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Why Do We Follow Virtual Influencer Recommendations? Three Theoretical Explanations from Brain Data Tested with Self-Reports

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Abstract

Virtual influencers (VI) have received significant recent research attention. Past work has investigated users' perceptions of their human-likeness, uncanniness, trust, and ability to persuade. However, findings are mixed, which motivates new theoretical approaches and investigations into the antecedents of the typically utilized variables. We thus took an exploratory, inductive approach by conducting two neuroimaging experiments with complementary brain imaging techniques and then derived theoretical explanations based on the findings. We discovered three key antecedents that impact human and virtual influencer evaluations: i) expectancy violation, ii) emotion, and iii) cognitive effort. To validate their explanatory power, we tested their effects on intention to follow using uncanniness, trust and distrust as serial mediators in a third behavioral study. Results confirm our interpretation of neural results and reveal three explanatory paths towards following intentions with human and virtual influencers: expectancy violation → uncanniness, emotion → trust/distrust, and cognitive effort → follow intentions. Against the lacking theorizing of expectancy violation, emotion, and cognitive effort in the current state of research on VI, we provide a significant theoretical contribution to the field by showing how they fundamentally predict further evaluations. Our results can guide design theories for the creation of virtual influencer accounts and help companies to better evaluate the predictors for successful VI marketing, as well as inform future information systems studies that wish to take an exploratory, inductive approach using neurophysiological data.

Keywords: Virtual Influencers, NeuroIS, EEG, fNIRS, Expectancy Violation, Emotion, Cognitive Effort

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1 Introduction

Artificial intelligence (AI)-synthesized persuasive social media content is becoming more prominent, as evidenced by the rise of influential artificial celebrities, sometimes referred to as "virtual influencers" (Moustakas et al., 2020). In related works, virtual influencers were characterized as "virtual characters" (Ahn et al., 2022; Chiu & Ho, 2023; Kim & Wang, 2023), "virtual robots" (Batist & Chimenti, 2021; de Boissieu & Baudier, 2023), or as an amalgamation of "avatars" and "virtual agents"

(Arsenyan & Mirowska, 2021; Mirowska & Arsenyan, 2023; Yang et al., 2023a). Virtual influencers can thus be posited as a new phenomenon that is loosely related to works on conversational agents and avatars. Virtual influencers are social media accounts that consist of computer-generated content and, in most cases, represent a virtual human. Some of these accounts, such as Lil'Miquela on Instagram, have millions of followers, and generate revenue through marketing campaigns for major brands (Choudhry et al., 2022). For instance, Lil'Miquela is said to have estimated annual earnings of US$ 11 million in 2023 and the company that runs Guggimon, a non-human virtual influencer, has raised US$ 58 million in funding (Platter, 2023). Reasons why companies are increasingly cooperating with virtual influencers include reduced costs and that the virtual influencer can be freely customized for the designed advertisement as it does not come with its own ego (Moustakas et al., 2020; Platter, 2023). Companies thus increasingly see great merit in leveraging virtual influencers for their marketing campaigns.

However, it is not clear why virtual influencers are so effective at being persuasive. Research conducted so far has explored factors that foster perceived behavioral intention to follow their recommendations (Almasri, 2023; El Hedhli et al., 2023; Mirowska & Arsenyan, 2023; Sands et al., 2022a) and have discovered many potential explanations. Factors such as the appearance of the influencer in terms of attractiveness and human-likeness (Ahn et al., 2022; Ham et al., 2023; Kim & Park, 2023), the influencer's fit to the advertised product or brand (Franke et al., 2023; Yang et al., 2023a), and the influencer's credibility or perceived trust (Ozdemir et al., 2023; Yang et al., 2023b) were found to most significantly impact users' perceptions. Alongside these major impacting factors, researchers have also investigated a plethora of constructs to explain users' perceptions of virtual influencers including storytelling, persuasiveness, expertise, virtue signalling, cultural background, and parasocial relationships (Almasri, 2023; Dabiran et al., 2022; de Boissieu & Baudier, 2023; Hofeditz et al., 2023; Levkov et al., 2023; Zhang et al., 2023; Zhou et al., 2024a). The diversity of literature on the varying explanations for human behavior related to virtual influencers suggests that the subject already faces similar issues to research on conversational agents more broadly, and that there are many hypotheses that often compete with each other (Oberhofer et al., 2023).

To respond to this problem, we took an inductive approach that focuses on some of the most promising factors that have been suggested to impact a virtual influencer's success, namely their human-likeness and associated uncanniness, as well as their perceived trust. There are many reasons for this. Firstly, virtual influencers often range in degree of human-likeness; some of them are highly human-like, while others are obviously non-human, drawing inspiration from cartoons or animations. As a result, the human-likeness of virtual influencers was observed to both positively and negatively impact the likability and the intention to interact with them (Ahn et al., 2022; Arsenyan & Mirowska, 2021; Batist & Chimenti, 2021; Dabiran et al., 2022; El Hedhli et al., 2023; Yang et al., 2023a), which could seem contradictory. According to the uncanny valley hypothesis, however, increases in human-likeness only increase positive evaluations of artificial agents to a certain point. At this point, when human-likeness is high but not photo-realistic, evaluations become negative toward the artificial agent and only increase again when human-likeness is almost indistinguishable from real humans (Mori et al., 2012). While several works have investigated the effects of human-likeness levels in virtual influencers, fewer works have focused on its impact on perceived uncanniness of the influencer (Arsenyan & Mirowska, 2021; Robinson, 2020). Yet, we know from conversational agents literature, that perceived uncanniness has significant impacts on an agent's perceived likeability, attractiveness, and trustworthiness. Instead of focusing on authenticity and attractiveness as prior works have (Alboqami, 2023; Batist & Chimenti, 2021; de Brito Silva et al., 2022; Drenten & Brooks, 2020; Kim & Baek, 2023), we thus investigate perceived uncanniness of virtual influencers with its antecedents as well as its impact on intention to follow the influencer's recommendation.

Secondly, many works have investigated the role that credibility and trust perceptions of virtual influencers play in shaping behavior. Studies have focused either on factors that influenced trust building in virtual influencers (Alboqami, 2023; de Boissieu & Baudier, 2023; Yang et al., 2023a) or they investigated how influencer trust impacts behavioral intentions and brand perceptions (Chiu & Ho, 2023; Gerlich, 2023; Sakuma et al., 2023). Several studies on virtual influencer trust have also linked it to the level of the influencers' human-likeness. Results have included seemingly inconsistent findings that human-likeness leads to higher trusting beliefs (Kim et al., 2023; Yang et al., 2023a) and that human-like virtual influencers are less trustworthy than anime-like virtual influencers (Qu & Baek, 2023). Yet eliciting trusting beliefs in virtual influencers has also been found to significantly impact their persuasiveness (Sakuma et al., 2023), and influence on users' purchase intentions toward advertised products (Chiu & Ho, 2023; Gerlich, 2023).

We were thus motivated to conduct two neuroimaging experiments which could unveil new insights into the precise mechanisms that underlie users' perceptions of humanness and trust in virtual influencers. Specifically, we utilized electroencephalography

(EEG) and functional near-infrared spectroscopy (fNIRS), two lightweight methods that allow users to view influencer posts in a natural seated position. This approach allowed us to draw inferences about theoretical concepts directly from brain activity, which is one of the many potential applications of Neuro-Information Systems (NeuroIS) research (Dimoka et al., 2011a). We thus overcome shortcomings that might have been caused when researchers only investigated conscious thought through self-reports, especially as most human evaluation processes happen unconsciously (de Guinea & Markus, 2009; vom Brocke et al., 2013). Utilizing neuroimaging can help us identify hidden processes that may pose as antecedents to the typically utilized constructs of perceived uncanniness, perceived trust, and intention to follow recommendations (Dimoka et al., 2011b), and hence, it can help to understand how virtual influencers give rise to these perceptions.

Based on the insights of the two neurophysiological studies, we form and test three theoretical explanations via mediation hypotheses that explain on which basis users form uncanniness and trust perceptions, and how these impact their intend to follow the recommendations of human influencers versus virtual influencers. Our studies not only contribute methodologically to virtual influencer literature, but also open theoretical avenues to eventually reach higher consensus on antecedent processes to influencer evaluation. Having knowledge of such processes can further inform design theory and thus, helps practitioners to better design virtual influencer profiles or utilize them in marketing campaigns.

2 Theoretical Background

2.1 Virtual Influencers

Virtual influencers are computer-generated avatars – whether human-like or not – designed and maintained by experts and media agencies that help brands reach and appeal to desirable target groups effectively through their digital personalities (Audrezet & Koles, 2023; Zhao et al., 2024). Virtual influencers do not exist in the physical world (Franke et al., 2023), but share many of the same traits as human influencers, though researchers have raised questions about whether social media users perceive these as different from real human influencers (Dabiran et al., 2022; Hofeditz et al., 2022; Sands et al., 2022a).

A famous example for a virtual influencer is Lil'Miquela (@lilmiquela) who describes herself as a 21-year-old robot living in LA that "exhibits her personal life through posts" (Vaiciukynaite, 2019) to her 2.5 million followers on Instagram. She creates notable user engagement (Block & Lovegrove, 2021) by sharing emotionally charged photos and language in which she, for example, ponders about how overwhelming life can be or the beauty of aging. Lil'Miquela is also known for her sponsored partnerships with fashion brands, such as Prada and Calvin Klein (Allal-Chérif et al., 2024), but also technology brands such as Samsung and others. To get an impression of other successful virtual influencers, an overview of the top 15 "female" virtual influencers in 2024 on Instagram can be seen in Appendix A. Virtual influencers are created by media experts or agencies and thus, they are not intelligent or autonomous agents (Zhao et al., 2024) in the sense that they are in pursuit of their own agenda, select their own actions independently (Franklin & Graesser, 1997, p. 26), can converse with other agents, and react to their environment (Wooldridge & Jennings, 1995). These agentic characteristics are mimicked by their designers. Nonetheless, users *ascribe* agency to virtual influencers (Zhao et al., 2024), making them similarly persuasive as human influencers. Like their human counterparts, virtual influencers can be seen as "digital opinion leaders" with significant social influence over their followers (Leung et al., 2022). They provide sponsoring organizations with greater flexibility to control and customize their advertisements compared to working with human influencers (Moustakas et al., 2020). Also compared to other marketing strategies, such as product placement, customer review programs, or native advertisement, virtual influencers are considered to have the ability to create deeper engagement with the potential customer base (Leung et al., 2022).

Virtual influencers share many similarities with other artificial agents utilized in organizations, such as chatbots, voice assistants, or even social robots. These agents are conversational in nature, which earned them the name conversational agents. This means that they mimic human interaction (Chandra et al., 2022) through text- or speech-based language, and can express non-verbal cues, such as gestures or facial expressions (Feine et al., 2019). We argue that virtual influencers differ from organizational conversational agents in at least five dimensions: type of interaction, organizational benefit, control in relationship, message style, and appearance. This highlights the importance of considering virtual influencer research as a related but distinct stream within the broader study of artificial agents.

Type of interaction: In contrast to virtual influencers, conversational agents engage in bi-directional interactions with one or multiple users. Thanks to increasingly sophisticated AI algorithms, conversational agents are able to deduce the intent of their human conversation partners, are dialogue-aware, understand sentiment in text, and respond emotionally with either pre-defined responses or even synthetically-generated responses (Adamopoulou &

Moussiades, 2020). Virtual influencers differ from organizational conversational agents as they engage in one-directional, so-called parasocial relationships, with their users. Originally, parasocial relationships describe social relationships between a media character (e.g., real or fictive singer) and their audience, which can today also be applied to virtual influencers describing a fictive persona and its users (Zhou et al., 2024a). Parasocial relationships mimic intimate, interpersonal relationships such as friendship, while in fact they are one-way relationships (Zhou et al., 2024a).

Organizational benefit: Organizational conversational agents are most often implemented as question-and-answering options in customer support or enabling digitalized processes (e.g., order placement) (Bavaresco et al., 2020). In large parts, their raison d'être is fundamentally about enhancing organizational efficiency, reducing costs, and increasing customer satisfaction. In contrast, virtual influencers are the core revenue-stream for creators and a popular product marketing strategy for sponsoring organizations. For example, the Brazilian retailer Magazine Luiza created the virtual influencer Lu do Magalu who has around 7 million followers and estimated earnings per post between US$ 55.5k 74.2k (Zhou et al., 2024b). Sponsoring organizations can benefit from online influencers as they "attempt to leverage these influencers' unique resources to promote the firm's offerings, with the ultimate goal of enhancing firm performance" (Leung et al., 2022).

Control in relationship: For organizations using conversational agents to communicate with customers, it is crucial that these agents provide highly accurate responses to avoid customer dissatisfaction (Waizenegger et al., 2020) and legal liabilities. Particularly in high-stake environments, such as the healthcare sector, artificial agents with low accuracy are risky, which is why such organizations would only invest in the artificial agent when responses are accurate and justifiable (Lebovitz et al., 2021). Thus, many organizations still rely on conversational agents that provide curated responses and where the reply is in the full control of the developer and can be assessed in terms of accuracy. Virtual influencers are tightly controlled by their creators (Dondapati & Dehury, 2024). However, compared to conversational agents, organizations that sponsor virtual influencers for product endorsements have less control over the created content as the creator is in full control of aligning the virtual persona with the sponsored product (Bringé, 2022).

Message style: Conversational agents in customer service need to answer customer requests fast and factually correct (Waizenegger et al., 2020). The message style may include emotional aspects, such as displaying warmth and compassion, to appropriately match the emotional state of the customer (Chandra et al., 2022). In contrast, successful virtual influencers utilize storytelling in their messages to persuade users (Allal-Chérif et al., 2024; Shen, 2024). These stories can evolve around their fictive hobbies, their friends and partners, experiences, and other human-like characteristics (Allal-Chérif et al., 2024). This can result in marketing campaigns where the virtual influencer conceals the product that is being promoted for higher user engagement because the obvious mentioning of products and brands was found less effective as users intentionally resist the persuasion attempt (Shen, 2024).

Appearance: Another distinguishing aspect is the appearance and the modality the artificial agents use to interact with the user. Conversational agents is an umbrella term for a number of artificial agents comprising chatbots, voice assistants, or social robots (Diederich et al., 2022). With this diversity of agents comes also a diversity of appearances and modalities. While chatbots appear dis-embodied and virtual (Araujo, 2018), social robots are embodied and physical (You & Robert, 2018). Also, conversational agents usually rely on a single modality to engage with users. Chatbots rely on text-based interaction, while voice assistants or social robots rely on speech-based modalities (Rzepka et al., 2022). In contrast, virtual influencers are avatars that exclusively exist in the virtual realm (Franke et al., 2023). For many of their product endorsement posts, virtual influencers use videos accompanied by messages, thus utilizing audiovisual modalities.

While the above-mentioned dimensions are aspects that set virtual influencers apart from (organizational) conversational agents (see Table 1 for a summary), their human-likeness is a design choice that brings them together. Thus, we review the most relevant literature on human-likeness in artificial agents next.

2.2 Human-Likeness in Artificial Agents

The starting point for studies on artificial agents, including virtual influencers, are often design characteristics of the agents, in particular the degree of human-likeness (sometimes also termed anthropomorphic design, human-like realism, or humanness). Virtual influencers, as other artificial agents, can be classified into animalistic, 2D animated, doll-like, and humanoid whereas the former represents low human-likeness and the latter high human-likeness (Shen, 2024). Depending on the investigated agent, the design facets and impact of human-like features might vary. For conversational agents, highly human-like language styles and voice have shown to positively influence the likability of the agent (Araujo, 2018), as well as higher hedonic quality (Haugeland et al., 2022), and higher user engagement with the agent (Chandra et al., 2022). In several works, human-likeness was also identified to be a direct predictor of perceived trust of the agent (Chandra et al., 2022; Konya-Baumbach et al., 2023; Lu et al., 2022). In shopping contexts, this can lead to positive impacts on purchase intentions (Schanke et al., 2021).

With increasing advances in generative AI such as deepfakes (S. Wang et al., 2022) and large language models, virtual influencers are becoming increasingly difficult to distinguish from human influencers affecting user perceptions (Hofeditz et al., 2022; Nightingale & Farid, 2022). As can be seen in Appendix A, almost all of the top 15 female virtual influencers have highly realistic human-like design. However, several recent studies showed that positive user reactions to highly human-like virtual influencers decreased, and more negative reactions occurred, compared to anime-like influencers (Arsenyan & Mirowska, 2021; Qu & Baek, 2023). This aligns with the uncanny valley theory (Mori, 1970), suggesting that the relationship between human-likeness and positive attitudes is not linear. Positive attitudes toward an artificial agent increase with levels of human-likeness to a certain tipping point. At this point, attitudes toward the agents become negative and only increase again when human-likeness of the artificial agent is almost indistinguishable from a real human (Mathur & Reichling, 2016; Mori, 1970; Mori et al., 2012). Consistent with the uncanny valley hypothesis, past studies on avatars reported that higher perceived uncanniness and less likability often appeared with high but not perfect human-likeness (Burleigh et al., 2013; MacDorman et al., 2009). Further, higher perceived uncanniness was also associated with negative emotional states of fear and disgust (Burleigh et al., 2013), and is related to higher uncertainty on how to correctly evaluate the agent’s expressed emotions and personality (Shin et al., 2019; Tinwell et al., 2011).

However, there is increasing empirical evidence that did not find the “valley” effect and thus a drop in positive attitudes towards avatars given different levels of human-likeness including photo-realistic avatars (Seymour et al., 2021; Xie-Carson, Magor, et al., 2023). Consequently, higher perceived human-likeness of virtual influencers can generate more positive perceptions of the influencer (Kim & Park, 2023; Um, 2023), rendering the uncanny valley hypothesis potentially obsolete for this type of virtual influencers. Moreover, cleverly placed design cues were found to mitigate the uncanny valley effect in virtual influencers (Lou et al., 2023); e.g., labeling the virtual influencer as such (Franke et al., 2023). Finally, while uncanniness is treated as a negative response to artificial agents in IS research, it might also spark curiosity in social media users, leading them to follow the virtual influencer (Block & Lovegrove, 2021).

