural environments can also be linked to AI literacy. For example, in highly contingent societies where communication is extremely dependent on underlying signals and common knowledge, high AI literacy might not undermine trust as much as in lower contingent, individualistic societies (Chien et al., 2018). Rather, it might increase consumers' perception of AI's tactical complexity or entertainment appeal (Chien et al., 2018). This highlights a deeper cultural dimension difference in how AI is viewed as an individual involved in cognitive and emotional parasocial interactions.

As a result, while AI influencers follow algorithms, their interpersonal perception by consumers varies by culture. For example, a very similar message can be received in various ways based on how society dictates standards of honesty, and technical trustworthiness, and how AI influencers convey emotions. Thus, integrating cultural environments as a moderating factor is critical for theoretical accuracy and effectiveness of the research. This is because the consumption of AI influencers is growing everywhere, particularly in places with diverse socio-cultural norms.

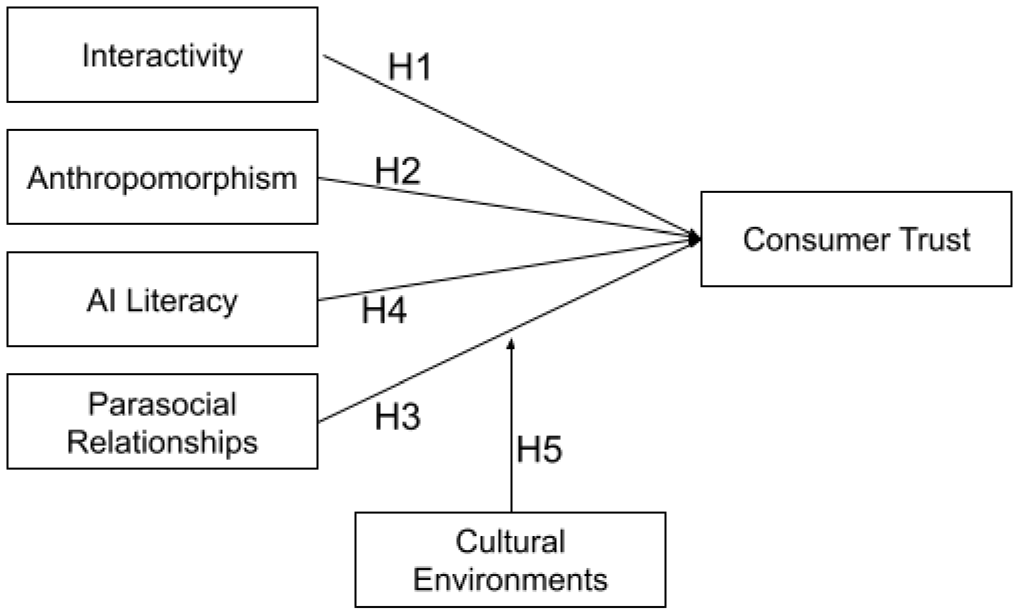

Figure 1. *Conceptual Framework*

3. Methodology

This chapter outlines the methodology used in this research. Firstly, an overview of the research design with its justification will be given. Secondly, the research sample and the sampling strategy will be provided. Further, the operationalization and measurements of the variables will be stated. Moreover, the experimental manipulation and the scales of the dependent and independent variables will be clarified. In addition, the data collection procedure, and the validity and reliability of the research will be argued for. Finally, the research's data analysis and research ethics will be explained in this section.

3.1 Research Design

This research studies how perceptions of and perceived relationship with AI influencers influence consumer trust. Therefore, a quantitative research design, specifically an online survey, was created using Qualtrics to examine the statistical relationships between the variables and foresee phenomena meticulously. Quantitative research involves gathering and analyzing organized, numerical data (Lim, 2024, p. 2). The main purpose is to create precise and credible measurements for statistical analysis (Goertzen, 2017, p. 12; Lim, 2024, p. 2). The fundamental aim of quantitative research is to find measurable patterns, investigate causal connections, and create applicable findings among populations (Bhandari, 2020). This research is a quantitative way to determine how different psychological and cognitive aspects influence trust in AI influencers. It particularly investigates how the perceptions of interactivity, AI literacy and parasocial interactions with AI influencers influence consumer trust, with cultural environments as a moderator. Through performing this, the study hopes to evaluate both direct and moderating factors such as the influence of interactivity on consumer trust, as well as the correlation of cultural environments on the relationship between parasocials interactions and consumer trust in AI influencers. This method enables strategic evaluation of ideas, which helps gain a deeper comprehension of trust dynamics in AI-driven digital marketing.

This thesis takes advantage of an online quantitative method that tests various variables and hypotheses, enabling a more comprehensive and extensive study scope (Zyoud et al., 2024, p. 12). Quantitative research enables international participation (Evans & Mathur, 2018, p. 856). With this global scope, researchers may collect diversified data from people from many cultural backgrounds. This leads to findings that are suitable for a larger amount of the world's population. Because this thesis involves time limits for data collecting, the researcher will benefit greatly from the availability of online survey forms. An online survey provides researchers with quick access to participants (Nayak & Narayan, 2019, p. 36). The accuracy with which online surveys are completed is an important advantage. Conducting online surveys permits researchers to set statements or questions mandatory to "force response" to ensure participants answer the current question before moving on to the next item, resulting in more thorough and quality replies (Evans & Mathur, 2018, p. 858; Nayak & Narayan, 2019, p. 35). Therefore, conducting a quantitative survey is beneficial for topics with multiple variables.

Furthermore, exploring previous research revealed that in this line of study, a quantitative research strategy is applied to measure the impacts of one variable on to another variable (Bhandari, 2023). The research in this study also focuses on a variety of factors and evaluates their connection to one another (Greenwood, 2021, p. 217). As a result, a questionnaire-style survey is important for gaining a more comprehensive knowledge of the IV's effects on the DV. It was selected for this research thesis because it is regarded to be the most effective way for obtaining a big number of participants (Evans & Mathur, 2018, p. 858). It serves as a method which is useful not just to acquire demographic data, but additionally to acquiring opinions and perceptions by employing various factors and measurements (Evans & Mathur, 2018). A benefit of an online survey is that the researcher remains absent in every manner throughout the filling out of the survey, removing any sense of obligation from the respondents as well as reducing experimental bias during the research process (Nayak & Narayan, 2019, p. 36; Reips, 2000, p. 94).

3.2 Sample

3.2.1 Target Population

The target group focused on social media users from various international backgrounds who interact with any influencers in any way. This provides for a broad research and encourages anyone over the age of 18 to participate. For this research purpose, respondents were not limited by geography, current residence or any other demographics. The only criteria was: (i) be 18 years or older, (ii) having followed or engaged with any influencer in any form. By establishing basic answer requirements, such as a 7-point Likert Scale, it enables individuals of all backgrounds and environments to provide their perspectives on the topic of consumer trust in AI influencers. Because it is an ongoing topic across many market sectors, a wide sample group is necessary to provide a more precise response to the research topic. There is a general paucity of studies on consumer trust in AI influencers with predictors such as interactivity and cultural environments. Establishing a single condition makes the survey comprehensible to people of all cultural backgrounds and ages.

3.2.2 Sampling Procedure

The survey was distributed on *WhatsApp* in numerous large groups consisting of students and other members in the Netherlands. Moreover, it was also allocated on Instagram. This allowed for responses from individuals from various ages, countries, and cultural environments as the connections on WhatsApp and Instagram of the researcher are very diverse. The major experiment's data was collected from 27th May 2025 till 2nd June 2025 via the aforementioned social media platforms. The individuals participating were chosen through non-probability sampling methods. Non-probability sampling is a sampling strategy in which merely a subset of the sample has the same chance to engage in the study (Vehovar et al., 2016, pp. 328-339). Non-probability sampling includes convenience sampling to be specific. Convenience sampling involves selecting respondents according to practical considerations such as availability, accessibility, and desire to engage (Vehovar et al., 2016, pp. 328-339).

3.2.3 Research Procedure

As mentioned before, the empirical data was collected through an online survey which was created on Qualtrics. Firstly, the survey stated an explanation of the research purpose. The explanation provided a concise overview of the research topic without revealing additional details regarding the survey questions. Additionally, an approximate completion time was mentioned to notify participants of an indication to how much time they would need to allocate to completing the survey, which in turn helps encourage participation by setting clear expectations. Further, it was stated that participation is voluntary, however an incentive to gather responses was given. At the end of the survey, participants were given the option to choose to enter a raffle for a chance to win a bag of beauty products. Moreover, they were reassured of anonymity and confidentiality. The researcher also offered contact information in case of any further questions about the survey. Upon agreeing to participate, respondents were asked if they ever followed or engaged with any influencer as the research topic is about influencers, the participants would need to have some knowledge on it. If participants selected ‘no’, they were directed to the end of the survey. Additionally, individuals were questioned on their age, this was asked for the purpose of the research but also as an eligibility verification in order to prevent minors from partaking in the survey. They were also questioned on their gender, nationality, education level and how often they use social media. Throughout the survey, the participants were presented with AI influencer content within the fashion, lifestyle, or beauty context and requested to judge based on the different features of the influencers (Jayasingh et al., 2025).

The survey started off with questions about anthropomorphism related to PSI, for this set of questions, an image of a hyper realistic AI influencer was shown however, it was mentioned that the influencer may be real or AI and the participants did not need to decide but simply answer based on how the image came across to them. This image was chosen due to the hyperrealism of the AI influencer in order to see if respondents thought it was AI or not. This was followed by questions about parasocial relationships, for this set of questions, another image was shown of an AI influencer, this time it was mentioned that the influencer was AI. This image was chosen because the image depicted a very normal activity even humans do, therefore the respondent would feel more welcomed into the AI influencer’s life.

Moreover, questions about consumer trust were asked, for this set of questions, a last image of an AI influencer was presented and again it was mentioned the influencer is AI. This image is chosen to see how likely respondents are to believe an AI influencer's promotional content. The survey finished off with questions about AI literacy, interactivity and cultural environment.

The total number of items with demographics was 45. All of the survey questions were set to 'force response' as a response requirement. This removed the likelihood of partial replies. The data was analyzed using IBM's SPSS Statistics 29.0.1 application. The data required some cleaning in Qualtrics as not all respondents met the criteria of being over 18 years old and/or having followed or engaged with any influencer.

3.2.4 Sampling Results

There were 162 valid respondents in this survey after data cleaning. 22 were discarded due to incompleteness. The age range was between 18 and 64 (M_{age} = 26.00, SD = 9.74). There were 32 (19.80%) males, 129 (79.60%) females and one (0.60%) person who decided not to reveal their gender. All respondents received at least a high school degree with 32 (19.80%) people only acquiring a high school degree. 100 (69.70%) people received a Bachelor's degree, making it the biggest category of education levels. 29 (17.90%) people received a Master's degree and one (0.60%) person preferred not to say. Further, 153 (94.40%) people use social media daily and 9 (5.60%) people use social media several times a week. Lastly, the respondents were from 34 different nationalities.

3.3 Validity and Reliability

To establish the research's validity, already existing and tested scales are utilized. The scales have already been implemented in several studies, as stated above in the theoretical framework. Despite their complexities, these measures are frequently used to define underlying connections in various study areas. Using such scales assures that the data is valid and hence acceptable to apply in this study. Prior studies in this area support the study's multidimensionality, further contributing to its validity. Moreover, the scales used in this study have a Cronbach alpha (α) value of 0.7 or higher in the previous studies they were derived from.

The reliability of this research is verified by fully defining every research phase in the methodology chapter, allowing the research to be replicated with the same findings. An online convenience sampling method was employed to effortlessly reach participants while reducing bias. All measurement scales in this study were based on already tested and validated research. These original scales have previously demonstrated trustworthy findings, which justifies their usage here. Certain terminology was somewhat modified in order to address the topic of AI influencers, however the overall design of each scale remained unchanged to ensure that it is reliable.

3.4 Measures

The survey consists of questions regarding variables such as interactivity, parasocial interactions, specifically anthropomorphism and parasocial relationships, AI literacy, consumer trust and cultural environments. To guarantee the question validity, all scales were tested using already existing, peer-reviewed scales based on earlier research results. These measures or scales have been evaluated in a variety of settings and demonstrated to accurately reflect fundamental psychological variables (Netemeyer et al., 2003, p. 10). Every question or item was displayed on a consistent 7-point Likert scale ranging from 1 "strongly disagree" to 7 "strongly agree", which is commonly accepted in research as a beneficial design for enhancing answer discrimination and reliability without increasing the exhausting or confusing the respondent too much (Joshi et al., 2015, p.398). There was no need to adapt the original scales because they all applied the same 7-point Likert scale. The order in which the scales were presented was based on the logic of the topic and research question as well as the images that were shown. (See Appendix A for the full survey).

There were logistical challenges when exporting the data from Qualtrics to SPSS. The values did not match the labels of the 7-Point Likert scale, therefore new variables were computed prior to running the analyses.

3.4.1 Anthropomorphism

The Anthropomorphism (perceived realism of the AI influencer) construct from the AI Influencer Scale was used in order to measure anthropomorphism (Feng et al., 2024, p.37). The Cronbach’s alpha of the Anthropomorphism scale is .83 (Feng et al., 2024, p.39) indicating that the scale is reliable and acceptable to use. Before presenting the items, a hyper realistic AI influencer image was shown from the Instagram account Rozy_Beochueol Inpeullu-eonseoa (2023). The respondents were asked to answer based on how they perceived the image as it was not revealed to respondents if the image was a real influencer or an AI influencer in order to determine if respondents believed the influencer to be real or not. After viewing the image, all five items of the Anthropomorphism scale were presented on a 7-Point Likert scale.

The reliability analysis in this research showed a Cronbach’s alpha of .90 for the Anthropomorphism scale, making it a reliable scale (Pallant, 2011, p.303). The mean score is 4.77 (*SD* = 1.38), suggesting that the respondents had a moderately high level of perceived realism of the AI influencer or anthropomorphism.

The five items underwent exploratory factor analysis in order to explore the underlying dimensions. A Principal Component Analysis (PCA) was used with Direct Oblimin rotation based on Eigenvalues (> 1.00). The Kaiser-Meyer-Olkin (KMO) value of .80 verified the sampling adequacy, as this exceeds the acceptable minimum value of .60 (Pallant, 2011, p.187). Bartlett's Test of Sphericity was significant, $\chi2$ (N = 162, 10) 583.55, $p < .001$, therefore indicating that the correlations between items reached statistical significance, supporting the factorability of the correlation matrix (Pallant, 2011, p.187). The resultant model explained 72.9% of the variance in anthropomorphism. Table 3.4.1 shows the factor loadings of the individual items onto one factor, indicating unidimensionality. A forced 2-component extraction was also attempted, which revealed a divide between external realism (appearance/performance) and internal realism (emotion/personality), however this was not maintained because of the overlapping concepts, negative items and the scale's brief length. The default Eigenvalue (>1.00) one-factor solution is justified because it is unbiased and commonly accepted by Kaiser's (Pallant, 2011, p.183, pp.192-193) criteria. It provides simpler interpretation for composite scores and regression analysis, prevents over fragmentation due to the brief length of the scale, and shows adequate internal reliability if Cronbach's alpha is above .70 (Pallant, 2011, p.183, pp.192-193). Therefore, the one factor found was:

Perceived realism of the AI influencer: This factor consists of five items which depict an individual's visual perception of an influencer when it is not revealed if they are real or AI.

Table 3.4.1.

Factor loadings, explained variance and reliability of the one factor found for the scale 'Anthropomorphism'.

Item	Anthropomorphism
Q10. The influencer is a real person.	.89
Q7. I believe the influencer is real because of her appearance.	.88
Q9. I believe the influencer has personalities.	.87
Q8. I believe the influencer has emotions.	.86
Q6. I believe the influencer is real because of one's performance.	.77

R^2	.73
Cronbach's α	.90

3.4.2 Parasocial Relationship

The Parasocial Relationship (perceived parasocial relationships to the AI influencer) construct from the AI Influencer Scale was used in order to measure parasocial relationship (Feng et al., 2024, p.37). The Cronbach's alpha of the Parasocial Relationship scale is .85 (Feng et al., 2024, p.39) indicating that the scale is reliable and acceptable to use. Before presenting the items, another realistic AI influencer image was shown from the Instagram account Miquela (2025). The respondents were encouraged to answer based on how they personally felt after viewing the image. This time it was revealed that the image was of an AI influencer celebrating their birthday. After viewing the image, all six items of the Parasocial Relationship scale were presented on a 7-Point Likert scale.

The reliability analysis in this research showed a Cronbach's alpha of .85 for the Parasocial Relationship scale, making it a reliable scale (Pallant, 2011, p.303). The mean score is 2.03 (SD = 0.99), suggesting that the respondents had a moderately low level of perceived parasocial relationships to the AI influencer.

The six items underwent exploratory factor analysis in order to explore the underlying dimensions. A Principal Component Analysis (PCA) was used with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .81, $\chi 2$ (N = 162, 15) = 420.94, $p < .001$. KMO verified the sampling adequacy, as this exceeds the acceptable minimum value of .60 (Pallant, 2011, p.187). Bartlett's Test of Sphericity was significant, therefore indicating that the correlations between items reached statistical significance, supporting the factorability of the correlation matrix (Pallant, 2011, p.187). The resultant model explained 58.2% of the variance in parasocial relationship. Table 3.4.2 shows the factor loadings of the individual items onto one factor, indicating unidimensionality. A forced 2-component extraction was also attempted, which revealed a divide between emotional engagement (connected/understood/immersed) and intimate engagement (real-life closeness/personal relationship), however this was not maintained because of the overlapping concepts, negative items and the scale's brief length. The default Eigenvalue (>1.00) one-factor solution is justified because it is unbiased and commonly accepted by Kaiser's (Pallant, 2011, p.183, pp.192-193) criteria. Therefore, the one factor found was:

Perceived parasocial relationships to the AI influencer. This factor consists of six items which depict an individual's emotional and relational perception of an influencer when it is revealed they are AI.