Given these mixed findings regarding the existence of uncanniness perceptions in photo-realistic virtual influencers, it is imperative to examine how such virtual influencers impact user perceptions in comparison to human influencers. Thus, the following section and our studies will dive into how perceptions of virtual and human influencers are formed, and how they might differ from each other.

2.3 Human Versus Virtual Influencers

Virtual influencers and their effects on customer behavior compared to human influencers have been predominantly examined in Marketing and Tourism literature. Table 2 synthesizes the most pertinent research findings, highlighting that perceived trust and following intentions are the primary areas of scholarly focus. The prevailing consensus in the literature indicates that human influencers generally elicit higher following intentions (Xie-Carson et al., 2023; Zhou et al., 2024a), and are perceived as more trustworthy (Ozdemir et al., 2023; Seymour et al., 2020) compared to virtual influencers. However, some studies suggest that virtual influencers are more effective in generating following intentions than human influencers (Franke et al., 2023; Mirowska & Arsenyan, 2023) and are either as credible or even more credible (Qu & Baek, 2023) than their human counterparts. Despite the nascent stage of this research domain, findings remain inconclusive and cannot be fully explained by the inclusion or exclusion of moderating variables.

Related research has also explored various mediators to elucidate the underlying mechanisms distinguishing human influencers from virtual influencers (see Table 3). We have categorized these mechanisms into three broad categories: mentalizing capabilities, trusting beliefs, and emotional connections. *Mentalizing capabilities* pertain to the user’s attribution of influencers’ abilities to form intentions and engage in cognitive processing of information (Liu & Lee, 2024). For example, Zhao et al. (2024) showed that human influencers are perceived as having more agency than virtual influencers, which leads to higher attributions of responsibility. The higher perceived agency and responsibility towards human influencers are the reason why these influencers foster more positive behavioral responses than virtual influencers. Likewise, Liu and Lee (2024) found that human influencers are attributed more mind perception than virtual influencers, which is why users have a higher intention to share their content. The mechanism of *trusting beliefs* encompasses factors related to the perceived credibility of the influencer. The literature consistently indicates that human influencers are generally considered more trustworthy than virtual influencers. This enhanced trustworthiness often leads to higher purchasing intentions (Li et al., 2023a) and more favorable attitudes, which are positively correlated with purchasing intentions (Ozdemir et al., 2023). *Emotional connections* comprise factors that cover the positive and negative engagement towards influencers (Zhou et al., 2024a). The literature consistently shows that human influencers foster stronger emotional connections (Dondapati & Dehury, 2024; Zhou et al., 2024a) and less fear (Barari, 2023) than virtual influencers, which is why purchase intentions are higher.

In summary, despite the growing body of literature comparing human and virtual influencers, the findings remain inconclusive. Extant research has identified several mediating factors that can explain the differing impacts of human versus virtual influencers, such as mentalizing capabilities, trusting beliefs, and emotional engagement. However, these insights have predominantly been derived from self-reported measures, which are susceptible to biases such as social desirability and self-report inaccuracies. There is a notable lack of research employing more "objective" measurements to investigate these phenomena. Utilizing neuroimaging can address this gap by enabling researchers to draw inferences about theoretical concepts directly from brain activity (Kirwan et al., 2023; Riedl et al., 2017), thereby providing a more accurate and unbiased understanding of the cognitive and emotional processes underlying consumer responses to human and virtual influencers. This study addresses this gap and presents two neuroimaging studies to elicit deeper and more reliable insights into the mechanisms that drive consumer behavior in the context of influencer marketing.

Table 1. Differences Between Conversational Agents and Virtual Influencers

	Conversational Agents	**Virtual Influencer**
Type of Interaction	Bi-directional	One-directional (parasocial)
Organizational Benefit	Process efficiency	Product marketing (sponsor), revenue-stream (creator)
Control in Relationship	Self-extension relationship, high control over content	Sponsored-relationship, low control over content
Message Style	Factual information with emotional awareness	Storytelling
Appearance	Physical or virtual, high share of uni-modality	Virtual, high share of multi-modality

Table 2. Related Research on Human vs. Virtual Influencer Research

Concept studied	**Result**	**Authors**
Intention to follow recommendation (intention to purchase, attitude towards ad or brand)	Human >virtual influencer	Zhou et al., 2024b*, Xie-Carson, Magor, et al., 2023, Ozdemir et al., 2023*, Meng et al., 2024*, Dondapati and Dehury, 2024, Li et al., 2023a, Liu & Lee, 2024*, Zhou et al., 2024a
	Human == virtual influencer	Sands et al., 2022a, Belanche et al., 2021, Liu & Lee, 2024, Zhou et al., 2024b*, Mirowska & Arsenyan, 2023
	Human <virtual influencer	Franke et al., 2023, Meng et al., 2024*, Mirowska & Arsenyan, 2023[a]
Perceived Trust (credibility):	Human >virtual influencer	Sands et al., 2022a, Ozdemir et al., 2023*, Li et al., 2023a
	Human >human-like virtual influencer	Qu and Baek, 2023
	Human = anime-like virtual influencer	Qu and Baek, 2023
Sensory capability	Human >virtual influencer	Zhou et al., 2024b, Li et al., 2023a
Parasocial relationship	Human >virtual influencer	Zhou et al., 2024a, Dondapati & Dehury, 2024
Emotional engagement	Human >virtual influencer	Zhou et al., 2024a

Negative emotions	Human <virtual influencer	Barari, 2023
Homophily	Human >virtual influencer	Zhou et al., 2024a
Likability	Human >human-like virtual influencer	Qu & Baek, 2023
	Human = anime-like virtual influencer	Qu & Baek, 2023
Life satisfaction	Human >virtual influencer	Barari, 2023
Social attractiveness	Human <virtual influencer	Mirowska & Arsenyan, 2023
	Human = virtual influencer	Mirowska & Arsenyan, 2023[a]
Note: *under the condition that a moderating variable is present.		

Table 3. Mechanisms Studied in Human vs. Virtual Influencer

Mediator type	Mediation	Authors
Mentalizing capability	influencer type → agency → responsibility attribution → positive behavioral response, (human >virtual), IE*	Zhao et al., 2024
	influencer type → mind perception → brand attitude, (human >virtual), IE*	Liu & Lee, 2024
	influencer type → mind perception → intention to share, (human >virtual), IE*	Liu & Lee, 2024
	influencer type → usefulness → intention to follow advice (human >virtual), IE*	Belanche et al., 2021
	influencer type x sensory type → imagery difficulty → perceived sensory capacity → purchase intention, (human >virtual), IE*	Zhou et al., 2024b
Trusting beliefs	influencer type x language type → credibility → attitude towards brand, (human >virtual), IE*	Ozdemir et al., 2023
	influencer type x environment type → trust → likability, (virtual >human), IE*	Qu & Baek, 2023
	influencer type → sensory capability → credibility → a) brand attitude, b) purchase intention, (human >virtual), IE* for a) and b)	Li et al., 2023a
Emotional connections	type of influencer → parasocial relationship (emotional bond) → purchase intention, (human >virtual), IE*	Dondapati & Dehury, 2024
	influencer type → emotional engagement → parasocial relationship → purchase intention, (human >virtual), IE*	Zhou et al., 2024a
	influencer type → fear of missing out → life satisfaction, (human >virtual), IE*	Barari, 2023
Note: IE = indirect effect		

3 Methodological Approach

Neuroimaging can give additional insights into the cognitive factors and antecedents to human behavior; in the context of Information Systems (IS), this is often called the NeuroIS approach (Kirwan et al., 2023; Riedl et al., 2017). The benefits of NeuroIS have long focused on the application of brain measures to derive deeper insights into IS phenomena, such as by discovering antecedents to evaluations or behavior that reveal hidden processes behind IS phenomena (Dimoka et al., 2011b). In the case of virtual influencers, NeuroIS can help disentangle the evaluative behavior that leads to intentions to follow recommendations and its underlying cognitive processes.

Most of the NeuroIS studies published thus far follow a classical confirmatory research approach where hypotheses are derived from literature or based on theory, and one neuroimaging study is then run to validate the theorizing (most recent examples for this can be found in Fadel et al. (2022), Harmon et al.

(2024), Lutz et al. (2023), and Reeck et al. (2024)). However, there are ways to improve upon the confirmatory approach. NeuroIS studies are often observed in highly controlled contexts that are removed from the complex environments in which information technologies are actually used (Balapour & Riedl, 2024). Furthermore, the complexity of the approach and rigorous controls can lead to weaknesses in the study design. For example, when conducting a systematic review of high-quality NeuroIS studies, Balapour and Riedl (2024) found that nearly half of the studies drew on samples that solely consisted of students, and only a third of papers that reported neurophysiological measures sought to enhance the generalizability of the findings through a subsequent study. They argue that NeuroIS studies may not generalize to wider contexts of information technology use because they often lack corroborating evidence.

Kirwan et al. (2023) offer a response to some of these concerns and recommend a strategy for drawing inferences from complementary neurophysiological and behavioral studies. This strategy allows researchers not only to generate predictions that are informed by the neurophysiological data but also to replicate key findings with different populations and participant modalities, thereby overcoming some of NeuroIS' limitations. We thus propose using multiple neuroimaging techniques to first evaluate the phenomenon of virtual influencers, thereby increasing confidence in the key findings, and then to build testable theories which are independently validated in a less-controlled setting, in this case, an online study. Our approach thus builds on the recommendations made by leading NeuroIS researchers (Balapour & Riedl, 2024; Dimoka et al., 2011b; Kirwan et al., 2023), and offers a methodological model for leveraging an exploratory NeuroIS approach for building new insights into the cognitive antecedents of user behavior. Figure 1 illustrates our research approach.

For means of method triangulation, we draw on EEG and fNIRS, two well-studied neurophysiological techniques that have been extensively employed in the neuroscience discipline, and have been adapted by NeuroIS researchers for the technology context. EEG measures the differences in electrical potential on a person's scalp, which is analyzed either in the frequency or time domains (Newman, 2019). One common approach is the event-related potential (ERP) technique, in which data from multiple trials of a particular category are averaged, each time-locked to the onset of a stimulus (Luck, 2014).

Researchers have discovered associations between ERP patterns and various cognitive processes. For example, the N400 pattern is a negative potential signal often observed 300-500 ms following the onset of a stimulus, which has been associated with perceived uncanniness (Mustafa & Magnor, 2016; Mustafa et al., 2017). Similarly, the late-positive potential (LPP) is a positive potential signal often observed after 600 ms following a stimulus, which has been associated with human-likeness of faces (Sollfrank et al., 2021) and emotional processing of stimuli (Conrad et al., 2022; Sollfrank et al., 2021). While EEG measures the electrical activity (Müller-Putz et al., 2015), fNIRS measures regional changes in blood oxygenation that are secondary to changes in neural activity (Huppert et al., 2006; Sato et al., 2013). As we investigate antecedents to decision-making of behavior, the area of interest to investigate with fNIRS is the prefrontal cortex (PFC) (Carlén, 2017).

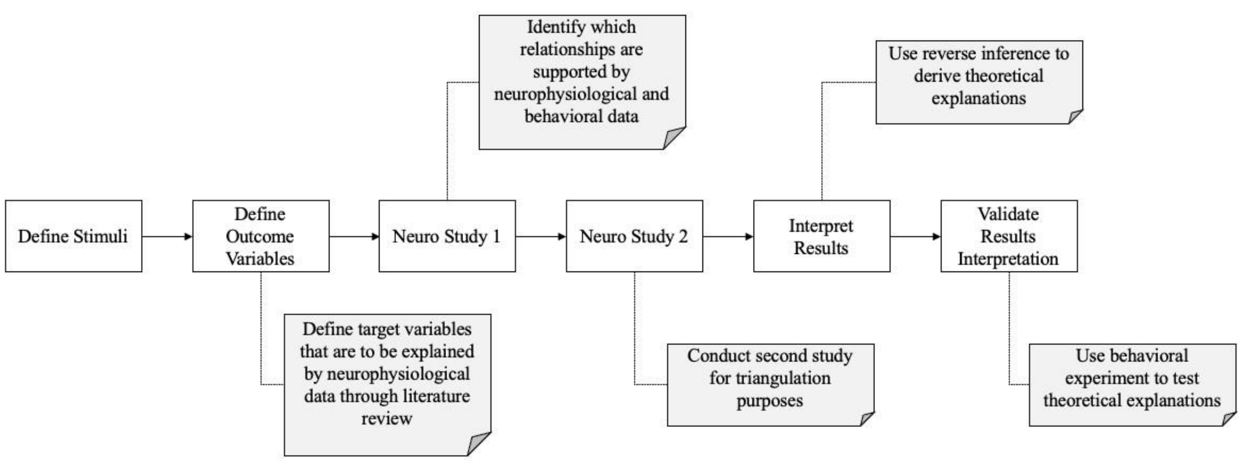


Figure 1. A Neuro-Behavioral Approach to the Derivation of Theoretical Explanation

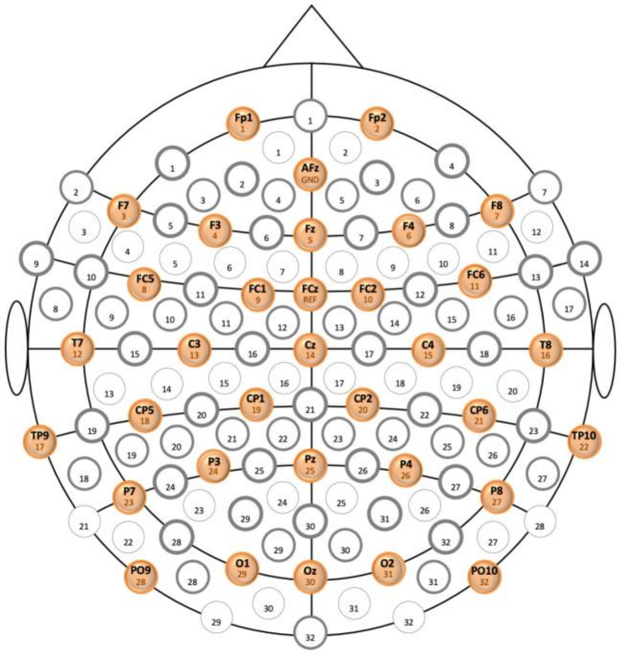


Figure 2. 32-Channel EEG Montage

Note: The upper row shows the human influencers, and the lower row shows similar virtual influencers.

Figure 3. A Sample of Stimuli Used in the Three Studies

It is against this context that we were motivated to take an exploratory, inductive approach with complementary EEG and fNIRS studies of evaluations of perceived uncanniness, trust, and intention to follow recommendations of virtual influencers (Study 1 and 2). We then derived related theoretical constructs with which we generated hypotheses to be tested in an online experiment (Study 3). Taken together, we validate that our interpretations of the neural results lead to accurate predictions of behavioral results based on the theoretical explanations that we derive.

4 Study 1: EEG

4.1 Method

Stimuli and study design: We employed the same 20 image stimuli of human and virtual influencers in all three studies, however, the three studies differed in the neuroimaging techniques, procedure, and collection of self-reported measures. In this study, we welcomed each participant individually to the lab, and went through the consent process, in which full information on the study procedure was given and remaining questions were answered. After giving informed consent to participate in the study, and receiving a compensation equivalent to CAD $20, the participant was asked to fill out a questionnaire including demographic and Instagram use behavior questions.

After participants finished the first questionnaire, the EEG cap was placed on their head. We used a whole-head cap fitted with 32 active electrodes (ActiCap, BrainVision, Munich, Germany) in a montage conforming to the International 10-10 System (depicted in orange in Figure 2). We also employed horizontal and vertical electrooculogram measurements (EOG) to control for electric potentials created by eye movements, by placing bipolar-referenced electrodes above and below one eye, and also just lateral to the outer canthus of each eye. The EEG data was recorded with an Refa8 amplifier (ANT, Enschende, The Netherlands) using ANT ASAlab software with an average reference and a sampling rate of 512 Hz, bandpass filtered between 0.01 and 170 Hz.

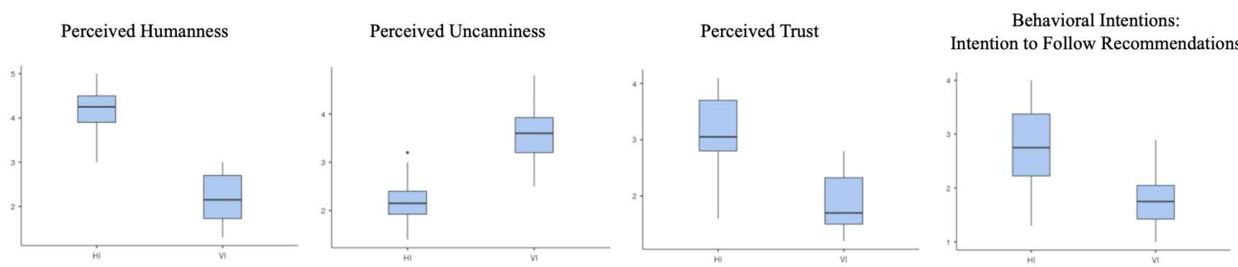
Each experimental trial involved presenting one of the influencer posts for 2 seconds on a computer monitor, followed by simplified, single-item measures: perceived trust ("The shown influencer is trustworthy."), uncanniness ("I perceived the influencer as eerie."), intentions to follow recommendations ("I would follow brand recommendations from the shown influencer."), and human-likeness ("The shown influencer is a human."), each measured on a 5-point Likert scale from 1 = I totally disagree to 5 = I totally agree. A fixation cross jittered between 2-3 seconds was then presented to neutralize the brain activation, after which followed the next trial. Trials proceeded in random order until each Instagram post was shown with each question. Examples of the presented influencers can be seen in Figure 3. Overall, 10 virtual and 10 comparable human influencers were manually collected from Instagram by the first author. The reason why a 2-second display of the influencer posts was selected is grounded in two lines of argument: first, studies have shown that the average fixation duration on Instagram posts lies between 2-5 seconds (Zhou & Xue, 2021). Secondly, research has shown how first cognitive evaluations made within the first 50-500 milliseconds stay consistent with evaluations made during longer stimulation (Lindgaard et al., 2006; Tuch et al., 2012). Given that related EEG studies utilize even shorter duration times (250-650ms) than the average fixation times on Instagram posts (Marzi et al., 2014; Schindler et al., 2017), we selected 2 seconds for stimulus duration as a means to keep the stimulus exposure similar to the fixation duration during actual Instagram use.