Table 3.4.2.

Factor loadings, explained variance and reliability of the one factor found for the scale 'Parasocial Relationship'.

Item	Parasocial Relationship
Q14. I feel deep connection with the AI influencer even if they are not a real human.	.80
Q11. I want to be friends with the AI influencer.	.80
Q12. I would like to have a relationship with the AI influencer.	.77
Q13. The AI influencer articulates my thoughts and emotions well.	.77
Q16. I feel a part of the AI influencer's world.	.74
Q15. I want to meet the AI influencer.	.71
R^2	.58
Cronbach's α	.85

3.4.3 AI Literacy

The AI Literacy Scale (AILS) was used in order to measure AI literacy (Wang et al., 2022, p.1324). Although the scale includes four more subsections for awareness, usage, evaluation, and ethics, Wang et al. (2022, p. 1334) recommend to use the AILS to evaluate AI literacy in general instead of individual subsections, since it increases the scale's reliability score. The Cronbach's alpha of the AI Literacy Scale is .83 (Wang et al., 2022, p.1322) indicating that the scale is reliable and acceptable to use. When presenting the items, the respondents were notified the statements were regarding their experience and understanding of AI so they were encouraged to answer based on their knowledge and use of AI technologies in everyday life. All 12 items of the AILS were presented on a 7-Point Likert scale.

The reliability analysis in this research showed a Cronbach's alpha of 0.80 for the AI Literacy Scale, making it a reliable scale (Pallant, 2011, p.303). The mean score is 5.12 ($SD = 0.71$), suggesting that the respondents had a moderately high level of AI literacy.

The 12 items underwent exploratory factor analysis in order to explore the underlying dimensions. A Principal Component Analysis (PCA) was used with Direct Oblimin rotation based on a fixed number of three factors. This outcome ended up following on Wang et al.'s (2022, pp.1326-1329) conclusions, which suggested that AI literacy is multifaceted, covering interconnected dimensions such as practical AI usage, ethical AI knowledge and AI awareness. Though the original Eigenvalue (> 1.00) test indicated four components, a three-factor solution was required to improve interpretability and prevent factors with weak, negative or isolated items in order to avoid over fragmentation (Costello & Osborne, 2005, pp. 2-3, Tabachnick & Fidell, 2013, p.613). KMO = .82, $\chi2$ (N = 162, 66) = 615.82, $p < .001$. KMO verified the sampling adequacy, as this exceeds the acceptable minimum value of .60 (Pallant, 2011, p.187). Bartlett's Test of Sphericity was significant, therefore indicating that the correlations between items reached statistical significance, supporting the factorability of the correlation matrix (Pallant, 2011, p.187). The resultant model of the three factors together explained 58.4% of the variance in AI literacy. The first factor consisted of seven items about practical AI usage, which explained 35.1% of the variance. The second factor consisted of three items about ethical AI knowledge, which explained 13.7% of the variance. Lastly, the third factor consisted of two items about AI awareness, which explained 9.6% of the variance. Table 3.4.3 shows the factor loadings of the individual items onto three factors. There were three factors found:

Practical AI Usage. This factor consists of seven items which depict an individual's practical skills in using AI applications and tools. This aligns with Wang et al.'s (2022) "usage" and "evaluation" subsections.

Ethical AI Knowledge. This factor consists of three items which show how alert against AI misuse an individual is, which represent a consumer's ethical and responsible behaviour towards AI tools. This aligns with Wang et al.'s (2022) "ethics" subsection.

AI Awareness. This factor consists of two items which show if an individual is able to recognize and be aware of privacy issues within AI applications. This aligns with Wang et al.'s (2022) "awareness" subsection.

Table 3.4.3.

Factor loadings, explained variance and reliability of the three factors found for the scale 'AI Literacy'.

Item	Practical AI Usage	Ethical AI Knowledge	AI Awareness
Q24. I can skilfully use AI applications or products to help me with my daily work.	.82		
Q26. I can use AI applications or products to improve my work efficiency.	.77		
Q29. I can choose the most appropriate AI application or product from a variety for a particular task.	.77		
Q28. I can choose a proper solution from various solutions provided by an AI.	.74		
Q27. I can evaluate the capabilities and limitations of an AI application or product after using it for a while.	.66		
*Q25. It is usually hard for me to learn to use a new AI application or product.**	.61		(.40)
*Q22. I do not know how AI technology can help me.**	.52		(.41)
Q32. I am always alert to the abuse of AI technology.		.76	
Q30. I always comply with ethical principles when using AI applications or products.		.66	
Q23. I can identify the AI technology	(.35)	.50	(.30)

employed in the applications and products I use.			
*Q31. I am never alert to privacy and information security issues when using AI applications or product.**			.81
Q21. I can distinguish between AI and non-AI applications.			.46
R^2	.35	.14	.10
Cronbach's α	.84	.56	.24

Note. * = reverse-coded items.

3.4.4 Interactivity

The Interaction scale was used in order to measure interactivity (Li & Peng, 2021, p.968). The Cronbach's alpha of the Interaction scale is .87 (Li & Peng, 2021, p.968) indicating that the scale is reliable and acceptable to use. When presenting the items, the respondents were notified the statements were regarding their interactivity with AI influencers on social media. All three items of the Interaction scale were presented on a 7-Point Likert scale.

The reliability analysis in this research showed a Cronbach's alpha of .83 for the Interaction scale, making it a reliable scale (Pallant, 2011, p.303). The mean score is 3.66 (SD = 1.06), suggesting that the respondents had a moderately low level of interactivity with AI influencers.

The three items underwent exploratory factor analysis in order to explore the underlying dimensions. A Principal Component Analysis (PCA) was used with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .63, $\chi2$ (N = 162, 3) = 233.30, p < .001. KMO verified the sampling adequacy, as this exceeds the acceptable minimum value of .60 (Pallant, 2011, p.187). Bartlett's Test of Sphericity was significant, therefore indicating that the correlations between items reached statistical significance, supporting the factorability of the correlation matrix (Pallant, 2011, p.187). The resultant model explained 75.8% of the variance in interactivity. Table 3.4.4 shows the factor loadings of the individual items onto one factor, indicating unidimensionality. The default Eigenvalue (>1.00) one-factor solution is justified because it is unbiased and commonly accepted by Kaiser's (Pallant, 2011, p.183, pp.192-193) criteria. The one factor found was:

Interactivity with AI Influencers. This factor consists of three items which indicate an individual's perception of AI influencers' accessibility and reactivity, which corresponds to Li and Peng's (2021, pp.961-962) idea of interaction in social media advertising and communication science.

Table 3.4.4.

Factor loadings, explained variance and reliability of the one factor found for the scale 'Interaction'.

Item	Interactivity
Q35. AI influencers I follow provide feedback to my comments and suggestions quickly.	.94
Q33. AI influencers I follow reply to my message quickly.	.87
Q34. I can contact AI influencers I follow easily.	.80
R^2	.76
Cronbach's α	.83

3.4.5 Cultural Environments

The Self-Identification with Global Consumer Culture construct from the Acculturation to Global Consumer Culture (AGCC) Scale was used in order to measure cultural environments (Cleveland & Laroche, 2007, p.255). The Cronbach's alpha of the Self-Identification with Global Consumer Culture scale is .83 (Cleveland & Laroche, 2007, p.255) indicating that the scale is reliable and acceptable to use. When presenting the items, the respondents were notified the statements related to their lifestyle preferences and how global influencers may affect their choices. After viewing the image, all eight items of the Self-Identification with Global Consumer Culture scale were presented on a 7-Point Likert scale.

The reliability analysis in this research showed a Cronbach's alpha of .76 for the Self-Identification with Global Consumer Culture scale, making it a reliable scale (Pallant, 2011, p.303).

The mean score is 3.90 (*SD* = 0.99), suggesting that the respondents had a moderately low level of identification with global consumer culture.

The eight items underwent exploratory factor analysis in order to explore the underlying dimensions. A Principal Component Analysis (PCA) was used with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .71, $\chi 2$ (N = 162, 28) = 385.34, $p < .001$. KMO verified the sampling adequacy, as this exceeds the acceptable minimum value of .60 (Pallant, 2011, p.187). Bartlett's Test of Sphericity was significant, therefore indicating that the correlations between items reached statistical significance, supporting the factorability of the correlation matrix (Pallant, 2011, p.187). The resultant model of the two factors together explained 59.2% of the variance in cultural environments. The first factor consisted of five items about a consumer's orientation, which explained 37.5% of the variance. The second factor consisted of three items about influencer oriented acculturation, which explained 21.8% of the variance. Table 3.4.5 shows the factor loadings of the individual items onto one factor, which generated a 2-factor solution that strongly displays two separate but interlinked themes. The two factors found were:

Global Consumer Orientation. This factor consists of five items which represent people's internal global consumer persona and lifestyle connection to worldwide trends, global fashion and products they choose.

Influencer Oriented Acculturation. This factor consists of three items which shows how aligned one is with international AI influencers.

Table 3.4.5.

Factor loadings, explained variance and reliability of the two factors found for the scale 'Self-Identification with Global Consumer Culture'.

Item	Global Consumer Orientation	Influencer Oriented Acculturation
Q39. I try to pattern my lifestyle, way of dressing, etc. to be a global consumer.	.76	
Q38. I pay attention to the fashion worn by people in my age-group that live in other countries.	.75	

Q40. I like scrolling on social media about the fashion, décor, and trends in other countries.	.74	
Q41. I prefer to wear clothing that I think is popular in many countries around the world rather than clothing traditionally worn in my own country.	.71	
Q42. I actively seek to buy products that are not only thought of as 'local'.	.67	
Q36. The (lifestyle) products I use are influenced by the advertising activities of foreign or global (AI) influencers.		.90
Q37. Advertising by foreign or global (AI) influencers has a strong influence on my purchasing choices.		.89
Q43. I identify with famous international (AI) influencers.		.67
R^2	.37	.22
Cronbach's α	.78	.77

3.4.6 Consumer Trust

The Trust Scale was used in order to measure consumer trust (Kim & Kim, 2021, p.227). The Cronbach's alpha of the Trust scale is .89 (Kim & Kim, 2021, p.227) indicating that the scale is reliable and acceptable to use. Before presenting the items, another realistic AI influencer image was shown from the Instagram account Aitana Lopez (2025). The respondents were encouraged to answer based on how they personally felt after viewing the image. This time it was also revealed that the image was of an AI influencer promoting some products on Amazon. After viewing the image, all four items of the Trust scale were presented on a 7-Point Likert scale.

The reliability analysis in this research showed a Cronbach's alpha of .78 for the Trust scale, making it a reliable scale (Pallant, 2011, p.303). The mean score is 2.59 (*SD* = 1.12), suggesting that the respondents had a very low level of trust towards the promotions of the AI influencer.

The four items underwent exploratory factor analysis in order to explore the underlying dimensions. A Principal Component Analysis (PCA) was used with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .76, $\chi 2$ (N = 162, 6) = 184.85, $p < .001$. KMO verified the sampling adequacy, as this exceeds the acceptable minimum value of .60 (Pallant, 2011, p.187). Bartlett's Test of Sphericity was significant, therefore indicating that the correlations between items reached statistical significance, supporting the factorability of the correlation matrix (Pallant, 2011, p.187). The resultant model explained 60.9% of the variance in consumer trust. Table 3.4.6 shows the factor loadings of the individual items onto one factor, indicating unidimensionality. A forced 2-component extraction was also attempted, which revealed a divide between moral integrity (truthfulness/honesty) and practical reliability (dependability/not taking advantage/believability), however this was not maintained because of the overlapping concepts, negative items and the scale's brief length. The default Eigenvalue (>1.00) one-factor solution is justified because it is unbiased and commonly accepted by Kaiser's (Pallant, 2011, p.183, pp.192-193) criteria. Therefore, the one factor found was:

Trust in AI influencers. This factor consists of four items which depict trust from a consumer's perspective towards an AI influencer's product recommendations.

Table 3.4.6.

Factor loadings, explained variance and reliability of the one factor found for the scale 'Trust'.

Item	Trust in AI influencers
Q18. I believe what this AI influencer says and that they would not try to take advantage of the followers.	.82
Q19. The AI influencer is straightforward and honest even though their self-interests are involved.	.82
Q20. The AI influencer would not tell a lie even if they could gain by it.	.79
Q17. The AI influencer can be relied upon on their content.	.67

R^2	.61
Cronbach's α	.78

3.5 Data Analysis Methodology

Linear regression analyses are going to be used to test the hypotheses and relationships among the variables. A regression analysis applies when its purpose is to predict data from a continuous dependent variable based on data from one continuous independent variable, referred to as simple regression, or data from multiple continuous independent variables, referred to as multiple or hierarchical regression (Sykes, 1993, p. 1-3). In this research, H1, H2, and H3, and H4 are going to be tested through multiple regression analysis since the independent variables in these hypotheses are interlinked and predict one dependent variable (Pallant, 2011). Hence, it is sensible to analyze these interlinked relationships together.

Another test will be used to test the moderating effect of cultural environments. A moderator affects the relationship between independent and dependent variables. This effect may appear as the direction, strength, or existence of any relationship (Hayes, 2012, p. 2). The moderator's effects can be tested at different degrees of presence (Hayes, 2012, p. 2-3). Therefore, *PROCESS*, an extension of the IBM SPSS software, was used to conduct the moderation testing.

4. Results

The chapter of the thesis will report on the findings drawn from the data. The data was obtained via Qualtrics and further analyzed using IBM SPSS software to evaluate hypotheses stated in Theoretical Framework of the thesis. The chapter will begin with hypothesis testing and either accepting or rejecting them determined by the outcomes. The multiple regression analysis addresses hypothesis 1, 2, 3, and 4. The chapter will conclude with a moderation analysis addressing hypothesis 5.

4.1 Direct Effect of Interactivity, Anthropomorphism and Parasocial Relationships with AI Influencers on Consumer Trust

A multiple linear regression was conducted with consumer trust as a dependent variable. Predictors were perceived interactivity, anthropomorphism and parasocial relationships. The model was found to be significant, $F(3, 158) = 17.60$, $p < .001$, $R^2 = .25$.

Among the three predictors, perceived parasocial relationships was found to be a significant positive predictor of consumer trust in AI influencers ($\boldsymbol{\beta}* = .48$, $t = 6.74$, $p < .001$, 95% *CI* [.38, .70]), suggesting that higher levels of parasocial relationships are associated with higher levels of consumer trust. It indicates that for every one-unit increase in perceived parasocial relationships, consumer trust in AI influencers increases by .54 units, thereby offering support for H3.

Furthermore, perceived interactivity was a positive but non-significant predictor of consumer trust in AI influencers ($\beta* = .12$, $t = 1.76$, $p = .080$, 95% *CI* [-.02, .27]). It indicates that for every one-unit in perceived interactivity with AI influencers, consumer trust in AI influencers increases by .13 units. However, because the confidence interval contains 0, the effect is statistically insignificant at the 95% confidence level (Fethney, 2010, p. 96). This regression analysis results do not support the hypothesis that higher levels of interactivity with AI influencers is associated with higher levels of consumer trust in AI influencers. H1 is therefore rejected.

Lastly, perceived anthropomorphism was a positive but non-significant predictor of consumer trust in AI influencers ($\beta* = .03$, $t = .40$, $p = .691$, 95% *CI* [-.10, .14]). It indicates that for every one-unit in perceived anthropomorphism with AI influencers, consumer trust in AI influencers increases by .02 units. However, because the confidence interval contains 0, the effect is statistically insignificant at the 95% confidence level (Fethney, 2010, p. 96). This regression analysis results do not support the hypothesis that higher levels of anthropomorphism of AI influencers is associated with higher levels of consumer trust in AI influencers. H2 is therefore rejected.

Table 4.1

Multiple Regression Analysis - Predicting Consumer Trust from Interactivity, Anthropomorphism, and Parasocial Relationship

Effect	*B*	*SE*	*β*	*t*	*p*	95% *CI* [*LL*, *UL*]
Intercept	.910	.415	—	2.194	.030	[.091, 1.728]
Interactivity	.128	.073	.122	1.762	.080	[-.016, .272]
Anthropomorphism	.023	.058	.029	.399	.691	[-.091, .138]
Parasocial Relationship	.542	.080	.482	6.737	<.001	[.383, .701]

Note. Dependent variable: Consumer Trust, *N* = 162. *CI* = Confidence Interval; *LL* = Lower Limit; *UL* = Upper Limit.

4.2 Direct Effect of AI Literacy on Consumer Trust

A multiple linear regression was conducted with consumer trust as a dependent variable. The predictor was AI literacy. The model was found to be significant, $F(1, 160) = 4.89$, $p = .028$, $R^2 = .03$.

AI literacy was found to be a significant negative predictor of consumer trust in AI influencers ($\beta^* = -.17$, $t = -2.21$, $p = .028$, 95% *CI* [-.51, -.03]), suggesting that higher levels of AI literacy are negatively associated with consumer trust. It indicates that for every one-unit increase in AI literacy, consumer trust in AI influencers decreases by (-).27 units, thereby offering support for H4.

Table 4.2.

Multiple Regression Analysis - Predicting Consumer Trust from AI Literacy

Effect	*B*	*SE*	*β*	*t*	*p*	95% *CI* [*LL*, *UL*]
Intercept	3.976	.633	—	6.285	<.001	[2.727, 5.226]
AI Literacy	–.270	.122	–.172	–2.211	.028	[–.512, –.029]

Note. Dependent variable: Consumer Trust, *N* = 162. *CI* = Confidence Interval; *LL* = Lower Limit; *UL* = Upper Limit.