As we are interested in the condition "influencer type" (10 virtual, 10 human), and not in the individual influencers, this design resulted in 40 repetitions per condition (e.g., 4 questions times 10 virtual influencers), and 80 repetitions in total. Due to this high number in repetitions, we utilized single-item measures to keep the study as short with as little strain as possible for our participants (Allen et al., 2022). This is supported by works that have shown how more homogenous constructs can be accurately assessed by single-item measures (Postmes et al., 2013). More precisely, especially perceived trust and uncanniness can be effectively measured with single-item scales (Castro et al., 2023; Diel & Lewis, 2024). Given that we collect the neural data to receive deeper insights into the complexity of influencer perception, the self-rated constructs rather serve as additional dependent variables to better interpret the neural data. Thus, the use of single-item measures was deemed to be the most reasonable study design for both Study 1, and the following Study 2. The measurement procedure lasted about 15-20 minutes. Then, the EEG cap was removed from the participant and they were debriefed on the study by thanking them for their participation, and showing which of the presented influencers was human and which was virtual. This study procedure was approved by a Canadian University's research ethics board and were found to be consistent with the Canadian Tri-Council Policy for Ethical Conduct for Research Involving Humans (TCPS) 2.

Sample: Using Monte Carlo simulations, Boudewyn et al. (2018) provided convincing arguments that event-related potential studies, similar to the one described here with differences around 0.75 microvolts and 40 trials, achieve a statistical power of 0.8 with as few as 20 participants. Similarly, prominent recent research from our field, which used EEG in this way, demonstrated effects with samples with even fewer than 20 participants (Lakhiwal et al., 2023). Therefore, n = 22 participants were recruited from a population of a large Canadian university (54.5% female, 45.5% male; average age M = 28.2 years, SD = 9.37, Min = 18, Max = 49). 45.5% held a postgraduate degree from a university, 31.8% have a bachelor's degree, and 22.7% high school/GED. There were no participants with a college or post-secondary certificate or a degree below high school/GED. Regarding their Instagram use, 72.7% reported using the app several times per day (9.1% several times per week, 4.5% at least once per month, 13.6% less than monthly). 22.7% claimed to follow fewer than 5 influencers on Instagram, while 9.1% reported following at least 5, 40.9% reported following at least 10, and 27.3% reported following more than 50 influencers. None of the participants followed more than 100 influencers on Instagram.

Data analysis: After each presentation of a picture stimulus, we collected self-reported measures on perceived human-likeness, uncanniness, trust, and intention to follow recommendations. These were each analyzed using linear mixed effect models (LME), with the influencer types treated as a fixed effect, and participant intercepts as random effects. The raw EEG data were converted from the ASAlab to the EEGlab format (Delorme & Makeig, 2004) and processed using the *MNE* (v. 0.23.0) (Gramfort et al., 2014) package in Python. The EEG data were first bandpass filtered from 1-40 Hz and segmented into contiguous 1 s epochs. Independent components analysis was then fit to these epochs using the *fastica* algorithm (Hyvärinen, 1999) with a stopping criterion of explaining 99.5% of the data variance. Independent components containing ocular artifacts were identified automatically by computing the correlation between each and the EOG channels; additional components were manually removed for 12 participants based on visual inspection. Following this, the original raw data were bandpass filtered from 0.1-40Hz and then segmented into epochs time-locked to the onset of each influencer image, from 200 ms prior to onset of an image to 2000 ms afterwards. The components identified for rejection by ICA were removed from these epochs, and then the *AutoReject* (v. 0.2.2) (Jas et al., 2017) algorithm was used to identify and correct any additional noisy trials and to interpolate data from individual noisy channels. Data were re-referenced to the average of all electrodes, and saved for further analysis.

Group level analysis was conducted by calculating the mean amplitude for each trial and electrode between 300 – 500 ms post stimulus onset, corresponding to the N400 component, and between 600 – 1200 ms, corresponding to the LPP. Following electrode and scalp locations in prior literature, we selected the electrodes at Cz, CP1, CP2, and Pz for both the N400 (Šoškić et al., 2021) and the LPP (Conrad et al., 2022; Luck & Gaspelin, 2017). The resulting data were analyzed using LME (Davidson, 2009; Tremblay & Newman, 2015). The random intercepts for participants, random slopes for electrode by participant, and random slopes for influencer by participant were treated as random effects and the influencer type (human, virtual) was treated as a fixed effect.



Construct	M (SD) HI	Min, Max HI	M (SD) VI	Min, Max VI	beta	se	lower CI	upper CI	t	p_{Holm}	partial η^2
Perceived Humanness	4.16 (0.49)	3.00, 5.00	2.20 (0.57)	1.30, 3.00	-1.96	0.16	-2.27	-1.65	-12.40	< .001	0.88
Perceived Uncanniness	2.20 (0.44)	1.40, 3.20	3.60 (0.61)	2.50, 4.80	1.40	0.16	1.08	1.72	8.69	< .001	0.78
Perceived Trust	3.14 (0.64)	1.60, 4.10	1.84 (0.48)	1.20, 2.80	-1.30	0.13	-1.55	-1.05	-10.10	< .001	0.70
Behavioral Intentions	2.77 (0.76)	1.30, 4.00	1.77 (0.47)	1.00, 2.90	-1.00	0.12	-1.24	-0.77	-8.35	< .001	0.60

Descriptives:
Human Influencer (HI) and Virtual Influencer (VI)

Comparison:
Virtual Influencer (VI) − Human Influencer (HI)

Figure 4. Results of Subjective Ratings of Virtual and Human Influencers

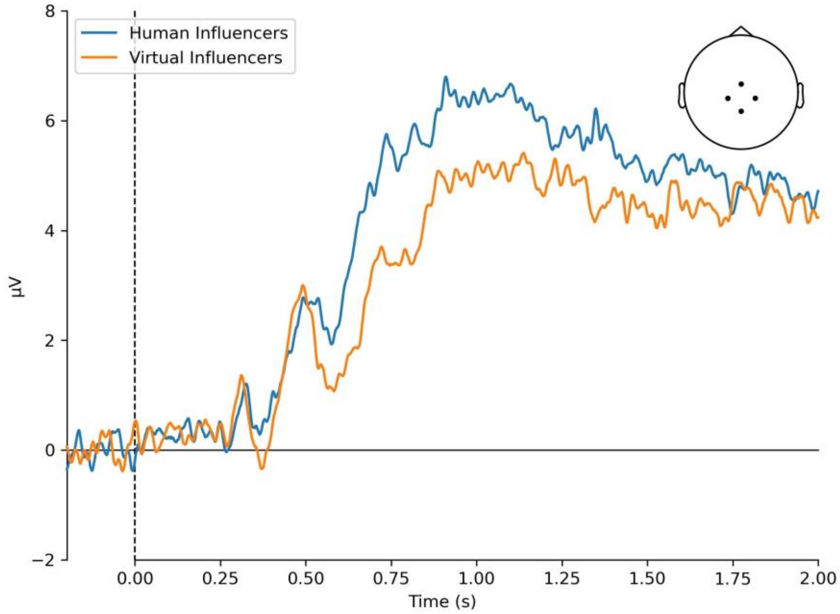


Figure 5. ERP Grand Average Amplitude at Electrodes Fz, Cz, Pz, Oz

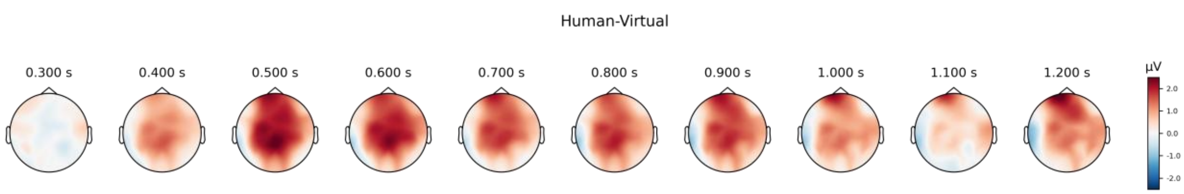


Figure 6. EEG Results on Topographic Maps of Average Activation Across the Time Frames of the N400 (300 - 500ms) and the LPP (600-1,200ms)

4.2 Results

Self-reported responses: The boxplots and table in Figure 4 present the descriptive and inferential statistics for human influencers and virtual influencers across the four included constructs: perceived human-likeness, perceived uncanniness, perceived trust, and intention to follow the influencer's recommendations. From the descriptive statistics, it can be seen that virtual influencers were rated higher in their perceived uncanniness. The perceived human-likeness, perceived trust, and intentions to follow recommendations were rated in favor of the human influencers.

Results from mixed effects models that account for the influencer type (human, virtual) as fixed effect, and that take into account individual differences between participants as random effects, show that the evaluation between human and virtual influencers differs. Human-likeness also serves as our manipulation check, which shows that virtual influencers were rated consistently lower in human-likeness compared to human influencers ($\beta = -1.96$, $SE = 0.16$, $95\%CI[-2.27, -1.65]$, $t(21) = -12.4$, $p_{Holm} < .001, \eta_p^2 = .88$). Further, virtual influencers were rated significantly higher in perceived uncanniness compared to human influencers ($\beta = 1.40$, $SE = 0.16$, $95\%CI[1.08, 1.72]$, $t(21) = 8.69$, $p_{Holm} < .001, \eta_p^2 = .78$). Related literature on conversational agents has suggested that with higher perceived uncanniness often comes lower perceived trust (e.g., Nissen & Jahn, 2021). This is also the case in this study, as perceived trust was rated in favor of the human influencers ($\beta = -1.30$, $SE = 0.13$, $95\%CI[-1.55, -1.05]$, $t(21) = -10.10$, $p_{Holm} < .001, \eta_p^2 = .70$). Similarly, the intention to follow recommendations was also lower for virtual influencers compared to their human counterparts ($\beta = -1.00$, $SE = 0.12$, $95\%CI[-1.24, -0.77]$, $t(21) = -8.35$, $pHolm < .001, \eta p2 = .60$).

EEG patterns: We followed up with analysis of the EEG data. The average ERP wave pattern for each condition are plotted at the midline electrodes in Figure 5. The ERP responses to human and virtual influencers is highly similar for the first few hundred milliseconds and begins to diverge with a more positively amplitude for human influencers around 400 ms.

These differences persist until approximately 1200 ms. The difference appears largest over the electrodes predicted a priori to show effects of our experimental manipulation (Cz and Pz). The scalp topographical maps in Figure 6 confirm that this effect was largest over this region. This suggests that also the EEG data shows brain activity of participants differed between conditions and within the expected timeframes (i.e. 300-500 ms for N400 and 600 - 1200 for LPP).

The timing and scalp topography of this difference is consistent with effects of the N400 and LPP. We observed greater negativity for virtual than human influencers over the vertex from approximately 300–600 ms. The direction of the subtraction makes the difference appear positive, but a greater positivity for human influencers corresponds to a greater negativity for virtual influencers. The results are consistent with the LPP insofar as the effect is more positive for human influencers from 600–1200 ms. The results of LME modeling confirmed these observations. The N400 was analyzed over the electrodes in the regions of interest (ROI) from 300–500 ms, where electrical potential was more negative in response to virtual than human influencers ($\beta = -1.16$, $SE = 0.51$, 95%[−2.16, −0.16], $t = -2.16$, $p = .023$). In the LPP time window (600–1200 ms), the signal was more positive for human compared to virtual influencers ($\beta = -1.24$, $SE = 0.52$, 95%[−2.26, −0.02], $t = -2.40$, $p = .016$).

Integrated self-report and EEG patterns: To better understand the relationship between the self-reported data and the ERP components, we further ran mixed-effects models to evaluate the influence on the mean amplitude of each ERP component on self-reported perceived trust, uncanniness, and intention to follow recommendations. That is, for each component (N400 and LPP), we ran three LME models, each one using the rating of each construct as a single fixed effect in the model. The random intercepts for participants, random slopes for electrode by participant, as well as random slopes for condition-by-participant, were taken into account as random effects. The results of these analyses were corrected for multiple comparisons using the Bonferroni–Holm method.

The results show that mean amplitude at the N400 window seems to be especially associated with intentions to follow recommendations, with more positive amplitudes associated with greater intent to follow ($\beta = 0.69$, $SE = 0.20$, 95%[0.18,1.20], $t = 3.41$, $p < .001$, $p_{Holm} = .003$). ERP amplitude in the N400 time window was negatively related to uncanniness ($\beta = -0.33$, $SE = 0.16$, 95%[−0.74,0.07], $t = -2.05$, $p = .04$, $p_{Holm} = .08$) of influencers (i.e. greater negativity at the N400 window for higher uncanny ratings). But this effect was only marginally significant. N400 was not related to ratings of perceived trust of influencers ($\beta = 0.25$, $SE = 0.20$, 95%[−0.24,0.74], $t = 1.26$, $p_{Holm} = .208$).

Similar to the N400 results, the results of the LPP data show a positive association between LPP and intentions to follow the influencer's recommendations ($\beta = 0.70$, $SE = 0.20$, 95%[0.13,1.28], $t = 3.06$, $p = .002$, $p_{Holm} = .009$). In contrast to the negative association between the N400 and perceived uncanniness, the LPP did not show a significant relation to ratings of perceived uncanniness of influencers ($\beta = -0.28$, $SE = 0.18$, 95%[−0.69,0.23], $t = -1.24$, $p_{Holm} = .302$). Finally, also the LPP does not seem to be related to perceived trust ratings of influencers ($\beta = 0.32$, $SE = 0.22$, 95%[0.24,0.87], $t = 1.44$, $p_{Holm} = .302$). All of the EEG results, as well as the integrated results are presented in Table 4.

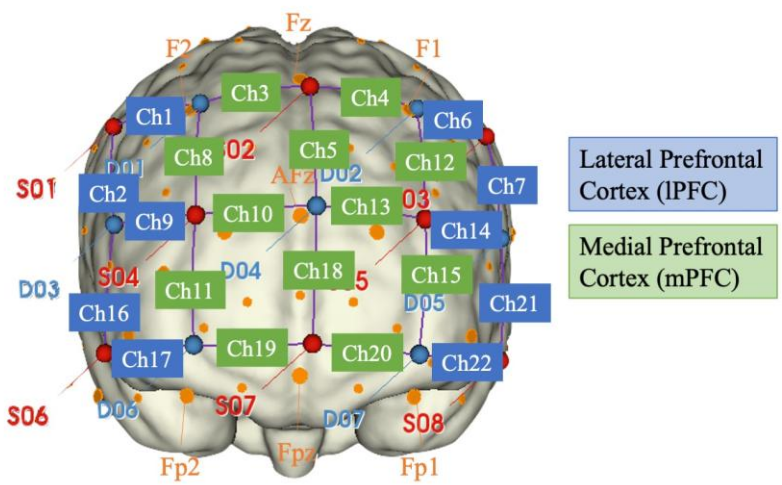
4.3 Discussion of Study 1

Our findings suggest that human influencers are perceived as less uncanny, more trustworthy, and elicit higher behavioral intentions compared to virtual influencers in accordance to our self-reported results. These differences indicate strong preferences for human influencers over virtual ones across all measured constructs. In the EEG signal, we identified that virtual influencers elicited a more pronounced response in the N400, and the response in the LPP was greater for human influencers. The integrated analyses suggest that the N400 in this case may be an early indicator for perceived uncanniness and behavioral intentions. This is in line with related studies that identified an association between the N400 and increased uncanniness of virtual characters (Mustafa & Magnor, 2016; Mustafa et al., 2017), strengthening the assumption that the presence of greater N400 amplitude may be an indicator of perceived uncanniness of a presented stimulus. Related works have shown how increased perceived uncanniness can be detrimental to behavioral intentions (Cornelius et al., 2023; Nissen & Jahn, 2021). Therefore, it is plausible that we find a direct relation between changes in the N400 and in the self-reported behavioral intentions to follow an influencer's recommendations. Thus, we may conclude that the N400 seems to predict uncanniness perceptions and behavioral intentions, and thus, further analyses of processes associated with the N400 from the broader body of cognitive sciences seem promising to better *explain why* virtual influencers trigger higher uncanniness and lower behavioral intentions. We will come back to this later when developing our hypotheses.

Another early neural indicator for behavioral intentions could be identified in the LPP that was higher for human influencers. Related works support our findings as they have found associations between the LPP and higher human-likeness of human versus artificially created faces (Schindler et al., 2017; Sollfrank et al., 2021). Furthermore, related literature established a relationship between the LPP signal and the perceived trust of human faces (Kyriakopoulou & Nowland, 2017; Marzi et al., 2014). In our study, however, this association could not be established. Instead we identified a relationship between the LPP and behavioral intentions that we could not identify being studied in related works. Thus, we will come back to this later in the hypotheses development section where we discuss why this relationship may exist.

Table 4. EEG Results for the Human vs. Virtual Influencer Comparison, and Relation EEG Signals with Self-Reported Constructs

EEG Component	**beta**	***SE***	**lower CI**	**upper CI**	***t***	**P**
N400	-1.16	0.51	-2.16	-0.16	-2.28	0.023
LPP	-1.24	0.52	-2.26	-0.02	-2.40	0.016
EEG → Self-report	**beta**	***SE***	**lower CI**	**upper CI**	***t***	p_{Holm}
N400 → uncanniness	-0.33	0.16	-0.74	0.07	-2.05	0.08
N400 → trust	0.25	0.20	-0.24	0.74	1.26	0.208
N400 → behavioral intentions	0.69	0.20	0.18	1.20	3.41	0.003
LPP → uncanniness	-0.28	0.18	-0.69	0.23	-1.24	0.302
LPP → trust	0.32	0.22	-0.24	0.87	1.44	0.302
LPP → behavioral intentions	0.70	0.23	0.13	1.28	3.06	0.009



Note: Blue channels refer to the lateral prefrontal cortex (lPFC), green channels refer to the medial prefrontal cortex (mPFC)

Figure 7. Utilized fNIRS Montage

5 Study 2: fNIRS

5.1 Method

Stimuli and study design: We employed the same 20 image stimuli of human and virtual influencers as described and shown in Study 1. Similarly, we welcomed each participant for this study individually to the lab, and went through the consent process, in which full information on the study procedure was given and remaining questions were answered. After giving informed consent to participate in the study, and receiving a compensation equivalent to 20e, the participant was asked to fill out the same questionnaire including demographic and Instagram use behavior questions as utilized in Study 1.

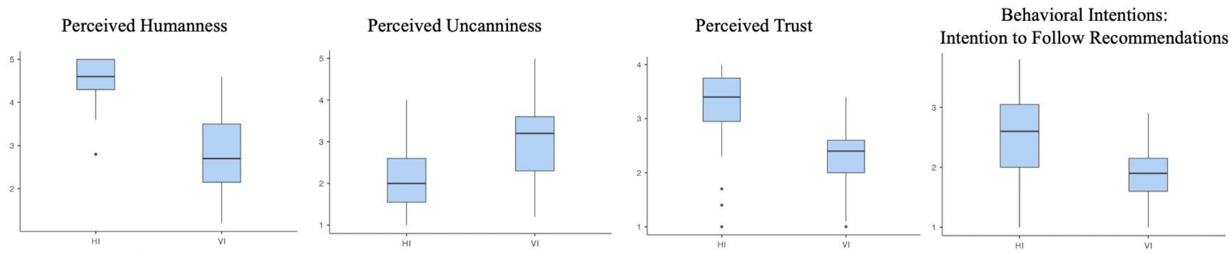
After participants finished the questionnaire, the fNIRS headband was placed on the participants' forehead, using the ridge of the nose between the eyebrows as central point to achieve comparable measuring points of the fNIRS optodes. The neural data was collected with a NIRSport 1 mobile fNIRS device (NIRx Medical Technologies, Orlando, United States) which holds 22 channels to cover the cortical areas of the PFC brain area (see Figure 7). Source-detector distance for the channels is approximately 30 mm, and short-distance channels are included at each source as means to filter out extracerebral activity from the data (Brigadoi & Cooper, 2015; Yücel et al., 2016). In each of the depicted channels, the relative changes in the oxygenated and deoxygenated hemoglobin (HbO and HbR, respectively) are measured on two wavelengths (760 and 850 nm), and serve as indicators to neural activation.

Similar to Study 1, each experimental trial involved presenting one of the influencer posts on a computer monitor, though this time for 4 seconds. Note here that this is longer than the EEG study stimulus duration of 2 seconds. Although the hemodynamic response can also be triggered with 2 seconds duration (or less), it is stronger with longer duration times. A study on an fNIRS brain-computer-interface (BCI) found that stimulation around 5 seconds yields the most accurate, predictable results (Afzal Khan & Hong, 2021). This motivated us to present the stimulus for a longer period, while also keeping it within a short timeframe which would be characteristic of how long an Instagram viewer typically views an image.

The influencer post presentation was followed by simplified, single-item measures: perceived trust ("The shown influencer is trustworthy."), uncanniness ("I perceived the influencer as eerie."), intentions to follow recommendations ("I would follow brand recommendations from the shown influencer."), and human-likeness ("The shown influencer is a human."), each measured on a 5-point Likert scale from 1 = I totally disagree to 5 = I totally agree. A fixation cross jittered between 3-4 seconds was then presented to neutralize the brain activation, after which followed the next trial. Trials proceeded in random order until each Instagram post was shown with each question. The presented influencers can be seen in the stimuli section of Study 1 in Figure 3. After participants evaluated all influencers and questions, the fNIRS headband was removed from the participant and they were debriefed on the study by thanking them for their participation, and showing which of the presented influencers was human and which was virtual. This study procedure was reviewed and approved by a German University's research ethics board.

Sample: Similar to the prior EEG study, fNIRS studies require samples sizes of around 20 participants to receive sufficiently powered results for medium-sized effects (i.e., power = .80) (Vassena et al., 2019). Therefore, we sampled $N = 27$ participants from a large German university for the second study (37% female, 63% male; average age $M = 27.4$ years, $SD = 7.36$, $Min = 19$, $Max = 50$). 22.2% held a postgraduate degree from a university, 25.9% have a bachelor's degree, and 33.3% had a high school/GED degree. The remaining participants had a college or post-secondary certificate (14.8%) or were below high school/GED degree (3.7%). Regarding their Instagram use, 18.5% report using the app several times per hour, 59.3% use it several times per day (the remainder uses the app several times per week (7.4%), per month (3.7%), or less than on a monthly basis (11.1%). 22.2% followed fewer than 5 influencers, 25.9% follow more than 5 influencers, 29.6% follow more than 10, 18.5% follow more than 50, and the remaining 3.7% follow more than 100 influencers on Instagram.

Data analysis: The fNIRS data was preprocessed with the MATLAB Brain AnalyzIR toolbox (Santosa et al., 2018). The raw fNIRS data comes with a sampling frequency of 7.81 Hz, and was checked for over- and undersaturated channels, and then resampled to 4 Hz to address the high auto-correlation in fNIRS data (Huppert, 2016). After that, optical density was calculated, and short-channel regression was used as filtering in the next step. This serves to filter out movements, Mayer waves, and extracerebral, task-unrelated activation (Saager & Berger, 2005; Scholkmann et al., 2014). After filtering was done, optical density was transformed into hemoglobin values by using the modified Beer-Lambert Law with a partial pathlength factor of 0.1 (Delpy et al., 1988; Kocsis et al., 2006). The hemoglobin values were then fed into a subject-level general linear model (GLM) that uses the canonical hemodynamic response function as baseline, and applied the AR-IRLS algorithm to identify the subject-level changes for each trial and condition (Barker et al., 2013). The results of this were used to analyze differences on a group level in which the used conditions (human influencers vs. virtual influencers) were set as fixed effects, and the individual differences between participants were treated as random effects. From this group analysis, we then drew contrasts between the human and virtual influencers to explore the differences. As a threshold to achieve robust results, we selected only channels that come with false discovery rate (FDR) corrected p-values with $p_{FDR} < .001$ and sufficient power levels with $power > .80$ in the HbO and HbR changes. Regarding interpretation of the fNIRS signals, it has to be noted that an increase in HbO often comes with a decrease in HbR; both of which point to neural activation.

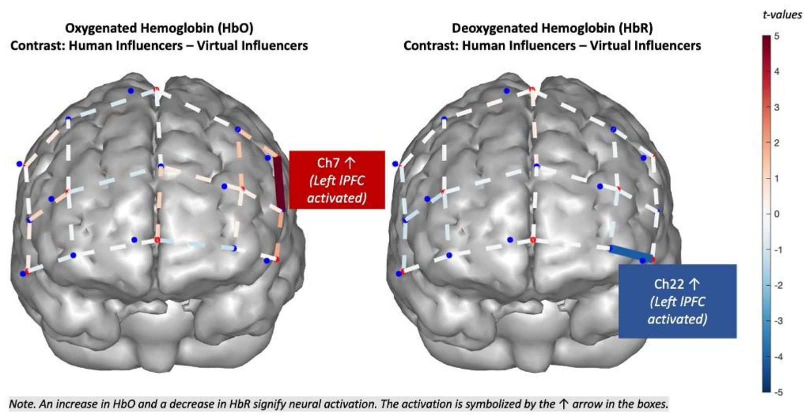


Construct	M (SD) HI	Min, Max HI	M (SD) VI	Min, Max VI	beta	se	lower CI	upper CI	t	p_{Holm}	partial η^2
Perceived Humanness	4.51 (0.55)	2.80, 5.00	2.78 (0.99)	1.20, 4.60	-1.73	0.17	-2.07	-1.39	-9.96	< .001	0.79
Pecerived Uncanniness	2.09 (0.80)	1.00, 4.00	2.98 (0.94)	1.20, 5.00	0.89	0.15	0.59	1.19	5.88	< .001	0.57
Perceived Trust	3.15 (0.77)	1.00, 4.00	2.28 (0.59)	1.00, 3.40	-0.87	0.14	-1.15	-0.60	-6.19	< .001	0.60
Behavioral Intentions	2.41 (0.86)	1.00, 3.80	1.84 (0.52)	1.00, 2.90	-0.58	0.12	-0.81	-0.35	-4.93	< .001	0.48

Descriptives:
Human Influencer (HI) and Virtual Influencer (VI)

Comparison:
Virtual Influencer (VI) — Human Influencer (HI)

Figure 8. Results of Subjective Ratings of Virtual and Human Influencers of Study 2 Self-Reported Responses



fNIRS channel	beta	se	lower CI	upper CI	t	p_{FDR}
left PFC (ch7) HbO	4.93	0.77	3.59	6.75	6.42	0.001
left PFC (ch22) HbR	-1.16	0.30	-1.91	-0.67	-3.95	0.005

Comparison:
Human Influencer (HI) —
Virtual Influencer (VI)

fNIRS -> Self-Report	beta	se	lower CI	upper CI	t	p_{Holm}
left lPFC (ch7) -> uncanniness	-0.20	0.16	-0.51	0.12	-1.29	0.208
left lPFC (ch7) -> trust	0.33	0.16	0.01	0.65	2.05	0.05
left lPFC (ch7) -> behavioral intentions	0.25	0.22	-0.20	0.69	1.11	0.277
left lPFC (ch22) -> uncanniness	0.15	0.17	0.84	-0.20	0.50	0.405
left lPFC (ch22) -> trust	-0.07	0.18	-0.44	0.30	-0.40	0.692
left lPFC (ch22) -> behavioral intentions	0.10	0.25	-0.38	0.60	0.40	0.693

Relation of significant channels with included self-reports

Figure 9. fNIRS HbO and HbR Mixed-Effects Model Results Analysis

5.2 Results

Similar to Study 1, we present the boxplots, descriptives, and inferential statistics of our analyses in Figure 8. The figure shows our results from the self-reported responses to human versus virtual influencers along the four constructs of perceived human-likeness for the manipulation check, as well as perceived uncanniness, perceived trust, and intentions to follow the influencer's recommendation. From the descriptive statistics, it can be seen that virtual influencers were rated higher in their perceived uncanniness. The perceived human-likeness, perceived trust, and behavioral intentions were rated in favor of the human influencers.

Results from mixed effects models that account for the influencer type (human vs. virtual) as fixed effect, and that take into account individual differences between participants as random effects, show that the evaluation between human and virtual influencers differs. The manipulation check for perceived human-likeness was successful in this study as well, as virtual influencers were rated lower compared to human influencers ($\beta = -1.73$, $SE = 0.17$, $95\%CI[-2.07, -1.39]$, $t(26) = -9.96$, $p_{Holm} < .001, \eta_p^2 = .79$). Further, virtual influencers were rated higher in perceived uncanniness compared to human influencers ($\beta = 0.89$, $SE = 0.56$, $95\%CI[0.59,1.19]$, $t(26) = 5.88$, $p_{Holm} < .001, \eta_p^2 = .57$). These results align with our findings from Study 1. This is also the case for perceived trust that was rated in favor of the human influencers ($\beta = -0.87$, $SE = 0.14$, $95\%CI[-1.15, -0.60]$, $t(26) = -6.19$, $p_{Holm} < .001, \eta_p^2 = .60$). Finally, the intention to follow recommendations was also lower for virtual influencers compared to their human counterparts ($\beta = -0.58$, $SE = 0.12$, $95\%CI[-0.81, -0.35]$, $t(26) = -4.93$, $pHolm < .001, \eta p2 = .48$).

fNIRS results: In the fNIRS results, we see a neural activation of the left lPFC indicated by an increased HbO signal for the human compared to the virtual influencers (ch7: $\beta = 4.93$, $SE = 0.77$, $95\%CI[3.59,6.75]$, $t(54) = 6.42$, $p_{FDR} < .001$). In the HbR signal, we see a neural activation signified by a decrease in HbR in the left lPFC for human influencers compared to virtual ones (ch22: $\beta = -1.16$, $SE = 0.30$, $95\%CI[-1.91, -0.67]$, $t(54) = -3.95$, $p_{FDR} = .005$). Both findings are shown in Figure 9, together with the results table and the relation of the neural activation to the self-reported constructs.

Integrated self-reported and fNIRS results: For analyzing the relationships between fNIRS and self-reported data, we extracted the subject-level t-values for each condition that indicate the deviation of HbO and HbR changes from the baseline model. After that, we reduced the data to the channels that reached significance in the group. We analyzed the relationships by using mixed-effects models to explore whether differences in the fNIRS signal were modulated by differences in the self-reported constructs while accounting for the intercept per participant as random effects. Results show that channel 7 in the HbO (i.e., left lPFC) signal showed a positive relationship with self-reported ratings of perceived trust ($\beta = 0.33$, $SE = 0.16$, $95\%CI[0.01,0.65]$, $t(28.17) = 2.05$, $p_{Holm} = .05$), but not with perceived uncanniness, nor with intentions to follow the influencer's recommendations. Similarly, channel 22 in the HbR signal did not reveal a relationship with any of the self-reported constructs of perceived uncanniness, perceived trust, and intention to follow recommendations. The results of these analyses are depicted in the lower table in Figure 9.

5.3 Discussion of Study 2

All in all, the self-reported responses of Study 2 support the self-reported results from Study 1. That is, virtual influencers were rated consistently lower in their perceived human-likeness, but higher in their perceived uncanniness when compared to human influencers. The perceived trust of human influencers tends to be higher, and the intentions to follow an influencer's recommendations are also higher for human influencers.

The neural responses to influencer perception showed a greater neural activation in the left lPFC when participants saw the human influencers. Related works suggest the left lPFC to be sensitive to human-like design as it is more activated when looking at human faces compared to robot faces (Yorgancigil et al., 2022), and when robots imitate human-like gaze behavior (Li et al., 2023b). These findings thus support our results. Furthermore, we identified that the left lPFC activation is positively correlated with perceived trust evaluations of the influencers. This finding is supported by the broader NeuroIS literature where a first relationship has been established between lPFC activation and perceived trust of technology and agents (Gefen et al., 2014). While trust is often a predictor for behavioral intentions, studies indicate that the lPFC may also provide an indication for behavioral intentions toward a virtual agent (Aranyi et al., 2016). However, our integrated analyses for the relationship between lPFC activation and behavioral intentions do not support this finding for the context of virtual influencers.

Finally, in contrast to several related works on avatars and social robots (Krach et al., 2008; Riedl et al., 2014; Rosenthal-Von der Pütten et al., 2019; Y. Wang & Quadflieg, 2014), we did not identify significant neural activation changes in the mPFC between human and virtual influencers. A plausible reason for this might be that the human-like design of the included virtual influencers in our study is significantly closer to real humans than the avatars and robots utilized in the related works. Especially Rosenthal-Von der Pütten et al. (2019) argue that the mPFC "signaled the subjective likability of artificial agents as a nonlinear function of humanlikeness" and the included artificial humans that resemble our utilized stimuli most are already at the higher end of the uncanny valley. When looking at the self-reported responses on uncanniness in our Study 2, we see that while perceived uncanniness was rated higher for virtual influencers when compared to humans, it was not rated particularly high on the 5-point Likert scale but rather at the scale's median ($M = 2.98$). Overall, it becomes evident that literature on brain activation elicited by interaction with artificial agent adoption is still scarce. Therefore, following our neuroimaging findings, we revisited the broader neuroscientific literature to deduce three theoretical explanations that could explain behavioral intentions toward virtual influencers.

6 Interpretation of Studies 1 and 2: Deriving the Antecedents

The self-report data showed across both studies that human influencers are rated higher in perceived trust and intention to follow recommendations. Perceived uncanniness, however, was rated higher for the virtual influencers in both studies. These findings are consistent with results from the majority of related literature on virtual influencers (Arsenyan & Mirowska, 2021; Hofeditz et al., 2022; Sands et al., 2022b). Turning to the research goal of this paper, we dive deeper into the interpretation of the neural results to identify the antecedent mechanisms to perceived uncanniness, perceived trust, and intention to follow recommendations. To identify these mechanisms, we make use of what is referred to as “reverse inference” (Dimoka et al., 2011b; Poldrack, 2006), a process that is discussed in detail by Riedl et al. in Appendix C of their book on NeuroIS research (Riedl et al., 2017). That means that we infer a cognitive process from the observed brain activity, and by means of our integrated analysis of neural activity and self-report data, claim this cognitive process to be an antecedent to one of the observed variables of uncanniness, trust, and intention to follow recommendations. That also means, we look at each of the identified neural activation from Study 1 and 2, and deduce the most likely associated cognitive process given i) the context of our study in the sense of the manipulation we employed, and ii) the cognitive processes that are most often associated with the given brain activation identified. Because there is no “one-to-one” connection that can be made between one brain activation and one construct (e.g., Dimoka et al., 2011b), we formulate hypotheses that are to be tested in the next study. Thus, the interpretation made here based on reversed inference is validated in the following Study 3.