4.3 Moderation Effect of Cultural Environments on Relationship Between Parasocial Relationships and Consumer Trust

A moderation analysis was conducted using Hayes' PROCESS macro in SPSS (Hayes, 2012). Parasocial relationship (PSR) acted as the independent variable (*X*), consumer trust as a dependent variable (*Y*), and cultural environments as the moderator (*W*). Each of the variables were mean-centered ahead of running the analysis, and a heteroscedasticity-consistent interference (HC3) was implemented (Hayes, 2012; Pallant, 2011). The model was found to be significant, $F(3, 158) = 19.47$, $p = <.001$, $R^2 = .28$. The moderation analysis demonstrated that cultural environments significantly moderated the relationship between parasocial relationships and consumer trust in AI influencers ($\beta^* = .15$, $t = 2.31$, $p = .022$, 95% *CI* [.02, .28]), thereby offering support for H5.

AI literacy was found to be a significant negative predictor of consumer trust in AI influencers ($\beta^* = -.17$, $t = -2.21$, $p = .028$, 95% *CI* [-.51, -.03]), suggesting that higher levels of AI literacy are negatively associated with consumer trust. It indicates that for every one-unit increase in AI literacy, consumer trust in AI influencers decreases by (-).27 units, thereby offering support for H4.

Further, the Johnson-Neyman approach was implemented to investigate the interactive effect of parasocial relationships on consumer trust at different levels of the moderator, being cultural environments. This approach reveals certain moderator values at which the effect of the focal predictor (parasocial relationships), shifts from statistically significant to non-significant (Hayes, 2012). This approach is especially beneficial in moderation analyses since it provides a deeper understanding of the relationship versus simply testing at predefined levels (e.g., mean ± 1 *SD*) (Hayes, 2012). In Table 4.3.2, it shows the conditional effects of parasocial relationships on consumer trust across three standards of cultural environments: below the mean (-1 *SD*), average (mean), and above the mean (+1 *SD*). Below the mean cultural environment levels ($W = -.99$), parasocial relationships substantially predicted consumer trust, ($\beta^* = .31$, $SE = .11$, $t = 2.90$, $p = .004$, 95% *CI* [.10, .53]). At the mean cultural environments level ($W = 0$), the effect was both significant and higher ($\beta^* = .46$, $SE = .08$, $t = 5.58$, $p < .001$, 95% *CI* [.30, .63]). Above the mean cultural environments level ($W = .99$), the effect was highest, with ($\beta^* = .61$, $SE = .10$, $t = 6.01$, $p < .001$, 95% *CI* [.41, .81]).

Table 4.3.1.

Moderation Effect of Cultural Environments

Effect	*B*	*SE*	*t*	*p*	95% *CI* [*LL*, *UL*]
Intercept	2.55	.08	32.23	<.001	[2.39, 2.70]
Parasocial Relationships	.46	.08	5.58	<.001	[.30, .63]
Cultural Environments	.18	.09	2.02	.045	[.00, .35]
Interaction (PSR X Cultural Environments)	.15	.07	2.32	.022	[.02, .28]

Note. Dependent variable: Consumer Trust, *N* = 162. *CI* = Confidence Interval; *LL* = Lower Limit; *UL* = Upper Limit.

Table 4.3.2.

Conditional Effect of Consumer Trust

Moderator Level (CulturalM)	*B*	*SE*	*t*	*p*	95% *CI* [*LL*, *UL*]
Low (-1 SD, W = -.985)	.31	.11	2.90	.004	[.10, .53]
Mean (W = 0)	.46	.08	5.58	<.001	[.30, .63]
High (+1 SD, W = .985)	.61	.10	6.01	<.001	[.41, .81]

Note. Dependent variable: Consumer Trust, *N* = 162. *CI* = Confidence Interval; *LL* = Lower Limit; *UL* = Upper Limit.

Table 4.4.

Hypotheses Results on the Research Framework

Hypothesis	Result
H1: Perceived interactivity with AI influencers is positively associated with consumer trust.	Rejected
H2: Perceived anthropomorphism with AI influencers is positively associated with consumer trust.	Rejected
H3: Perceived parasocial relationships with AI influencers is positively associated with consumer trust.	Accepted
H4: AI literacy is negatively associated with consumer trust.	Accepted
H5: Cultural environments moderate the relationship between parasocial relationships and consumer trust in AI influencers.	Accepted

5. Discussion and Conclusion

5.1 Overview and Interpretation of Key Findings

This research sought to address the main research question, "*How do perceptions of and perceived relationships with AI influencers influence consumer trust?*" through a focus on four concepts being perceived interactivity, perceived anthropomorphism, perceived parasocial relationships, and AI literacy, and the moderating impact of cultural environments. The findings depict how consumers gain trust in AI influencers extensively and intricately, showing some predicted but also unpredicted outcomes. This overview delves into those outcomes in depth, analytically connects it to the theoretical assumptions provided in the theoretical framework, and discusses these results regarding a large academia of communications and media.

5.1.1 A Non-Significant Effect of Perceived Interactivity on Trust

As opposed to previous research indicating that interaction is a crucial predictor of trust in digital settings (Bayer et al., 2020, p. 475; Byun & Ahn, 2023, p. 4), perceived interactivity did not significantly predict consumer trust in AI influencers. This finding raises questions about a prevailing body of studies which has repeatedly stressed the positive impact of interactivity, like responsiveness and personalization on trust development (Go & Sundar, 2019, p. 305). Although interactivity is commonly regarded as improving consumer experience while causing AI to appear more human-like, the insignificant effect in this research indicates that interactivity on its own might be inadequate to build trust if anthropomorphic or parasocial relationship aspects are not there.

Furthermore, this outcome could indicate a change in consumers' assumptions. In the media landscape filled with interactive chatbots, automated processes, and algorithmic curation, people could not want to associate interaction with authenticity or dependability (Curry & Curry, 2023, p. 8125). Thus, consumers may perceive interactivity as a functional activity instead of a personal relationship. This supports Guzman and Lewis' (2020, p. 167) argument that interactions may change consumer experiences, however it only creates trust when it aligns with how consumers make sense of a scenario.

5.1.2 A Non-Significant Effect of Perceived Anthropomorphism on Trust

Additionally, perceived anthropomorphism also did not significantly predict trust. This contrasts the CASA paradigm (De Cicco et al, 2024, p.2; Gu et al., 2024, p. 3), which states that human-like characteristics lead to social reactions. Previous research has found that visual and behavioral anthropomorphism promotes perceived empathy and thus, trustworthiness (Rungruangjit et al., 2024, p. 3; Maeda & Quan-Haase, 2024, p. 1070). However, the findings of this research provide a surprising contrast: anthropomorphic signals can be visually appealing but inadequate to instill actual trust.

A potential cause is consumer skepticism and knowledge of AI in the media. As people become more aware of artificial and synthetic entities, people can become opposed to anthropomorphic tactics that appear unnatural or deceitful (Kim & Wang, 2023, p. 3). In this context, anthropomorphism might fail when consumers notice an inconsistency across human-like appearances and fabricated or programmed behavior (Georgievskaya et al., 2023, p.107). The study could potentially indicate a level where excess human features no longer serve meaningful aspects to trust and can lead to irritation due to the uncanny valley effect (Mara et al., 2022, pp. 34-35; Cambridge University Press, 2025). Therefore, this finding calls into question the heavy dependency on human-like design in AI influencers.

5.1.3 A Significant Effect of Perceived Parasocial Relationships on Trust

Perceived parasocial relationships significantly predicted consumer trust in AI influencers. This finding is consistent with Labrecque (2014, p. 138), and Horton and Wohl (1956, p. 215), who claim that parasocial relationships increase closeness and perceived authenticity. This result is especially interesting regarding AI influencers, because despite the unawareness or lack of true social reciprocity, artificial entities can create strong and significant relationship connections that build trust.

This supports the findings of Stein et al. (2022, p. 3437), who discovered that perceived similarity and anthropomorphism impact trust outcomes. Particularly, the influence of parasocial relationships can be increased in AI settings since AI influencers are programmed, avoiding the uncertain behavior and errors of real influencers. As Shil (2025, p. 64) points out, AI influencers frequently develop stronger engagement rate and empathic closeness simply because their interpersonal behaviors are based on an algorithm to fit consumer needs.Therefore, parasocial relationships are more than an emotional side effects of digital engagement, but parasocial relationships also serve an important part in trust development.

This result raises questions about the belief that everything has to be "real" in order to be believable or trustworthy. It illustrates how an influencer acts and engages with individuals might be more important instead of worrying about if they are human or AI. This leads us to think about the marketing belief that AI influencers are less reliable and trustworthy than humans (Belanche et al., 2024, p. 10). Additionally, the emotional attachments that humans develop, which are parasocial relationships, appear to exist similarly with AI as it does with real influencers regardless of social media channel.