Antecedent 1—Expectancy violation: One of the key neurophysiological findings was that images of virtual influencers elicited a greater negative potential than humans, corresponding to the N400 EEG component in Study 1. In the broader literature, the N400 is most often associated with the cognitive processing of semantic mismatch (e.g., a response upon hearing “I take my coffee with milk and dog”), but is recognized as the result of a multimodal neural network shaped by long-term experience broadly (Kutas & Federmeier, 2011). As a result, it has also been associated with expectancy violation where there is a conflict between the expected stimulus and the incoming stimulus (Ganis et al., 1996; Kutas & Federmeier, 2011; Proverbio et al., 2015), resonating with the context observed in our studies. Our correlational analysis between the N400 and the self-report results in Study 1 reveals that the N400 appears as a direct predictor of perceived uncanniness and intention to follow recommendations.

Related research shows that humans form expectations about human and artificial agents before starting an interaction. According to expectancy violation theory, negative social judgments are formed when the ensuing interaction with the agent results in a violation of prior expectation (Burgoon & Jones, 1976; Burgoon et al., 2016). Given that perceived uncanniness is such a negative social judgment, it follows that perceived uncanniness appears as a result of the mismatch between the expectation of a human influencer, and the incoming stimulus of a virtual influencer (Schindler et al., 2017). We could also argue that confirming the user’s expectation leads to more positive perceptions and use intentions (Bhattacherjee, 2001; Oliver, 1980). We hypothesize that expectancy violation is, therefore, an antecedent mechanism that gives rise to uncanniness perceptions. Based on the observed correlation between the N400 and intention to follow recommendations, it follows that expectancy violation also directly predicts intentions to follow recommendations. We thus propose that expectancy violation is an antecedent and serial mediator to uncanniness and intention to follow recommendations of virtual influencers:

H1: Expectancy violation and uncanniness serially mediate the relationship between virtual versus human influencer perception and intention to follow recommendations.

Antecedent 2—Emotion: In addition to the N400, we observed an elevated LPP signal for human compared to virtual influencers in Study 1. The LPP is well-studied in broader literature in the context of emotional processing, and is observed to be elevated in response to emotionally-charged stimuli (Hajcak & Olvet, 2008; Pastor et al., 2008). Our results are consistent with past literature in which the LPP has been repeatedly found to be increased for human or highly human-like avatars compared to virtual avatars (Schindler et al., 2017; Sollfrank et al., 2021), as well as for more trustworthy faces (Kyriakopoulou & Nowland, 2017; Marzi et al., 2014). In the correlational analysis, the LPP component significantly correlated with intention to follow recommendations, but not with perceived uncanniness or trust. There is thus reason to believe that emotion acts as an antecedent to behavioral intentions directly.

Further support for emotion as a key antecedent to behavioral intentions can also be derived from interpreting the neural results of Study 2. We identified greater activation for human compared to virtual influencers in the left lPFC. The left lPFC has been related to perceived trust in a prior NeuroIS study (Gefen et al., 2014). In the broader neuroscientific literature, the left lPFC is frequently associated with positive emotional experiences (among other processes) (Herrington et al., 2005; M.-Y. Wang et al., 2018), further supporting the inferences drawn from LPP. However, our correlational analysis for Study 2 reveals that the left lPFC significantly correlated with perceived trust, but not with uncanniness nor with intention to follow recommendations. While this contradicts the findings from our Study 1 where no correlation between LPP and trust was found, it aligns with studies that show how emotional trust has more predictive power on behavioral intentions than (cognitive) trusting beliefs (Lee et al., 2015; Qiu & Benbasat, 2005). This finding further seems reasonable in the context of social media, as users have to rely on their "gut feeling" about the influencer (i.e., emotional evaluation) because they form evaluations based on limited information. Yet, investigations on the mediating effects of emotion on engagement in social media content are largely missing in the broader social media literature (Schreiner et al., 2021).

Taken together, we can conclude that emotion plays a significant role in virtual influencer perception. Following our correlational results from both Study 1 and Study 2, we were led to assert that emotion acts as a direct antecedent to intentions to follow recommendations on the one hand (as identified in Study 1), while it also poses an antecedent to perceived trust of the influencer on the other hand (as evidenced in Study 2). Therefore, we argue that behavioral intentions toward social media influencers are serially mediated through emotion and perceived trust:

H2: Emotion and perceived trust serially mediate the relationship between virtual versus human influencer perception and intention to follow recommendations.

Antecedent 3—Perceived cognitive effort: While the left lPFC can be an indicator of positive emotional engagement, it may also signify increased cognitive engagement. The reason for this is that emotional and cognitive processes have a reciprocal relationship, and especially PFC areas of the brain involve both emotional valence (i.e., positive, negative), as well as associated cognitive functions of emotional experiences (for e.g., appraisal processes, emotion regulation) (Dolcos et al., 2011; Grimm et al., 2006). The lPFC is frequently associated with functions of working memory, memory load, cognitive tasks, and task difficulty (as evidenced by a corpus of 3,489 neuroimaging studies on neurosynth.org (Yarkoni et al., 2011)). This association leads to the conclusion that (positive) perceived trust of human influencers not only triggers positive emotional experiences, but also requires more cognitive resources compared to virtual influencers. A reason for this can be that when users have more trust in an agent, they also show higher engagement (Alimamy & Kuhail, 2023; Chandra et al., 2022). On a neurophysiological level, the lPFC processes goal-relevant emotional information, thereby also representing cognitive effort in addition to emotional valence (Dolcos et al., 2011). This goal-relevant information then leads to resulting trust evaluations.

Even though there is some evidence that there is a cognitive and an emotional component to trust formation, we could not identify works that explicate a theoretical route through cognitive effort and its positive mediating impact on perceived trust. Yet, there is neurophysiological support as the left lPFC activation was also associated with higher approach intentions in human-artificial agent interactions, potentially as a result of positive cognitive engagement (Aranyi et al., 2016; De Castro Martins et al., 2022). We propose that perceived cognitive effort and perceived trust serially mediate the effects of virtual versus human influencers on behavioral intentions:

H3: Perceived cognitive effort and perceived trust serially mediate the relationship between virtual versus human influencer perception and intention to follow recommendations.

Finally, when diving into how perceived trust shapes behavioral intentions, it may also be considered if it is really perceived trust that impacts intentions to follow virtual influencer recommendations. A closely related concept that adds an explanation for variation is *distrusting* beliefs. It has been shown both by neurophysiological evidence, as well as through linguistic analyses, that perceived trust and distrust are two closely related, yet distinct concepts (Dimoka, 2010; Gefen et al., 2020; Riedl et al., 2010). While familiarity is thought to build trust, it can also elicit distrust at first in things unfamiliar (Gefen et al., 2020). In the context of our study, distrust in the virtual influencers may, therefore, be an important additional explanatory factor as users are not yet as familiar with artificially created influencers as they are with human influencers (Miyake, 2023). Therefore, we extend H2 and H3 and propose that similar explanatory explanations may also exist for perceived distrust:

H4: Emotion and perceived distrust serially mediate the relationship between virtual versus human influencer perception and intention to follow recommendations.

H5: Perceived cognitive effort and perceived distrust serially mediate the relationship between virtual versus human influencer perception and intention to follow recommendations.

To validate our antecedents, we conducted an online experiment (Study 3) in which standardized questionnaire scales for the suggested mediators (e.g., expectancy violation, emotion, perceived cognitive effort) were utilized as means to test the relationships suggested from the neural data interpretation.

7 Study 3: Online Experiment

7.1 Method

Sample: According to our a priori power analyses using G*Power 3.1, a sample size of around 99 participants reveals medium effects with a statistical power of .90 in linear multiple regressions for each of the theoretical models. Therefore, we collected a sample size of n = 98 participants from Prolific for the third study (67.3% female, 30.6% male, 1% non-binary or third gender; 1% preferred not to state their gender; average age was M = 34.6 years, SD = 9.14,Min = 19,Max = 65). 25.5% held a postgraduate degree from a university, 46.9% have a bachelor's degree, and 8.2% had a high school/GED degree. The remaining participants had a college or post-secondary certificate (8.2%) or were below high school/GED degree (2%). Regarding their Instagram use, 13.3% report using the app several times per hour, 58.2% use it several times per day (the remainder uses the app several times per week (16.3%), per month (9.2%), or less than on a monthly basis (3.1%). 27.6% followed fewer than 5 influencers, 13.3% follow more than 5 influencers, 28.6% follow more than 10, 15.3% follow more than 50, and the remaining 15.3% follow more than 100 influencers on Instagram.

Stimuli and study design: The stimuli for this validation study were kept consistent with the stimuli from Study 1 and Study 2. That means, we included the same grey-scale posts of 10 human and 10 virtual influencers (see Figure 3). To control for study disengagement, which is common in online studies, we randomly selected 5 virtual influencers and 5 human influencers for each participant, rather than the full set. For each randomly selected influencer post, questions regarding the expectancy violation, perceived emotion, and perceived cognitive effort came first; the items of which were randomized. After that came a question block including items for perceived uncanniness, trust, distrust, and intention to follow recommendations. Once again, the items within this block were randomized. Finally, we asked the manipulation check question of human-likeness. As a result of this procedure, we get a total of N = 490 observations for each construct and influencer type (human vs. virtual influencer).

Measures: For each of the included influencers, participants had to first answer questions for the constructs derived from Study 1 and 2. That is, emotion measured with pleasure and arousal (scales taken from Huang et al. (2017)), perceived cognitive effort to evaluate the influencer (scales adapted from Wang & Benbasat, 2009), and the degree of perceived expectancy violation (scales adapted from Afifi & Metts, 1998). After that came questions for the constructs also included in the prior studies, but this time we used validated items for perceived trust (adapted from Kim & Kim, 2021) which was further complemented by perceived distrust as additional dimension (adapted from Dimoka, 2010). Further, we included perceived uncanniness (adapted from Tinwell & Sloan (2014), perceived human-likeness (adapted from Mathur & Reichling, 2016), and intention to follow recommendations (adapted from Jiménez-Castillo and Sánchez-Fernández (2019)). At this point it needs to be noted that all of the selected scales were developed and validated by prior research, and have also been used in other studies that either investigated the effects of conversational agents and avatars, or of social media influencers.

Table 5. Descriptives and Inferential Statistics of the Included Constructs

	Descriptives: Human Influencer (HI) and Virtual Influencer (VI)				Comparison: Virtual Influencer (VI) − Human Influencer (HI)						
Construct	**M (SD) HI**	**Min, Max HI**	**M (SD) VI**	**Min, Max VI**	**beta**	**se**	**lower CI**	**upper CI**	**t**	$\mathbf{p_{Holm}}$	**partial** $\boldsymbol{\eta^2}$
Perceived Humanness	3.50 (1.42)	0.00, 5.00	1.98 (1.77)	0.00, 5.00	-1.51	0.09	-1.70	-0.13	-16.50	< .001	0.24
Expectancy Violation	3.44 (0.94)	1.00, 5.00	3.77 (0.87)	1.67, 5.00	0.34	0.05	0.25	0.42	7.32	< .001	0.06
Emotion	1.91 (0.92)	1.00, 5.00	1.65 (0.79)	1.00, 4.83	-0.26	0.04	-0.34	-0.18	-6.44	< .001	0.04
Cognitive Effort	1.94 (0.96)	1.00, 5.00	2.12 (1.09)	1.00, 5.00	0.18	0.05	0.08	0.27	3.61	< .001	0.01
Perceived Uncanniness	2.09 (0.93)	1.00, 4.75	3.06 (1.28)	1.00, 5.00	0.98	0.07	0.84	1.10	14.80	< .001	0.20
Percieved Trust	2.44 (0.85)	1.00, 5.00	2.12 (0.86)	1.00, 4.50	-0.32	0.04	-0.40	-0.24	7.71	< .001	0.06
Percieved Distrust	3.06 (0.97)	1.00, 5.00	3.39 (1.00)	1.00, 5.00	0.33	0.05	0.23	0.42	6.83	< .001	0.05
Behavioral Intentions	2.16 (1.07)	1.00, 5.00	1.80 (0.94)	1.00, 4.67	-0.36	0.05	-0.46	-0.27	-7.54	< .001	0.06

Table 6. Results of Mediation Model 1 with Bootstrap Confidence Intervals

Mediation paths Model 1	Beta	*SE*	Lower CI	Upper CI
Direct effect: Influencer → Behavioral Intentions	0.02	0.06	-0.09	0.14
Influencer → Expectancy violation	0.33	0.06	0.22	0.44
Expectancy violation → Uncanniness	0.45	0.04	0.38	0.51
Expectancy violation → Behavioral intentions	-0.52	0.03	-0.58	-0.46
Uncanniness → Behavioral intentions	-0.22	0.03	-0.27	-0.17
Influencer → Expectancy violation → Behavioral intentions	-0.17	0.03	-0.24	-0.11
Influencer type → Expectancy violation → Uncanniness → Behavioral intentions	-0.03	0.01	-0.05	-0.02

The construct expectancy violation makes an exception and is also represented as the only formative measure (though its dimensions are weighted equally). The reason for this is that according to expectancy violation theory, expectancy violation is not a uni-dimensional construct (Afifi & Metts, 1998; Burgoon, 2016; Burgoon et al., 2016). That is, it consists at least of i) the expectation itself (item ExpVio), ii) the valence of the expectancy violation that took place (item ExpVal), and iii) the impact of the event on uncertainty regarding future interactions (item ExpCer). Therefore, to at least approximate the different dimensions of expectancy violation, we included it as a formative indicator. An overview of all included items, as well as results from validity and reliability analyses can be seen in Appendix B.

7.2 Results

7.2.1 Differences Between Human and Virtual Influencers

Analogous to Study 1 and 2, we first tested for each of the included constructs if there are differences between virtual and human influencers. Table 5 provides an overview of the descriptives and inferential analyses of each included construct. Results of the mixed effects models that take the influencer type as fixed effects, and individual differences between participants as random intercepts, show differences in all constructs.

The perceived human-likeness was higher for human compared to virtual influencers ($\beta = -1.51$, $SE = 0.09$, 95%$CI[-1.70, -0.13]$, $t(881) = -16.5$, $p_{Holm} < .001, \eta_p^2 = .24$). Thus, the manipulation succeeded. Similar to the results in Study 1 and Study 2, we identified that the perceived uncanniness of virtual influencers was higher than for human influencers ($\beta = 0.98$, $SE = 0.07$, 95%$CI[0.84,1.10]$, $t(881) = 14.80$, $p_{Holm} < .001, \eta_p^2 = 0.20$). Further, also supporting our findings from Study 1 and 2, the perceived trust and behavioral intentions were rated in favor of the human influencers (trust: $\beta = -0.32$, $SE = 4$, 95%$CI[-0.40, -0.24]$, $t(881) = -7.71$, $p_{Holm} < .001, \eta_p^2 = 0.06$, intention to follow recommendations: $\beta = -0.36$, $SE = 0.05$, 95%$CI[-0.46, -0.27]$, $t(881) = -7.54$, $p_{Holm} < .001, \eta_p^2 = 0.06$). Contrary to perceived trust, perceived distrust was higher for virtual influencers ($\beta = 0.33$, $SE = 0.05$, 95%$CI[0.23,0.42]$, $t(881) = 6.83$, $p_{Holm} < .001, \eta_p^2 = 0.05$).

The identified antecedents to the self-reported responses from the neural data were also translated into self-reported constructs for this study. Results show that the expectancy violation for virtual influencers was higher when compared to human influencers ($\beta = 0.34$, $SE = 0.05$, 95%$CI[0.25,0.42]$, $t(881) = 7.32$, $p_{Holm} < .001, \eta_p^2 = 0.06$). Further, the emotional evaluation of human influencers was more positive compared to their virtual counterparts ($\beta = -0.26$, $SE = 0.04$, 95%$CI[-0.34, -0.18]$, $t(881) = -6.44$, $p_{Holm} < .001, \eta_p^2 = 0.04$), though both influencer types were evaluated below the scale's median. Finally, we identified cognitive effort as third antecedent from the neural data. Similar to emotion it was rated below the scale median for both influencer types, but higher for virtual influencers when compared to their human counterparts ($\beta = 0.18$, $SE = 0.01$, 95%$CI[0.08,0.27]$, $t(881) = 3.61$, $p_{Holm} < .001, \eta_p^2 = 0.01$).

7.2.2 Mediation Analysis – Testing the Hypotheses

As the main target of this study is to validate the theoretical assumptions derived from the brain data, we calculate serial mediation analyses using ordinary least squares path analysis for each hypothesis. The models were calculated using the PROCESS function (version 4.3) in R (Hayes, 2017). For testing the hypotheses, we use serial mediation (Hayes model 6). All models were tested with a 95% confidence interval and 5,000 bootstrap re-samples.

Antecedent 1—Expectancy violation: Based on our serial mediation model to test H1 (results summarized in Table 6 and depicted in Figure 10), the influencer type indirectly impacts intentions to follow an influencer's recommendation through its impact on expectancy violation and perceived uncanniness. Virtual influencers lead to higher expectancy violation compared to human influencers ($\beta = 0.33$; $F(1,977) = 33.11$, $p < .001$, $\eta_p^2 = .03$, $R^2 = .033$). Higher expectancy violation further predicted higher perceived uncanniness ($\beta = 0.45$; $F(2,976) = 180.1$, $p < .001$, $\eta_p^2 = .27$, $R^2 = .27$). Finally, higher violations of expectancy and subsequently higher uncanniness perceptions have a negative impact on intentions to follow the influencer's recommendations ($\beta = -0.03$; $F(3,975) = 202.09$, $p < .001$, $\eta_p^2 = .38$, $R^2 = .38$). Because the influencer type does not have a direct effect on intention to follow recommendations ($\beta = 0.03$), full mediation can be assumed. These results support H1. We conclude that virtual influencers lead to lower intentions to follow recommendations *because* the influencer does not match the users' expectations leading to feelings of uncanniness towards the influencer.

Antecedent 2—Emotion: In H2, we hypothesized that intentions to follow recommendations are indirectly predicted by influencer type, through positive emotion and perceived trust. Serial mediation analyses support this hypothesis (summarized in Table 7 and depicted in Figure 11). Virtual influencers lead to less positive emotion when compared with human influencers (*beta* $= -0.26$, $F(1,977) = 21.74$, $p < .001$, $\eta_p^2 = .02$, $R^2 = .02$). Positive emotion, however, has a positive influence on perceived trust of the influencer (*beta* $= 0.54$, $F(2,976) = 226.95$, $p < .001$, $\eta_p^2 = .32$, $R^2 = .32$). The indirect effect is significant such that positive emotion and perceived trust serially mediate impact of influencer type on behavioral intentions to follow the influencers recommendation (*beta* $= -0.07$, $F(3,975) = 382.48$, $p < .001$, $\eta_p^2 = .54$, $R^2 = .54$). This supports H2. There was no evidence that influencer type predicted behavioral intentions independent of its effect on emotion and perceived trust ($c' = -0.09$, $95\%CI[-0.18, 0.00]$). We conclude that social media users have a lower intention to follow recommendations from virtual influencers compared to human influencers, *because* virtual influencers trigger less positive emotions, which results in lower trust with the influencer.

In addition to the validation of the effect of emotion and perceived trust, we further wanted to add the dimension of perceived distrust to the theoretical explanation, testing H4 (model 2b depicted in Figure 11 and summarized in Table 8)). Serial mediation analysis show that influencer type has a direct influence on behavioral intentions ($c' = -0.13$, $95\%CI[-0.23, -0.03]$), and also indirectly impacts them through elicited emotion and distrust. That is, the detrimental impact of virtual influencers on positive emotion also influences the perceived distrust of the influencer (*beta* $= -0.38$, $F(2,976) = 72.91$, $p < .001$, $\eta_p^2 = .13$, $R^2 = .13$). While positive emotion is positively influencing behavioral intentions, perceived distrust has a negative impact. Considering both effects, an overall negative impact on behavioral intentions toward virtual influencers can be noted (*beta* $= -0.02$, $F(3,975) = 258.10$, $p < .001$, $\eta_p^2 = .44$, $R^2 = .44$). This means that social media users have a lower intention to follow recommendations from virtual influencers compared to human influencers, *because* virtual influencers trigger less positive emotions, which results in higher distrust with the influencer. All in all, these results support H4.

Antecedent 3—Perceived cognitive effort: Finally, our neural results from Study 1 and 2 suggested cognitive effort as third major antecedent to behavioral evaluations. We transferred this into a scale asking for the perceived (cognitive) effort when evaluating the influencers. To test H3 we conducted serial mediation analysis (model 3a depicted in Figure 12, results summarized in Table 9). Results show that virtual influencers require higher perceived effort compared to human influencers (*beta* $= 0.18$, $F(1,977) = 7.58$, $p = .006$, $\eta_p^2 = .01$, $R^2 = .008$). However, the elevated perceived effort does not seem to impact perceived trust (*beta* $= 0.01, 95\%CI[-0.04, 0.06]$). Finally, while the model explains 45% of behavioral intentions ($F(3,975) = 260.34$, $p < .001$, $\eta_p^2 = .44$, $R^2 = .045$), this is mainly due to perceived trust and the direct effect of influencer type (*beta* $= -0.13, 95\%CI[-0.23, -0.03]$), and not due to perceived effort (*beta* $= 0.04, 95\%CI[0.00, 0.09]$). The findings suggest that social media users' intention to follow recommendations from virtual compared to human influencers *can not be explained* through differences in perceived cognitive effort and its effect on the perceived trust in the influencer. All in all, H3 needs to be rejected.

We repeated the analysis and included perceived distrust to test H5 (model 3b depicted in Figure 12, results summarized in Table 10). Virtual influencers elicited higher perceived cognitive effort (*beta* $= 0.18$, $F(1,977) = 7.58$, $p = .006$, $\eta_p^2 = .01$, $R^2 = .008$), that further has an impact on perceived distrust (*beta* $= 0.18$, $F(2,976) = 30.71$, $p < .001$, $\eta_p^2 = .06$, $R^2 = .059$). Perceived distrust further negatively impacts the intention to follow recommendations (*beta* $= -0.42$, $F(3,975) = 78.18$, $p < .001$, $\eta_p^2 = .19$, $R^2 = .19$). While there is evidence that influencer type has a direct effect on behavioral intentions ($c' = -0.25, 95\%CI[-0.37, -0.13]$), the mediation analysis revealed no indirect effect of cognitive effort and distrust as serial mediators (*beta* $= -0.01, 95\%CI[-0.03, 0.00]$). All in all, and especially given the reverse effect of influencer type on cognitive effort, we have to reject H5. In other words, social media users' lower intention to follow recommendations from virtual influencers *can not be explained* through virtual influencers causing more cognitive effort to form an impression about the influencers, which results in higher established distrust towards the influencers.

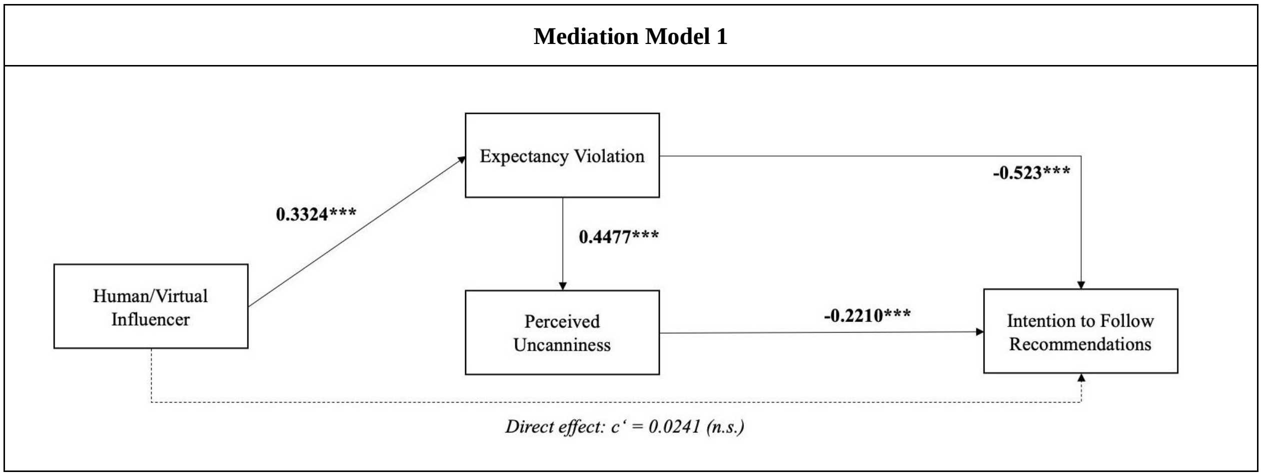
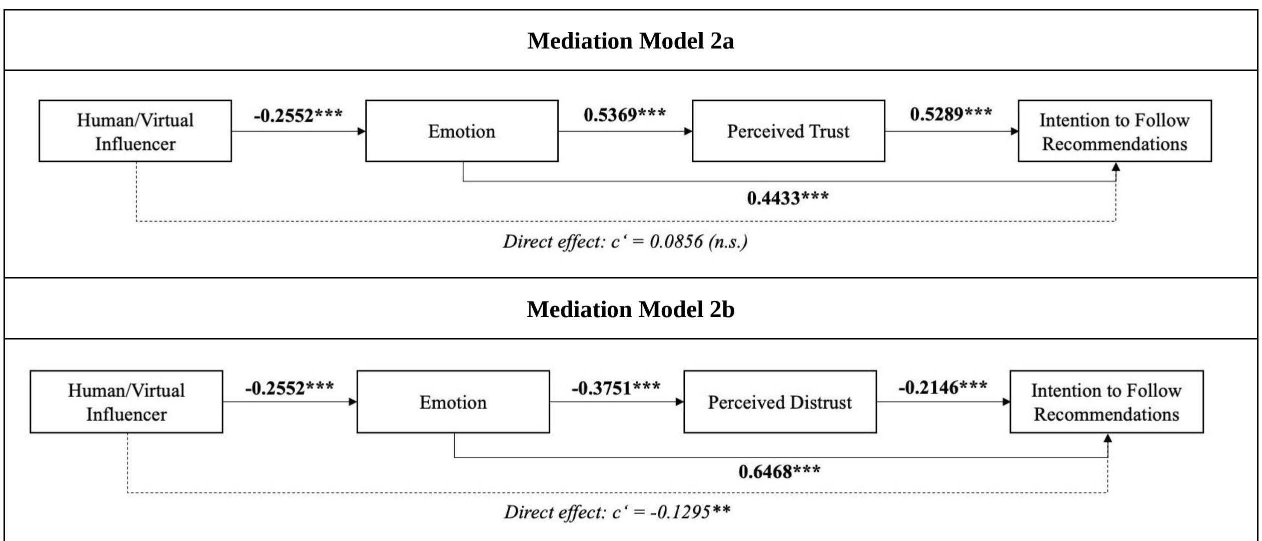


Figure 10. Mediation Model 1: Testing H1 (Note. **p < .01, ***p < .001)

Table 7. Results of Mediation Model 2a with Bootstrap Confidence Intervals

Mediation paths Model 2a	Beta	*SE*	Lower CI	Upper CI
Direct effect: Influencer → Behavioral intentions	-0.09	0.05	-0.18	0.00
Influencer → Emotion	-0.26	0.06	-0.36	-0.14
Emotion → Trust	0.54	0.03	0.48	0.59
Emotion → Behavioral intentions	0.44	0.03	0.37	0.52
Trust → Behavioral intentions	0.53	0.03	0.46	0.60
Influencer → Emotion → Behavioral intentions	-0.11	0.03	-0.16	-0.06
Influencer → Emotion → Trust → Behavioral intentions	-0.07	0.02	-0.11	-0.04



Note. ***p* < 0.01, ****p* < 0.001

Figure 11. Mediation Model 2: Testing H2 and H4

Table 8. Results of Mediation Model 2b with Bootstrap Confidence Intervals

Mediation paths Model 2b	**Beta**	***SE***	**Lower CI**	**Upper CI**
Direct effect: Influencer → Behavioral intentions	-0.13	0.05	-0.23	-0.03
Influencer → Emotion	-0.26	0.06	-0.36	-0.14
Emotion → Distrust	-0.38	0.03	-0.44	-0.30
Emotion → Behavioral intentions	0.65	0.03	0.58	0.72
Distrust → Behavioral intentions	-0.21	0.03	-0.27	-0.16
Influencer → Emotion → Behavioral intentions	-0.17	0.04	-0.24	-0.09
Influencer → Emotion → Distrust → Behavioral intentions	-0.02	0.01	-0.03	-0.01

Table 9. Results of Mediation Model 3a with Bootstrap Confidence Intervals

Mediation paths Model 3a	**Beta**	***SE***	**Lower CI**	**Upper CI**
Direct effect: Influencer → Behavioral intentions	-0.13	0.05	-0.23	-0.03
Influencer → Cognitive effort	0.18	0.07	0.05	0.31
Cognitive effort → Trust	0.01	0.03	-0.04	0.06
Cognitive effort → Behavioral intentions	0.04	0.02	0.00	0.09
Trust → Behavioral intentions	0.77	0.03	0.72	0.83
Influencer → Cognitive effort → Behavioral Intentions	0.01	0.01	0.00	0.02
Influencer → Cognitive effort → Trust → Behavioral intentions	0.00	0.00	-0.01	0.01

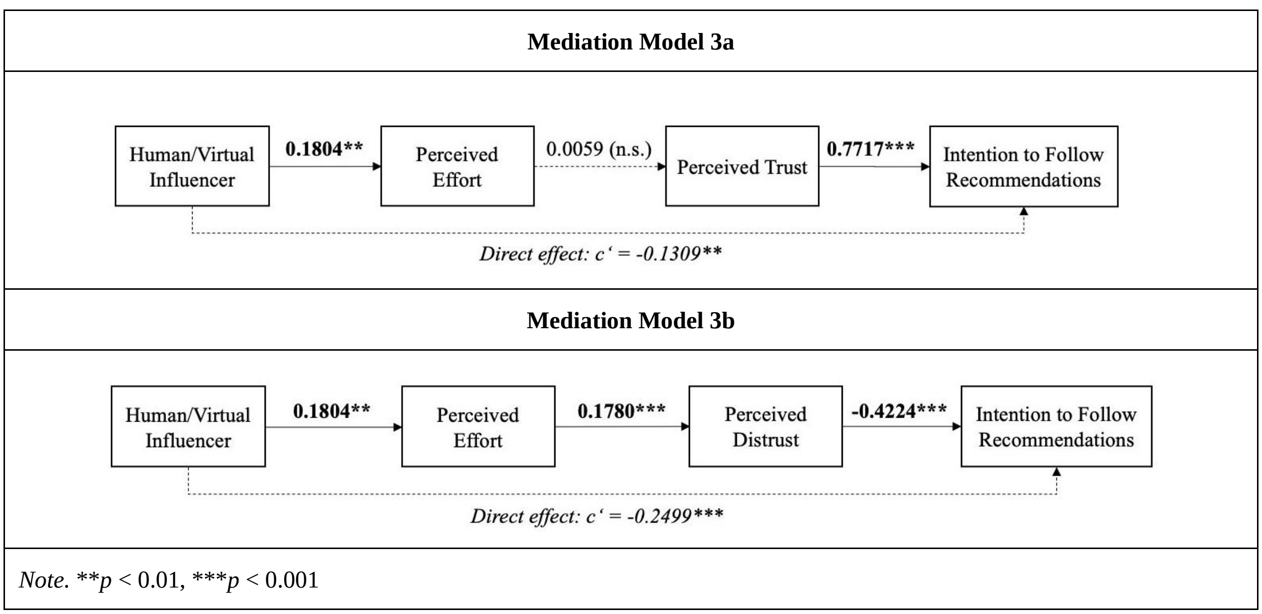


Figure 12. Mediation Model 3: Testing H3 and H5

Table 10. Results of Mediation Model 3b with Bootstrap Confidence Intervals

Mediation paths Model 3b	Beta	*SE*	Lower CI	Upper CI
Direct effect: Influencer → Behavioral intentions	-0.25	0.06	-0.37	-0.13
Influencer → Cognitive effort	0.18	0.07	0.05	0.31
Cognitive effort→ Distrust	0.18	0.03	0.12	0.23
Cognitive effort → Behavioral intentions	0.12	0.03	0.07	0.18
Distrust → Behavioral intentions	-0.42	0.03	-0.49	-0.36
Influencer → Cognitive effort → Behavioral intentions	0.02	0.01	0.01	0.04
Influencer → Cognitive effort → Distrust → Behavioral intentions	-0.01	0.01	-0.03	0.00

8 Discussion

8.1 Theoretical Implications

The main theoretical contribution of our work lies in the identification of three explanatory pathways for understanding influencer evaluations, each centered on one of the previously understudied antecedents: expectancy violation, emotion, and cognitive effort. Taken together, we also show how an exploratory data-driven approach and the addition of neuroimaging to self-report measures can reveal hidden processes and research gaps, furthering parsimonious theorizing.

First, we identified *expectancy violation - uncanniness - intention to follow recommendations* as crucial explanatory path to explain when and why we would (not) follow an influencer's recommendations. While the violation of expectation had a negative impact on the intention to follow recommendations in our study, it does not necessarily have a negative impact in all contexts. For example, expectancy violation theory proposes that the valence and magnitude of the violation matter (Burgoon, 2016). As a result, a positive violation of expectations can also lead to better results than positive expectancy confirmation in some contexts. Our results lead us to believe that it is very important to incorporate expectancy violation as a crucial antecedent to virtual influencer perceptions. Diving into related literature, only one study could be identified that uses expectancy violation as a predictor for engaging with virtual influencers (Muniz et al., 2023). Even in the broader literature on artificial agents, studies that account for this significant predictor are scarce (Gnewuch et al., 2022; Grimes et al., 2021). Our findings thus contribute to the literature with a call for the consideration of expectation theories when investigating the effects of virtual influencers.

Second, our neural results provide evidence that *emotion - trust / distrust intention to follow recommendation* is also an essential explanatory path to explain user perceptions and behavioral intentions toward virtual versus human influencers. The role of emotion in human decision-making is by now established and has received attention in IS research more broadly. In the context of social media, investigating emotion as a crucial antecedent to behavioral outcomes seems particularly reasonable. Users have to rely on their early emotional evaluations of the influencer because they form evaluations based on limited information. Yet, investigations on the mediating effects of emotion on engagement in social media content are largely missing in the broader social media literature (Schreiner et al., 2021). Furthermore, studies that incorporate emotion as a behavioral predictor for interacting with artificial agents are also comparatively scarce (Rapp et al., 2021). Researchers would thus benefit by investigating emotional responses as impact factors on social media engagement behavior in general, and for the phenomenon of virtual influencers in particular. Our results also show how emotion is not only a predictor of intention to follow recommendations, but specifically also for the formation of perceived trust and distrust of the virtual influencer. We contribute by providing empirical evidence for theorizing the relationship between emotional appraisals and trust or distrust in IS research more broadly.

Finally, our findings provide evidence that *(perceived) cognitive effort - intention to follow recommendations* is a third explanatory path. This theoretical explanation is more challenging than the others because our neurophysiological results showed lPFC activation, and thereby more cognitive effort, as an indication for the processing of human influencers. This diverges from the self-reported cognitive effort that was rated higher for the virtual influencers. Furthermore, while the cognitive effort signified by neural data correlated with perceptions of trust, the self-perceived cognitive effort correlates only with perceptions of distrust. This disparity may also explain why we did not observe a correlation between perceived cognitive effort and trust in Study 3, but only between perceived cognitive effort and distrust, as these appear to capture distinct dimensions of the concept. While we have to reject H3 and H5, this also shows that the left lPFC activation was an indicator of positive emotion rather than cognitive effort. Given this diverging result, future work is needed to expand on these findings and analyze the relation of neurophysiological and self-reported cognitive effort, and its relation to perceived (dis-)trust in virtual influencers. For example, future studies could investigate the relationship between trust, distrust, and potential antecedents such as cognitive effort or stress. Such investigations can significantly improve trust and distrust theory in IS research more broadly.