5.1.4 A Significant Effect of AI Literacy on Trust

The findings confirm Börekci & Çelik's (2024, p. 231) and Carolus et al.'s (2023, p. 5) findings that knowledgeable consumers can more accurately judge and interpret AI activity. Unlike interpersonal aspects such as parasocial relationships, AI literacy offers a cognitive framework that allows consumers to perceive influencer activities as the outcome of design developments, algorithmic behavior, and strategic purposes, rather as magical automation (Börekci & Çelik's, 2024, p. 231; Carolus et al., 2023).

Cengiz and Peker (2025, p. 4) argue that AI literacy decreases anxiety and opposition towards AI technology, swapping fear with a feeling of being informed. This is consistent with the observations of Schiavo et al. (2024, p. 3), who state that consumers with higher AI literacy show increased acceptance and interactivity because they are less exposed to algorithmic influence. In the realm of trust in influencers, this indicates that awareness fosters justified trust that is thoughtful instead of ignorant.

Lastly, the importance of AI literacy shows a wide socio-technical transition in society. As AI gets more embedded into marketing and communication industries, consumers will need to gain additional literacies to deal with these settings responsibly and successfully (Ng et al., 2021a, p. 505). Therefore, trust in AI influencers could be based less on how realistically human they look and more on how well consumers grasp the design and reasoning driving these entities.

5.1.5 Cultural Environment as a Significant Moderator on Trust

Cultural environments was a significant moderator between parasocial relationships and consumer trust. This suggests that cultural aspects influence how interpersonal relationships are understood and adopted. This is consistent with previous research by Chien et al. (2018, p. 12) and Omeish et al. (2025, p. 9), who argue that trust in artificial entities is heavily influenced by collectivist vs individualist attitudes (Hofstede, 2001). Parasocial relationships are perceived to be socially valuable and hence positive to consumer trust. Therefore, it supports the hypothesis that trust based on parasocial relationships depends on the cultural environments one chooses to follow, especially when influenced by/on social media.

5.2 Theoretical Implications

This research contributes to ongoing concerns about how individuals engage with AI, create trust on the internet, and develop parasocial (one-sided) relationships online. Rather than just confirming or criticizing current theories, the results indicate that our theories must be adapted when considering AI influencers.

5.2.1 Reconsidering the Media Equation Theory and CASA Paradigm

The insignificant effects of perceived interactivity and anthropomorphism urge for a thorough review of fundamental frameworks like the Media Equation Theory and the CASA paradigm. Based on those ideas, people react to media and automated systems as if they were humans, particularly when they display human-like signals (De Cicco et al., 2024; Go & Sundar, 2019, pp. 304-305; Reeves & Nass, 1996). Since anthropomorphism and interactivity imitate human behavior, they are thought to automatically also generate emotional reactions including reciprocity, empathy, and trust.

On the other hand, the results of this research indicate that individuals do not respond the same way to AI influencers as they do to humans. A possible explanation could be that individuals' perceptions about AI have shifted. As Guzman and Lewis (2020, p. 168) illustrate, the distinction between AI and human interactions is hard to seperate, resulting in new cultural standards. Nowadays, consumers are increasingly conscious and aware that AI influencers are fabricated and cautiously developed. As a result, people might perceive interactivity or human-like characteristics as marketing methods without emotions behind them rather than trust (Kim & Wang, 2023, p. 4).

This shows that the CASA paradigm related concepts are merely effective in limited settings, particularly when humans are unaware they are engaging with AI. As Baronchelli (2024, p. 2) notes, the emergence of AI requires fresh methods of approaching theories rather than relying solely on outdated paradigms. This research emphasizes the importance of updating socio-technical theories for users who are aware they are interacting with artificial intelligence.

5.2.2 Confirming the Parasocial Interaction Theory

The significant effect of parasocial relationships strengthens and broadens Parasocial Interaction Theory (Horton & Wohl, 1956, p. 215). Initially it was developed to define how consumers relate to human media personalities, now the idea has been confirmed to be useful in virtual contexts too (Labrecque, 2014, p. 136; Stein et al., 2022, p. 3435). The research found that parasocial relationships can also be developed with AI influencers, not just humans online, implying that the perception of relationship, instead of real human engagement, creates trust.

This is consistent with Shil (2025, p. 66) and Maeda & Quan-Haase (2024, p. 1072), who state that AI influencers can simulate emotional connection by designing, programming and creating algorithms. PSRs serve as an "emotional shortcut" that make individuals feel less vulnerable during online interactions (Bayer et al., 2020, p. 474). Therefore, Parasocial Interaction Theory should be extended to incorporate emotional relationships with automated, AI entities.

5.2.3 Enhancing the Role of AI Literacy in Trust

The significant effect of AI literacy demonstrates that consumers' trust in AI is driven by how thoroughly they comprehend and evaluate AI technologies, rather than by their emotions or actions. As Carolus et al. (2023, p. 6) and Pinski & Benlian (2024, p. 17) define, AI literacy enables consumers to effectively use AI systems, resulting in increased comprehension, control, and trust. This research indicates that AI literacy constitutes as more than just technical knowledge, but it also serves as a psychological buffer, minimizing fear and increasing consumer trust (Cengiz and Peker, 2025, p. 7).

This leads to belief in prior trust frameworks that emphasized characteristics such as trustworthiness and empathy (Li & Peng, 2021, p. 962; Kim & Kim, 2021, p. 225). For AI influencers, trust is highly dependent on how well consumers comprehend and evaluate AI behavior. This emphasizes AI literacy as an essential aspect of trust, rather than merely an added aspect.

This additionally backs up Floridi and Cowls' (2019, p. 537) claim that trust in AI must be established. Trust can only be ethical and dependable if people have the understanding to critically evaluate AI.

5.2.4 Acculturation and Cultural Theories

The result that cultural environments moderates how parasocial relationships affect trust, offers support to the Acculturation to Global Consumer Culture (AGCC) paradigm (Cleveland & Laroche, 2007, p. 253). It demonstrates that trust is not global, but it is influenced by local customs, one's identity, and consumption of media. In collectivist societies, for instance, ideals such as peace and community driven may enhance the effectiveness of parasocial signals increasing trust in AI influencers (Omeish et al., 2025, p.16). This is consistent with research demonstrating that AI is not evenly trusted amongst different cultures (Chien et al., 2018, p. 9).

These findings emphasize the requirement for a better cultural awareness approach to AI trust. According to Hofstede (2001) and Soares et al. (2007, p. 279), cultural norms have a major impact on consumer behavior. This research indicates that AI systems need to be fitted to local cultural situations in order to successfully establish trust.

5.3 Societal and Practical Implications

This research provides valuable information for marketers and policymakers as AI influencers grow to be more popular. Learning how these artificial entities gain, maintain or lose trust from consumers is a realistic and social concern.

An important insight is that consumer trust is driven by a psychological relationship rather than an AI influencer's appearance. The significant effect of parasocial relationships demonstrates that consumers prefer deeper connections compared to superficial relations. Businesses should prioritize consistent communication and similar ideals on social media pages instead of focusing on human-like design aesthetic or interactivity. This contrasts the general consensus that purely making AI influencers look human is sufficient to establish trust (Go & Sundar, 2019, p. 305).

One more crucial takeaway is the significance of AI literacy. Consumers with higher levels of understanding of AI technologies were not more skeptical; rather, they proved to be more aware and competent. This highlights the need for informative and open discussion, and clear explanations of how AI influencers work. Establishing these systems to be more interpretable fosters ethical persuasive marketing by business and their AI influencers (Floridi et al., 2019, p. 537; Toff & Simon, 2023, p. 14).

The results also indicate how cultural environments influences trust development. The moderating effect of cultural environments on the parasocial relationships and consumer trust reveals that various consumers prioritize diverse characteristics, for example, emotional intimacy in collectivist societies, autonomy or usefulness in individualist ones (Chien et al., 2018, p. 9). AI influencers must best be adapted to the local consumer instead of attempting to appeal to the entire world.

However, with increased emotional connection lies risk factors. Parasocial relationships may encourage fake intimacy, enabling consumers, particularly very young and very old consumers to assume that AI entities actually reciprocate (Fengler, 2019, p. 11). Business behind these AI influencers have to be open regarding the artificial origin of their entities while refraining from generating designs that generate psychological deception of real connection (Karami et al., 2024, p. 15).

Finally, the results point to a change in the influencer sector. AI entities are no longer merely assisting human influencers, but they are taking over and taking on significant functions. This change requires new ethical design guidelines, collaborations, and monitoring to ensure AI influencers are authentic, responsible, and appropriate (Gerlich, 2025, p. 9; De Cicco et al., 2024, p. 5).

5.4 Limitations and Future Research

Though this research provides substantial insights regarding the relationship between consumer trust and AI influencers, certain limitations can be recognized. These include sampling range, methods constraints, and the extent of the tested framework.