8.2 Practical Implications

Our results have implications for companies that wish to design virtual influencer profiles for advertising campaigns or other customer relationship purposes. Past research suggested that virtual influencers trigger greater uncanniness, and so should be avoided (Hofeditz et al., 2022). However, our findings suggest that expectancy violation explains the uncanniness evaluation of influencer recommendations. The implications are that in some contexts, such as video games or television, virtual influencers might be more amenable to the target audience because they are either expected in those contexts, or might lead to positive expectancy violation because they have a higher product-fit. However, in other contexts where an artificial agent is not expected and human taste is required, firms may instead benefit from advertising with a human influencer. This is in line with expectancy violation theory that explains how a positive expectancy violation can lead to better outcomes than expectancy confirmation (Burgoon, 2016).

As with other advertisement forms, virtual influencers need to be able to elicit positive emotional experiences when consumers interact with their content. We show that emotional reactions appear in the first seconds of evaluating a post. Content should be thus highly immersive and facilitate quick judgments. Given that the reactions were immediate, virtual influencers' content needs to focus on trust-building mechanisms even more so than do human influencers. The advertised method for virtual influencers should furthermore fit as best as possible with the underlying message of the influencer, so as to keep self-perceived cognitive effort manageable. Hence, when virtual influencers are utilized, it becomes even more important that the message they provide is simple, easy to understand, and transparent. Another reason for the higher perceived effort with virtual influencers could be a lack of familiarity with virtual influencers that leads to higher distrust (Gefen et al., 2020; Miyake, 2023). Given that virtual influencers appeared first in 2016 (Moustakas et al., 2020), social media users may need more time to get more familiar with these agents in order to develop trust.

8.3 Limitations and Future Research

A major limitation of our research is that all three of our studies followed a similar design with identical, highly controlled stimuli. This helped ensure the integrity of our neurophysiological findings, as neuroimaging indicators are known to be highly sensitive to confounds such as differences in color, brightness, or experimental timing (Newman, 2019). Furthermore, our approach of complementing the neuroimaging studies with an online study helps overcome some of the limitations of these controls. However, it is still possible that the results do not generalize to other settings with, for example, brand own influencers for which past research found decreased engagement (Shen, 2024). Future work could therefore replicate this study and alter the design of the stimuli (e.g., branded virtual influencers or animated Instagram posts) to assess the ecological validity of our findings. Furthermore, given that our methodological approach was exploratory with relatively small samples, we suggest future research to validate our findings with larger and more diverse samples.

A second limitation is that while we abstracted some of our conclusions to artificial agents broadly, we only studied virtual influencers specifically, and in a way that did not explicitly manipulate other factors such as uncanniness, gender, and with stimuli that were highly controlled (i.e., black and white images of influencers presenting as women). The selection of virtual influencers brings numerous advantages, not least the fact that we can verify whether a particular agent is indeed artificial. However, such influencers are designed for fashion and beauty purposes, rather than political persuasion or disinformation. Additional studies can consider potential differences in context and employ stimuli that are specifically designed for persuasion for disinformation. Furthermore, future studies can investigate the interaction effects of the features of the stimuli themselves, such as gender, and its effects among the study population.

Finally, while we confirmed many of our hypotheses in Study 3, we did not observe a mediating effect of perceived cognitive effort on perceived (dis)trust. As previously discussed, we interpret this finding in support of past research which described differences between trust and distrust (Dimoka, 2010; Lewicki et al., 1998; McKnight & Chervany Norman, 2001). However, it is also possible that this finding is circumstantial. Replication of this finding is warranted before drawing firm conclusions about the differences between cognitive effort and *perceived* cognitive effort.

9 Conclusion

This study investigates antecedent mechanisms that give rise to virtual influencer evaluations of perceived uncanniness, trust, and intention to follow recommendations. We motivated this investigation by showing how research on this recent phenomenon suffers from abundant literature that tests a multitude of hypotheses without diving into the mechanisms that give rise to these evaluations in the first place. To address this gap, we conducted two neuroimaging studies to explore brain activation during virtual influencer perception. The identified brain activation for N400, LPP, and lPFC differed between human and virtual influencers. They were also correlated with self-report measures of uncanniness, trust, and intention to follow recommendations. By interpreting the neural results and their correlation with self-reports, we identified three key antecedents that seem to give rise to virtual influencer evaluations: i) expectancy violation, ii) emotion, and iii) cognitive effort. To validate their predictive impact on uncanniness, trust, and intention to follow recommendations, we tested their effects with mediation analyses in an online experiment. Results show that the interpretation of neural results hold true and reveal the significant predictive power of the identified antecedents. Against the lacking consideration of expectancy violation, emotion, and cognitive effort in the current state of research on virtual influencers, social media marketing, and conversational agents, we provide significant theoretical contribution to the field. Finally, our results can guide design theories for the creation of virtual influencer accounts and help companies to better evaluate the predictors for successful virtual influencer marketing.

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References

Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. *Machine Learning with Applications*, *2*(July), 100006.

Afifi, W. A., & Metts, S. (1998). Characteristics and Consequences of Expectation Violations in Close Relationships. *Journal of Social and Personal Relationships*, *15*(3), 365–392.

Afzal Khan, M. N., & Hong, K.-S. (2021). Most favorable stimulation duration in the sensorimotor cortex for fNIRS-based BCI. *Biomedical Optics Express*, *12*(10), 5939.

Ahn, R. J., Cho, S. Y., & Sunny Tsai, W. (2022). Demystifying Computer-Generated Imagery (CGI) Influencers: The Effect of Perceived Anthropomorphism and Social Presence on Brand Outcomes. *Journal of Interactive Advertising*, *22*(3), 327–335.

Alboqami, H. (2023). Trust me, I'm an influencer! - Causal recipes for customer trust in artificial intelligence influencers in the retail industry. *Journal of Retailing and Consumer Services*, *72*(December 2022), 103242.

Alimamy, S., & Kuhail, M. A. (2023). I will be with you Alexa! The impact of intelligent virtual assistant's authenticity and personalization on user reusage intentions. *Computers in Human Behavior*, 143(December 2022), 107711.

Allal-Chérif, O., Puertas, R., & Carracedo, P. (2024). Intelligent influencer marketing: how AI-powered virtual influencers outperform human influencers. *Technological Forecasting and Social Change*, 200(October 2023).

Allen, M. S., Iliescu, D., & Greiff, S. (2022). Single item measures in psychological science [Editorial]. *European Journal of Psychological Assessment*, 38(1), 1–5.

Almasri, Y. (2023). Fashion Virtual Influencers: Antecedents Influencing Females' Behavioral Intentions in Jordan. *Dirasat: Human and Social Sciences*, *50*(3), 390–402.

Aranyi, G., Pecune, F., Charles, F., Pelachaud, C., & Cavazza, M. (2016). Affective interaction with a virtual character through an fNIRS brain-computer interface. *Frontiers in Computational Neuroscience*, 10(JULY), 1–14.

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior*, *85*, 183–189.

Arsenyan, J., & Mirowska, A. (2021). Almost human? A comparative case study on the social media presence of virtual influencers. *International Journal of Human Computer Studies*, *155*(July), 102694.

Audrezet, A., & Koles, B. (2023). Virtual Influencers as a Brand Avatar in Interactive Marketing. In The palgrave handbook of interactive marketing (pp. 1–1048). Springer International Publishing.

Balapour, A., & Riedl, R. (2024). Ecological validity in neurois research: Theory, evidence, and a roadmap for future studies. *JAIS Preprints*, *153*.

Barari, M. (2023). Unveiling the dark side of influencer marketing: how social media influencers (human vs virtual) diminish followers' well-being. *Marketing Intelligence and Planning*, *41*(8), 1162–1177.

Barker, J. W., Aarabi, A., & Huppert, T. J. (2013). Autoregressive model based algorithm for correcting motion and serially correlated errors in fNIRS. *Biomedical Optics Express*, *4*(8), 1366.

Batist, A., & Chimenti, P. (2021). "Humanized Robots": A Proposition of Categories to Understand Virtual Influencers. *Australasian Journal of Information Systems*, *25*, 1–27.

Bavaresco, R., Silveira, D., Reis, E., Barbosa, J., Righi, R., Costa, C., Antunes, R., Gomes, M., Gatti, C., Vanzin, M., Junior, S. C., Silva, E., & Moreira, C. (2020). Conversational agents in business: A systematic literature review and future research directions. *Computer Science Review*, *36*, 100239.

Belanche, D., Casalo, L. V., Flavian, M., & Ibanez-Sanchez, S. (2021). Building influencers' credibility on Instagram: Effects on followers' attitudes and behavioral responses toward the influencer. *Journal of Retailing and Consumer Services*, *61*(June).

Bhattacherjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly*, *25*(3), 351–370.

Block, E., & Lovegrove, R. (2021). Discordant storytelling, 'honest fakery', identity peddling: How uncanny CGI characters are jamming public relations and influencer practices. *Public Relations Inquiry*, *00*(0), 1–29.

Boudewyn, M. A., Luck, S. J., Farrens, J. L., & Kappenman, E. S. (2018). How many trials does it take to get a significant ERP effect? It depends. *Psychophysiology*, *55*(6), 100–106.

Brigadoi, S., & Cooper, R. J. (2015). How short is short? Optimum source–detector distance for short-separation channels in functional near-infrared spectroscopy. Neurophotonics, 2(2), 1–9.

Bringé, A. (2022). The Rise Of Virtual Influencers And What It Means For Brands. *Forbes*.

Burgoon, J. K. (2016). Expectancy Violations Theory. In C. R. Berger & M. E. Roloff (Eds.), *The international encyclopedia of interpersonal communication* (pp. 1–9). John Wiley & Sons.

Burgoon, J. K., Bonito, J. A., Lowry, P. B., Humpherys, S. L., Moody, G. D., Gaskin, J. E., & Giboney, J. S. (2016). Application of Expectancy Violations Theory to communication with and judgments about embodied agents during a decision-making task. *International Journal of Human-Computer Studies*, *91*, 24–36.

Burgoon, J. K., & Jones, S. B. (1976). Toward a Theory of Personal Space Expectations and Their Violations. *Human Communication Research*, *2*(2), 131–146.

Burleigh, T. J., Schoenherr, J. R., & Lacroix, G. L. (2013). Does the uncanny valley exist? An empirical test of the relationship between eeriness and the human likeness of digitally created faces. *Computers in Human Behavior*, *29*(3), 759–771.

Carlén, M. (2017). What constitutes the prefrontal cortex? *Science*, *358*(6362), 478–482.

Castro, M. S., Bahli, B., Ferreira, J. J., & Figueiredo, R. (2023). Comparing Single-Item and Multi-Item Trust Scales: Insights for Assessing Trust in Project Leaders. *Behavioral Sciences*, 13(9).

Cenfetelli, R. T., & Bassellier, G. (2009). Interpretation of Formative Measurement in Information Systems Research. *MIS Quarterly*, *33*(4), 689–707.

Chandra, S., Shirish, A., & Srivastava, S. C. (2022). To Be or Not to Be ...Human? Theorizing the Role of Human-Like Competencies in Conversational Artificial Intelligence Agents. *Journal of Management Information Systems*, 39(4), 969–1005.

Chiu, C. L., & Ho, H. C. (2023). Impact of Celebrity, Micro-Celebrity, and Virtual Influencers on Chinese Gen Z's Purchase Intention Through Social Media. *SAGE Open*, *13*(1), 1–18.

Choudhry, A., Han, J., Xu, X., & Huang, Y. (2022). "I Felt a Little Crazy Following a 'Doll'": Investigating Real Influence of Virtual Influencers on Their Followers. *Proceedings of the ACM on Human-Computer Interaction*, 6(GROUP), 43:1–43:28.

Conrad, C. D., Aziz, J. R., Henneberry, J. M., & Newman, A. J. (2022). Do emotions influence safe browsing? toward an electroencephalography marker of affective responses to cybersecurity notifications. *Frontiers in Neuroscience*, 1176.

Cornelius, S., Leidner, D. E., & Bina, S. (2023). Significance of Visual Realism - Eeriness, Credibility, and Persuasiveness of Virtual Influencers. *Proceedings of the Annual* Hawaii

International Conference on System Sciences, 2023-January, 3421–3430.

Dabiran, E., Wang, F., & Farivar, S. (2022). Virtual Influencer Marketing: Anthropomorphism and Its Effect. *ECIS 2022 Research-in-Progress Papers*, 32.

Davidson, D. J. (2009). Functional mixed-effect models for electrophysiological responses. *Neurophysiology*, 41(1), 71–79.

de Boissieu, E., & Baudier, P. (2023). The perceived credibility of human-like social robots: virtual influencers in a luxury and multicultural context. *Journal of Organizational Change Management*, 36(7), 1163–1179.

de Guinea, A. O., & Markus, M. L. (2009). Why Break the Habit of a Lifetime? Rethinking the Roles of Intention, Habit, and Emotion in Continuing Information Technology Use. *MIS Quarterly*, *33*(3), 433–444.

de Brito Silva, M. J., de Oliveira Ramos Delfino, L., Alves Cerqueira, K., & de Oliveira Campos, P. (2022). Avatar marketing: a study on the engagement and authenticity of virtual influencers on Instagram. *Social Network Analysis and Mining*, *12*(1), 1–19.

De Castro Martins, C., Chaminade, T., & Cavazza, M. (2022). Causal Analysis of Activity in Social Brain Areas During Human-Agent Conversation. *Frontiers in Neuroergonomics*, 3(May), 1–13.

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1), 9–21.

Delpy, D. T., Cope, M., van der Zee, P., Arridge, S., Wray, S., & Wyatt, J. (1988). Estimation of optical pathlength through tissue from direct time of flight measurement. *Physics in Medicine and Biology*, *33*(12), 1433–1442.

Diamantopoulos, A., & Winklhofer, H. M. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research*, *38*(2), 269–277.

Diederich, S., Brendel, A. B., Morana, S., & Kolbe, L. (2022). On the Design of and Interaction with Conversational Agents: An Organizing and Assessing Review of Human-Computer Interaction Research. *Journal of the Association for Information Systems*, 23, 96–138.

Diel, A., & Lewis, M. (2024). Domain-general and -specific individual difference predictors of an uncanny valley and uncanniness effects. *Computers in Human Behavior:* Artificial Humans, 2(1), 100041.

Dimoka, A. (2010). What does the brain tell us about trust and distrust? Evidence from a functional neuroimaging study. *MIS Quarterly*, *34*(2), 373–396.

Dimoka, A., Pavlou, P. A., & Davis, F. D. (2011a). NeuroIS: The potential of cognitive neuroscience for information systems research. *Information Systems Research*, *22*(4), 687–702.

Dimoka, A., Pavlou, P. A., & Davis, F. D. (2011b). Research Commentary —NeuroIS: The Potential of Cognitive Neuroscience for Information Systems Research. *Information Systems Research*, *22*(4), 687–702.

Dolcos, F., Iordan, A. D., & Dolcos, S. (2011). Neural correlates of emotion - Cognition interactions: A review of evidence from brain imaging investigations. *Journal of Cognitive Psychology*, *23*(6), 669–694.

Dondapati, A., & Dehury, R. K. (2024). Virtual vs. Human influencers: The battle for consumer hearts and minds. *Computers in Human Behavior: Artificial Humans*, *2*(1), 100059.

Drenten, J., & Brooks, G. (2020). Celebrity 2.0: Lil Miquela and the rise of a virtual star system. *Feminist Media Studies*, *20*(8), 1319–1323.

El Hedhli, K., Zourrig, H., Al Khateeb, A., & Alnawas, I. (2023). Stereotyping human-like virtual influencers in retailing: Does warmth prevail over competence? *Journal of Retailing and Consumer Services*, *75*(April), 103459.

Fadel, K. J., Meservy, T. O., & Kirwan, C. B. (2022). Information Filtering in Electronic Networks of Practice: An fMRI Investigation of Expectation (Dis)confirmation. *Journal of the Association for Information Systems*, 23(2), 491–520.

Feine, J., Gnewuch, U., Morana, S., & Maedche, A. (2019). A Taxonomy of Social Cues for Conversational Agents. *International Journal of Human Computer Studies*, *132*(September 2018), 138–161.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39.

Franke, C., Groeppel-Klein, A., & Müller, K. (2023). Consumers’ Responses to Virtual Influencers as Advertising Endorsers: Novel and Effective or Uncanny and Deceiving? *Journal of Advertising*, *52*(4), 523–539.

Franklin, S., & Graesser, A. (1997). Is It an Agent, or Just a Program? A Taxomony of Autonomous Agents. *ECAI '96: Proceedings of the Workshop on Intelligent Agents* III, Agent Theories, Architectures, and Languages, 21–35.

Ganis, G., Kutas, M., & Sereno, M. I. (1996). The Search for Common Sense: An Electrophysiological Study of the Comprehension of Words and Pictures in Reading.

Journal of Cognitive Neuroscience, 8(2), 89–106.

Gefen, D., Ayaz, H., & Onaral, B. (2014). Applying Functional Near Infrared (fNIR) Spectroscopy to Enhance MIS Research. *AIS Transactions on Human-Computer Interaction*, *6*(3), 55–73.

Gefen, D., Fresneda, J. E., & Larsen, K. R. (2020). Trust and Distrust as Artifacts of Language: A Latent Semantic Approach to Studying Their Linguistic Correlates. *Frontiers in Psychology*, 11(March), 1–14.