5.4.1 Methodological Constraints and Measurement Issues

This research used a convenience sampling strategy which mostly attracted participants from Western countries, which could restrict the generalizability of the results, especially the moderating effect of cultural environments. Despite the fact that the participant pool consisted of 34 various nationalities, certain countries were represented by only one or two individuals. Future research could use stratified or other sampling methods to guarantee enough representation from various nationalities, especially when researching cultural moderators. The study used a survey which was sent online on platforms like Instagram and WhatsApp. Though this enabled rapid collection of data, it additionally raised the possibility of bias, which could have benefitted the researcher accessing respondents who were already acquainted with AI on social media and AI technology (Evans & Mathur, 2018, p. 860). This might have exaggerated AI literacy levels or influenced perceptions of interaction and parasocial relationships. Furthermore, this data could be impacted by desirability for the incentive offered or instead, a misunderstanding of AI jargon.

While pre-existing scales were used in this study, concepts such as parasocial relationships and AI literacy were initially created for human contexts, not AI. Adapting them to AI influencers, who exist in a gray area between automated systems and human portrayal, the scales could need more development. Further, a few reliability difficulties arose, particularly with the AI literacy scale, where subdimensions of "ethics" or "evaluation" could have been understood improperly by the participants. Future research should enhance these scales using items particular for AI influencers.

Despite the parasocial relationship scale being considered as a one-dimensional construct in the analysis, a forced two-factor analysis showed an unexpected conceptual divide. Items associated with emotional engagement (e.g., "I feel a part of the AI influencer's world") loaded positively on one factor, whereas items associated with intimate engagement (e.g., "I would like to have a relationship with the AI influencer") loaded significantly but negatively on the second factor. This shows a gap between emotionally connecting with AI influencers and wanting intimacy with them. Though it was not explored more in this paper, this split composition deserves more investigation in future research, especially in terms of psychological reactions towards AI vs human influencers (Labrecque, 2014; Stein et al., 2022).

5.4.2 Model Scope and Causal Relationships

This research focuses on just a few predictors and only one moderator. Additional, possibly significant concepts, like perceived authenticity, source credibility, and platform type could be considered for future research. Furthermore, while AI literacy had a significant correlation with trust, its potential relationship to other predictors such as interactivity or parasocial relationships was not investigated. Therefore, this could be interesting for future research. Furthermore, the cross-sectional design makes it impossible to definitely prove causal relationships (Kesmodel, 2018, p. 390). Lastly, experimental or longitudinal methods are advised for future research to investigate how trust develops over a long period of time after regular engagement with AI influencers (Farrington et al., 2010, pp.504-508).

5.4.3 Future Research Directions

These constraints open up a number of motivating possibilities. Future research should concentrate on stronger cultural comparisons by maintaining a diverse participant pool across major cultural groups. Researching how different cultural factors, like uncertainty avoidance or masculinity, affect confidence in AI influencers might provide further information (Hofstede, 2001). Additionally, researchers should investigate interaction effects, specifically if AI literacy decreases or increases the influence of parasocial relationships or anthropomorphism on trust. Furthermore, qualitative studies like interviews might add to the survey results by revealing deeper emotional responses to AI influencer appearances and programming.

In conclusion, as AI influencers continue to influence the evolution of marketing, their ethical and successful usage requires bridging disciplines such as combining perspectives of psychology, communications, and human and AI relationship. Only via this multidisciplinary perspective can we completely comprehend and direct how artificial entities impact actual behavior in humans.

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Appendix A: Full Survey

Start of Block: Instructions

Dear participant,   I am a Masters student at Erasmus University Rotterdam. Thank you for participating in my thesis survey as I am conducting research on **how people perceive and trust AI (artificial intelligence) influencers on social media.** The survey will take approximately **5-6 minutes** to complete. Your participation is **voluntary**, however at the end of the survey you could **enter a raffle to WIN a bag of beauty products**. Your responses will remain **anonymous and confidential**. Please answer each question carefully and honestly. I am sincerely interested in your **personal opinions**, there are no right or wrong answers. You may withdraw from the survey at any time. If you have any questions, please contact me via 563458ms@eur.nl.   By selecting **"I agree"**, you are consenting to participate in this research; consenting to the use of your personal data; and confirming you are at least **18** years old.

○ I agree (1)

○ I do not agree (2)

Skip To: End of Survey If QID1 = 2

Start of Block: Block 1: Demographics

Q1 How often do you use social media?

○ Daily (1)

○ Several times a week (2)

○ Once a week (3)

○ A few times a month (4)

○ Rarely/Never (5)

Q2 Have you ever followed or engaged with any influencer?

○ Yes (1)

○ No (2)

○ I'm not sure (3)

Skip To: End of Survey If Q2 = 2

Q3 How old are you? (Please indicate in numbers e.g. "25")

____

Skip To: End of Survey If Condition: How old are you? (Please in... Is Less Than 18. Skip To: End of Survey.

Q4 What is your gender?

○ Male (1)

○ Female (2)

○ Third gender / Non-binary (3)

○ Prefer not to say (4)

country What is your nationality?

▼ Afghanistan (1) ... Zimbabwe (1357)

Q5 What is the highest level of school you have completed or the highest degree you have received?

○ Less than high school degree (1)

○ High school graduate (2)

○ Bachelor's degree (5)

○ Master's degree (6)

○ Doctoral degree (7)

○ Prefer not to say (9)

Start of Block: Block 2: PSI (Anthropomorphism)

Image 1: Please take a look at the influencer image below. After viewing it, answer the following questions based on your impressions. There are no right or wrong answers—share your honest opinion. **The influencer may be real or AI**, but you don't need to decide. Respond based on how they come across to you.

Q6 I believe the influencer is real because of one's performance.

- ◯ Strongly disagree (1)
- ◯ Disagree (2)
- ◯ Somewhat disagree (3)
- ◯ Neither agree nor disagree (4)

○ Somewhat agree (5)

○ Agree (6)

○ Strongly agree (7)

Q7 I believe the influencer is real because of her appearance.

○ Strongly disagree (8)

○ Disagree (9)

○ Somewhat disagree (10)

○ Neither agree nor disagree (11)

○ Somewhat agree (12)

○ Agree (13)

○ Strongly agree (14)

Q8 I believe the influencer has emotions.

○ Strongly disagree (9)

○ Disagree (10)

○ Somewhat disagree (11)

○ Neither agree nor disagree (12)

◯ Somewhat agree (13)

◯ Agree (14)

◯ Strongly agree (15)

Q9 I believe the influencer has personalities.

◯ Strongly disagree (9)

◯ Disagree (10)

◯ Somewhat disagree (11)

◯ Neither agree nor disagree (12)

◯ Somewhat agree (13)

◯ Agree (14)

◯ Strongly agree (15)

Q10 The influencer is a real person.

◯ Strongly disagree (13)

◯ Disagree (14)

◯ Somewhat disagree (15)

◯ Neither agree nor disagree (16)

○ Somewhat agree (17)

○ Agree (18)

○ Strongly agree (19)

Start of Block: Block 3: PSI (Parasocial relationship)

Image 2: Please take a look at the **AI influencer image** below. After viewing it, answer the following questions based on your thoughts. There are no right or wrong answers. **Respond based on how you personally feel.**

Q11 I want to be friends with the AI influencer.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q12 I would like to have a relationship with the AI influencer.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q13 The AI influencer articulates my thoughts and emotions well.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q14 I feel deep connection with the AI influencer even if they are not a real human.

- Strongly disagree (11)
- Disagree (12)
- Somewhat disagree (13)
- Neither agree nor disagree (14)
- Somewhat agree (15)
- Agree (16)
- Strongly agree (17)

Q15 I want to meet the AI influencer.

○ Strongly disagree (9)

○ Disagree (10)

○ Somewhat disagree (11)

○ Neither agree nor disagree (12)

○ Somewhat agree (13)

○ Agree (14)

○ Strongly agree (15)

Q16 I feel a part of the AI influencer's world.

○ Strongly disagree (10)

○ Disagree (11)

○ Somewhat disagree (12)

○ Neither agree nor disagree (13)

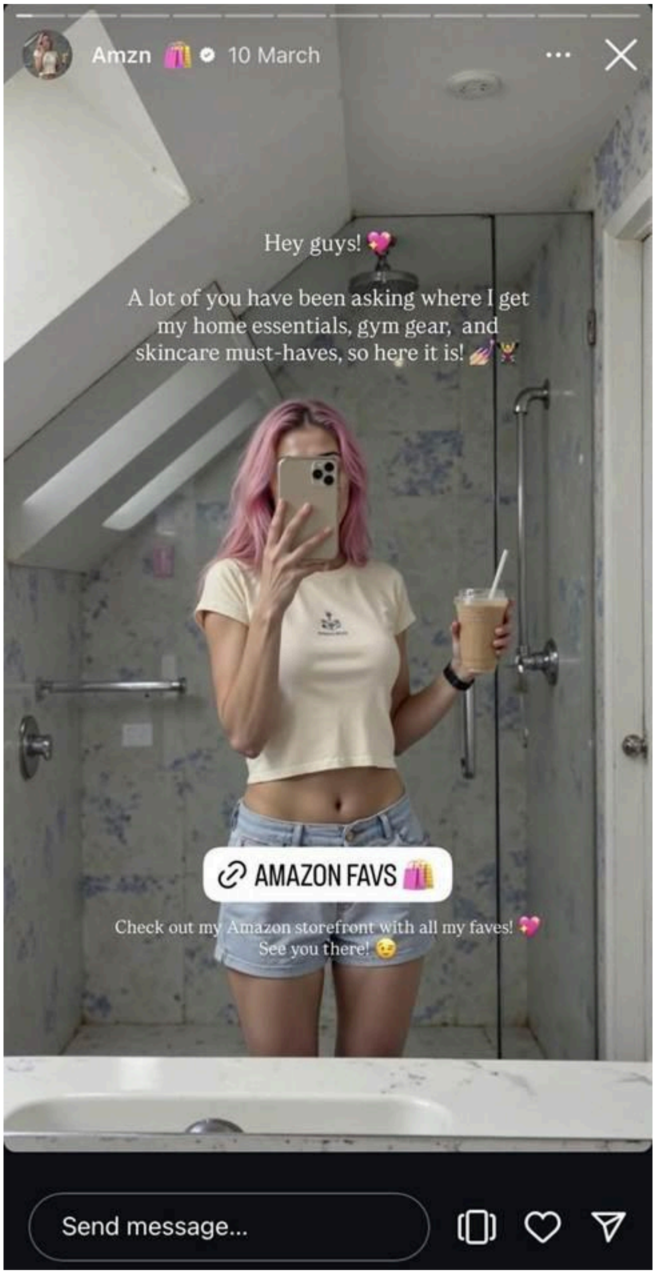
○ Somewhat agree (14)

○ Agree (15)

○ Strongly agree (16)

Start of Block: Block 4: Consumer Trust

Image 3: Please take a look at the **AI influencer image** below. After viewing it, answer the following questions based on your thoughts. There are no right or wrong answers. **Respond based on how you personally feel.**



Q17 The AI influencer can be relied upon on their content.

◯ Strongly disagree (9)

◯ Disagree (10)

- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q18 I believe what this AI influencer says and that they would not try to take advantage of the followers.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q19 The AI influencer is straightforward and honest even though their self-interests are involved.

- Strongly disagree (10)
- Disagree (11)

○ Somewhat disagree (12)

○ Neither agree nor disagree (13)

○ Somewhat agree (14)

○ Agree (15)

○ Strongly agree (16)

Q20 The AI influencer would not tell a lie even if they could gain by it.

○ Strongly disagree (9)

○ Disagree (10)

○ Somewhat disagree (11)

○ Neither agree nor disagree (12)

○ Somewhat agree (13)

○ Agree (14)

○ Strongly agree (15)

Start of Block: Block 5: AI Literacy

The following statements are about your **experience and understanding of artificial intelligence (AI).** Please answer honestly based on your **knowledge and use of AI technologies** in everyday life.

Q21 I can distinguish between AI and non-AI applications.

- ◯ Strongly disagree (9)
- ◯ Disagree (10)
- ◯ Somewhat disagree (11)
- ◯ Neither agree nor disagree (12)
- ◯ Somewhat agree (13)
- ◯ Agree (14)
- ◯ Strongly agree (15)

Q22 I do not know how AI technology can help me*.

- ◯ Strongly disagree (10)
- ◯ Disagree (11)
- ◯ Somewhat disagree (12)
- ◯ Neither agree nor disagree (13)
- ◯ Somewhat agree (14)
- ◯ Agree (15)

- Strongly agree (16)

Q23 I can identify the AI technology employed in the applications and products I use.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q24 I can skilfully use AI applications or products to help me with my daily work.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q25 It is usually hard for me to learn to use a new AI application or product*.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q26 I can use AI applications or products to improve my work efficiency.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q27 I can evaluate the capabilities and limitations of an AI application or product after using it for a while.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q28 I can choose a proper solution from various solutions provided by an AI.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q29 I can choose the most appropriate AI application or product from a variety for a particular task.

◯ Strongly disagree (9)

◯ Disagree (10)

◯ Somewhat disagree (11)

◯ Neither agree nor disagree (12)

◯ Somewhat agree (13)

◯ Agree (14)

◯ Strongly agree (15)

Q30 I always comply with ethical principles when using AI applications or products.

◯ Strongly disagree (9)

◯ Disagree (10)

◯ Somewhat disagree (11)

◯ Neither agree nor disagree (12)

◯ Somewhat agree (13)

◯ Agree (14)

◯ Strongly agree (15)

Q31 I am never alert to privacy and information security issues when using AI applications or product*.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q32 I am always alert to the abuse of AI technology.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Start of Block: Block 6: Interactivity

The following statements are about your **interactivity with AI influencers**.

Q33 AI influencers I follow reply to my message quickly

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q34 I can contact AI influencers I follow easily

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)

○ Strongly agree (15)

Q35 AI influencers I follow provide feedback to my comments and suggestions quickly

○ Strongly disagree (9)

○ Disagree (10)

○ Somewhat disagree (11)

○ Neither agree nor disagree (12)

○ Somewhat agree (13)

○ Agree (14)

○ Strongly agree (15)

Start of Block: Block 7: Cultural Environment

The **last set of statements** relate to your **lifestyle preferences** and how global influencers may affect your choices.

Q36 The (lifestyle) products I use are influenced by the advertising activities of foreign or global (AI) influencers.

○ Strongly disagree (11)

○ Disagree (12)

○ Somewhat disagree (13)

○ Neither agree nor disagree (14)

○ Somewhat agree (15)

○ Agree (16)

○ Strongly agree (17)

Q37 Advertising by foreign or global (AI) influencers has a strong influence on my purchasing choices.

○ Strongly disagree (10)

○ Disagree (11)

○ Somewhat disagree (12)

○ Neither agree nor disagree (13)

○ Somewhat agree (14)

○ Agree (15)

○ Strongly agree (16)

Q38 I pay attention to the fashion worn by people in my age-group that live in other countries.

○ Strongly disagree (9)

○ Disagree (10)

○ Somewhat disagree (11)

- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q39 I try to pattern my lifestyle, way of dressing, etc. to be a global consumer.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q40 I like scrolling on social media about the fashion, décor, and trends in other countries.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)

◯ Neither agree nor disagree (12)

◯ Somewhat agree (13)

◯ Agree (14)

◯ Strongly agree (15)

Q41 I prefer to wear clothing that I think is popular in many countries around the world rather than clothing traditionally worn in my own country.

◯ Strongly disagree (9)

◯ Disagree (10)

◯ Somewhat disagree (11)

◯ Neither agree nor disagree (12)

◯ Somewhat agree (13)

◯ Agree (14)

◯ Strongly agree (15)

Q42 I actively seek to buy products that are not only thought of as ‘local’.

◯ Strongly disagree (9)

◯ Disagree (10)

◯ Somewhat disagree (11)

- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Q43 I identify with famous international (AI) influencers.

- Strongly disagree (9)
- Disagree (10)
- Somewhat disagree (11)
- Neither agree nor disagree (12)
- Somewhat agree (13)
- Agree (14)
- Strongly agree (15)

Start of Block: Block 8: Raffle

Q44 Would you like to enter the raffle for a chance to **win a bag of beauty products**? Your response will still remain anonymous.

- Yes (1)
- No (2)

Appendix B: AI Declaration Form

Erasmus School of
History, Culture and
Communication

Declaration Page: Use of Generative AI Tools in Thesis

Student Information

Name: Mehek Shah

Student ID: 563458

Course Name: Master Thesis CM5000

Supervisor Name: Vivian Chen

Date: 26/06/2025

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 ChatGPT, 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 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

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

Signature: [digital signature]
Date of Signature: [Date of Submission]

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:

Mehek. Shah

Date of Signature: 26/06/2025

Appendix C: Extent of AI Usage Prompts

These are some example prompts asked ChatGPT to assist with thesis related questions:

1. Distinguish interactivity and parasocial interactions in social media context
2. Can AI literacy be a cognitive factor and how?
3. Give me a structure for a theoretical framework with 4 IVs, 1 DV and 1 moderator
4. Does AI literacy always end up with people being skeptical of AI or can people also trust certain AI tools but only selectively?
5. What are pros and cons of convenience sampling? Can it lead to bias?
6. I think I reverse coded my negative variables incorrectly in SPSS, show me step by step to make sure I'm right
7. Why is descriptive mean statistics showing above 7 when likert scale is ranging from 1-7?
8. How to compute values with random numbers back between 1-7 for variables in SPSS?
9. Is it recommended to load a 3 item scale on 2 factors?
10. How do I interpret moderation analysis matrix by PROCESS in SPSS?
11. Give me a structure for a discussion section of a thesis