Gerlich, M. (2023). The Power of Virtual Influencers: Impact on Consumer Behaviour and Attitudes in the Age of AI. *Administrative Sciences*, *13*(8).

Gnewuch, U., Morana, S., Adam, M. T., & Maedche, A. (2022). Opposing Effects of

Response Time in Human–Chatbot Interaction: The Moderating Role of Prior Experience. *Business and Information Systems Engineering*, *64*(6), 773–791.

Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Parkkonen, L., & Hämäläinen, M. S. (2014). MNE software for processing MEG and EEG data. *NeuroImage*, *86*, 446–460.

Grimes, G. M., Schuetzler, R. M., & Giboney, J. S. (2021). Mental models and expectation violations in conversational AI interactions. *Decision Support Systems*, *144*(June 2020), 113515.

Grimm, S., Schmidt, C. F., Bermpohl, F., Heinzel, A., Dahlem, Y., Wyss, M., Hell, D., Boesiger, P., Boeker, H., & Northoff, G. (2006). Segregated neural representation of distinct emotion dimensions in the prefrontal cortex - An fMRI study. *NeuroImage*, *30*(1), 325–340.

Hajcak, G., & Olvet, D. M. (2008). The persistence of attention to emotion: Brain potentials during and after picture presentation. *Emotion*, *8*(2), 250.

Ham, J., Li, S., Shah, P., & Eastin, M. S. (2023). The "Mixed" Reality of Virtual Brand Endorsers: Understanding the Effect of Brand Engagement and Social Cues on Technological Perceptions and Advertising Effectiveness. *Journal of Interactive Advertising*, *23*(2), 98–113.

Harmon, K. A., Lee, H., Khasraghi, B. J., Parmar, H. S., & Walden, E. A. (2024). Delays in Information Presentation Lead To Brain State Switching, Which Degrades User Performance, and There May Not Be Much We Can Do About It. *MIS Quarterly: Management Information Systems*, 48(1), 273–298.

Haugeland, I. K. F., Følstad, A., Taylor, C., & Alexander, C. (2022). Understanding the user experience of customer service chatbots: An experimental study of chatbot interaction design. *International Journal of Human Computer Studies*, *161*(January).

Hayes, A. F. (2017). Introduction to Mediation, Moderation, and Conditional Process Analysis, Second Edition: A Regression-Based Approach. Guilford Press.

Herrington, J. D., Mohanty, A., Koven, N. S., Fisher, J. E., Stewart, J. L., Banich, M. T., Webb, A. G., Miller, G. A., & Heller, W. (2005). Emotion-Modulated Performance and Activity in Left Dorsolateral Prefrontal Cortex. *Emotion*, *5*(2), 200–207.

Hofeditz, L., Erle, L., Timm, L., & Mirbabaie, M. (2023). How Virtuous are Virtual

Influencers? - A Qualitative Analysis of Virtual Actors' Virtues on Instagram. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 3411–3420.

Hofeditz, L., Nissen, A., Schütte, R., & Mirbabaie, M. (2022). Trust Me , I'M an Influencer! - a Comparison of Perceived Trust in Human and Virtual Influencers. *European Conference on Information Systems (ECIS)*, 1–11.

Huang, M., Ali, R., & Liao, J. (2017). The effect of user experience in online games on word of mouth: A pleasure-arousal-dominance (PAD) model perspective. *Computers in Human Behavior*, *75*, 329–338.

Huppert, T. (2016). Commentary on the statistical properties of noise and its implication on general linear models in functional near-infrared spectroscopy. *Neurophotonics*, *3*(1), 1–10.

Huppert, T., Hoge, R., Diamond, S., Franceschini, M., & Boas, D. (2006). A temporal comparison of BOLD, ASL, and NIRS hemodynamic responses to motor stimuli in adult humans. *NeuroImage*, *29*(2), 368–382.

Hyvärinen, A. (1999). Fast and Robust Fixed-Point Algorithms for Independent Component Analysis. *IEEE Transactions on Neural Networks*, *10*(3), 626 634.

Jas, M., Engemann, D. A., Bekhti, Y., Raimondo, F., & Gramfort, A. (2017). Autoreject: Automated artifact rejection for MEG and EEG data. *NeuroImage*, *159*, 417–429.

Jiménez-Castillo, D., & Sánchez-Fernández, R. (2019). The role of digital influencers in brand recommendation: Examining their impact on engagement, expected value and purchase intention. *International Journal of Information Management*, *49*, 366–376.

Kim, D. Y., & Kim, H. Y. (2021). Trust me, trust me not: A nuanced view of influencer marketing on social media. *Journal of Business Research*, *134*, 223–232.

Kim, D., & Wang, Z. (2023). The ethics of virtuality: navigating the complexities of human-like virtual influencers in the social media marketing realm. *Frontiers in Communication*, *8*.

Kim, E., Kim, D., Zihang, E., & Shoenberger, H. (2023). The next hype in social media advertising: Examining virtual influencers' brand endorsement effectiveness. *Frontiers in Psychology*, 14(February), 1–7.

Kim, H., & Park, M. (2023). Virtual influencers' attractiveness effect on purchase intention: A moderated mediation model of the Product–Endorser fit with the brand. *Computers in Human Behavior*, *143*(February 2022).

Kim, M., & Baek, T. H. (2023). Are Virtual Influencers Friends or Foes? Uncovering the Perceived Creepiness and Authenticity of Virtual Influencers in Social Media Marketing in the United States. *International Journal of Human–Computer Interaction*, *0*(0), 1–14.

Kirwan, C. B., Vance, A., Jenkins, J. L., & Anderson, B. B. (2023). Embracing brain and behaviour: Designing programs of complementary neurophysiological and behavioural studies. *Information Systems Journal*, *33*(2), 324–349.

Kocsis, L., Herman, P., & Eke, A. (2006). The modified Beer–Lambert law revisited. *Physics in Medicine and Biology*, 51(5), N91–N98.

Konya-Baumbach, E., Biller, M., & von Janda, S. (2023). Someone out there? A study on the social presence of anthropomorphized chatbots. *Computers in Human Behavior*, *139*(October 2022), 107513.

Krach, S., Hegel, F., Wrede, B., Sagerer, G., Binkofski, F., & Kircher, T. (2008). Can machines think? Interaction and perspective taking with robots investigated via fMRI. *PLoS ONE*, *3*(7).

Kutas, M., & Federmeier, K. D. (2011). Thirty Years and Counting: Finding Meaning in the N400 Component of the Event-Related Brain Potential (ERP). *Annual Review of Psychology*, *62*(1), 621 647.

Kyriakopoulou, K., & Nowland, R. (2017). Should I trust you? Neural processing of unconscious influences on trustworthiness judgements. *BNA 2017 Festival of Neuroscience: Abstract Book, 1, Session 1 Monday 10th April, Poster number: P-M011*, 0-1.

Lakhiwal, A., Bala, H., & Léger, P. M. (2023). Ambivalence Is Better than Indifference: A Behavioral and Neurophysiological Assessment of Ambivalence in Online Environments. *MIS Quarterly*, *47*(2), 705–732.

Lebovitz, S., Levina, N., & Lifshitz-Assaf, H. (2021). Is AI ground truth really true? The dangers of training and evaluating AI tools based on experts' know-what. *MIS Quarterly*, *45*(3), 1501–1525.

Lee, H. S., Sun, P. C., Chen, T. S., & Jhu, Y. J. (2015). The effects of avatar on trust and purchase intention of female online consumer: Consumer knowledge as a moderator. *International Journal of Electronic Commerce Studies*, 6(1), 99–118.

Leung, F. F., Gu, F. F., & Palmatier, R. W. (2022). Online influencer marketing. *Journal of the Academy of Marketing Science*, *50*(2), 226–251.

Levkov, N., Santa, M., & Kitanovikj, B. (2023). Exploring Virtual Influencers' Potential to Reduce Reduce Interethnic Intolerance in Online Youth Communication. *European Conference on Information Systems (ECIS)*, 1–11.

Lewicki, R. J., McAllister, D. J., & Bies, R. J. (1998). Trust and Distrust: New Relationships and Realities. *Academy of Management Review*, *23*(3), 438–458.

Li, H., Lei, Y., Zhou, Q., & Yuan, H. (2023a). Can you sense without being human? Comparing virtual and human influencers endorsement effectiveness. *Journal of Retailing and Consumer Services*, 75(June), 103456.

Li, M., Guo, F., Wang, X., Chen, J., & Ham, J. (2023b). Effects of robot gaze and voice human-likeness on users' subjective perception, visual attention, and cerebral activity in voice conversations. *Computers in Human Behavior*, *141*(195), 107645.

Lindgaard, G., Fernandes, G., Dudek, C., & Brown, J. (2006). Attention web designers: You have 50 milliseconds to make a good first impression! *Behaviour & Information Technology*, *25*(2), 115–126.

Liu, F., & Lee, Y. H. (2024). Virtually responsible? Attribution of responsibility toward human vs.

virtual influencers and the mediating role of mind perception. *Journal of Retailing and Consumer Services*, *77*(November 2023), 103685.

Lou, C., Kiew, S. T. J., Chen, T., Lee, T. Y. M., Ong, J. E. C., & Phua, Z. X. (2023). Authentically Fake? How Consumers Respond to the Influence of Virtual Influencers. *Journal of Advertising*, *52*(4), 540–557.

Lu, L., McDonald, C., Kelleher, T., Lee, S., Chung, Y. J., Mueller, S., Vielledent, M., & Yue, C. A. (2022). Measuring consumer-perceived humanness of online organizational agents. *Computers in Human Behavior*, *128*(October 2021), 107092.

Luck, S. J. (2014). An Intorduction to the Event-Related Potential Technique (2nd ed.). MIT Press.

Luck, S. J., & Gaspelin, N. (2017). How to get statistically significant effects in any ERP experiment (and why you shouldn't). *Psychophysiology*, *54*(1), 146–157.

Lutz, B., Adam, M. T., Feuerriegel, S., Pröllochs, N., & Neumann, D. (2023). Affective Information Processing of Fake News: Evidence from NeuroIS. *European Journal of Information Systems*, *00*(00), 1–20.

MacDorman, K. F., Green, R. D., Ho, C.-C., & Koch, C. T. (2009). Too real for comfort? Uncanny responses to computer generated faces. *Computers in Human Behavior*, *25*(3), 695–710.

Marzi, T., Righi, S., Ottonello, S., Cincotta, M., & Viggiano, M. P. (2014). Trust at first sight: Evidence from ERPs. *Social Cognitive and Affective Neuroscience*, *9*(1), 63–72.

Mathur, M. B., & Reichling, D. B. (2016). Navigating a social world with robot partners: A quantitative cartography of the Uncanny Valley. *Cognition*, *146*, 22–32.

McKnight, D. H., & Chervany Norman, L. (2001). Trust and distrust definitions: One bite at a time. *Lecture Notes in Artificial Intelligence (Subseries of Lecture Notes in Computer Science)*, *2246*, 27–54.

Meng, L., Bie, Y., Yang, M., & Wang, Y. (2024). Watching it motivates me to become stronger: Virtual influencers' impact on consumer self-improvement product preferences. *Journal of Business Research*, *178*(April), 114654.

Mirowska, A., & Arsenyan, J. (2023). Sweet escape: The role of empathy in social media engagement with human versus virtual influencers. *International Journal of Human Computer Studies*, *174*(May 2022), 103008.

Miyake, E. (2023). I am a virtual girl from Tokyo: Virtual influencers, digital-orientalism and the (Im)materiality of race and gender. *Journal of Consumer Culture*, *23*(1), 209–228.

Mori, M. (1970). The uncanny valley. *Energy*, *7*(4), 33–35.

Mori, M., MacDorman, K. F., & Kageki, N. (2012). The uncanny valley. *IEEE Robotics and Automation Magazine*, *19*(2), 98–100.

Moustakas, E., Lamba, N., Mahmoud, D., & Ranganathan, C. (2020). Blurring lines between fiction and reality: Perspectives of experts on marketing effectiveness of virtual influencers. *International Conference on Cyber Security and Protection of Digital Services, Cyber Security* 2020.

Müller-Putz, G. R., Riedl, R., Wriessenegger, S., & Wriessnegger, S. C. (2015). Electroencephalography (EEG) as a research tool in the information systems discipline: Foundations, measurement, and applications. *Communications of the Association for Information Systems*, *37*(1), 911–948.

Muniz, F., Stewart, K., & Magalhães, L. (2023). Are they humans or are they robots? The effect of virtual influencer disclosure on brand trust. *Journal of Consumer Behaviour*, (August), 1–17.

Mustafa, M., Guthe, S., Tauscher, J. P., Goesele, M., & Magnor, M. (2017). How human am I? EEG-based evaluation of animated virtual characters. *Conference on Human Factors in Computing Systems - Proceedings*, 2017-May, 5098–5108.

Mustafa, M., & Magnor, M. (2016). EEG based analysis of the perception of computer-generated faces. *ACM International Conference Proceeding Series*.

Newman, A. (2019). Research Methods for Cognitive Neuroscience. SAGE Publications.

Nightingale, S. J., & Farid, H. (2022). AI-synthesized faces are indistinguishable from real faces and more trustworthy. *Proceedings of the National Academy of Sciences of the United States of America*, 119(8), 2–4.

Nissen, A., & Jahn, K. (2021). Between Anthropomorphism, Trust, and the Uncanny Valley: A Dual-Processing Perspective on Perceived Trustworthiness and Its Mediating Effects on Use Intentions of Social Robots. *Proceedings of the 54th Hawaii International Conference on System Sciences*, 360–369.

Nunnally, J. (1978). *Psychometric Theory* (2nd ed.). McGraw-Hill.

Oberhofer, V. M., Seeber, I., & Maier, R. (2023). Human-Robot Interaction: Mapping Literature Review and Network Analysis. *Proceedings of the 56th Hawaii International Conference on System Sciences*, *4*, 481–490.

Oliver, R. L. (1980). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*, *17*(4), 460.

Ozdemir, O., Kolfal, B., Messinger, P. R., & Rizvi, S. (2023). Human or virtual: How influencer type shapes brand attitudes. *Computers in Human Behavior*, *145*(March), 107771.

Pastor, M. C., Bradley, M. M., Löw, A., Versace, F., Moltó, J., & Lang, P. J. (2008). Affective picture perception: Emotion, context, and the late positive potential. *Brain research*, 1189, 145–151.

Platter, D. (2023). How Virtual Influencers Can Mean Real Sales. *Forbes Communications Council*.

Poldrack, R. A. (2006). Can cognitive processes be inferred from neuroimaging data? *Trends in Cognitive Sciences*, 10(2), 59–63.

Postmes, T., Haslam, S. A., & Jans, L. (2013). A single-item measure of social identification: Reliability, validity, and utility. *British Journal of Social Psychology*, *52*(4), 597–617.

Proverbio, A. M., Gabaro, V., Orlandi, A., & Zani, A. (2015). Semantic brain areas are involved in gesture comprehension: An electrical neuroimaging study. *Brain and Language*, *147*(100), 30 40.

Qiu, L., & Benbasat, I. (2005). Online consumer trust and live help interfaces: The effects of text-to-speech voice and three-dimensional avatars. *International Journal of Human-Computer Interaction*, *19*(1), 75–94.

Qu, Y., & Baek, E. (2023). Let virtual creatures stay virtual: tactics to increase trust in virtual influencers. *Journal of Research in Interactive Marketing*.

Rapp, A., Curti, L., & Boldi, A. (2021). The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots. *International Journal of Human Computer Studies*, 151(March), 102630.

Reeck, C., Guo, X., Dimoka, A., & Pavlou, P. A. (2024). Uncovering the Neural Processes of Privacy: A Neurally Informed Behavioral Intervention to Protect Information Privacy. *Information Systems Research*, *35*(2), 727–746.

Riedl, R., Davis, F. D., Banker, R., & Kenning, P. H. (2017). *Lecture notes in information systems and organization*. Springer.

Riedl, R., Hubert, M., & Kenning, P. (2010). Are There Neural Gender Differences in Online Trust? An fMRI Study on the Perceived Trustworthiness of eBay Offers. *MIS Quarterly*, *34*(2), 397–428.

Riedl, R., Mohr, P., Kenning, P., Davis, F., & Heekeren, H. (2014). Trusting humans and avatars: A brain imaging study based on evolution theory. *Journal of Management Information Systems*, *30*(4), 83–114.

Robinson, B. (2020). Towards an ontology and ethics of virtual influencers. *Australasian Journal of Information Systems*, 24, 1–8.

Rosenthal-Von der Pütten, A. M., Krämer, N. C., Maderwald, S., Brand, M., & Grabenhorst, F. (2019). Neural mechanisms for accepting and rejecting artificial social partners in the uncanny valley. *Journal of Neuroscience*, *39*(33), 6555–6570.

Rzepka, C., Berger, B., & Hess, T. (2022). Voice Assistant vs. Chatbot – Examining the Fit Between Conversational Agents' Interaction Modalities and Information Search Tasks. *Information Systems Frontiers*, *24*(3), 839–856.

Saager, R. B., & Berger, A. J. (2005). Direct characterization and removal of interfering absorption trends in two-layer turbid media. *Journal of the Optical Society of America A*, *22*(9), 1874.

Sakuma, H., Hori, A., Murashita, M., Kondo, C., & Hijikata, Y. (2023). YouTubers vs. VTubers: Persuasiveness of human and virtual presenters in promotional videos. *Frontiers in Computer Science*, 5.

Sands, S., Campbell, C. L., Plangger, K., & Ferraro, C. (2022a). Unreal influence: leveraging AI in influencer marketing. *European Journal of Marketing*, *56*(6), 1721–1747.

Sands, S., Ferraro, C., Demsar, V., & Chandler, G. (2022b). False idols: Unpacking the opportunities and challenges of falsity in the context of virtual influencers. *Business Horizons*, *65*(6), 777–788.

Santosa, H., Zhai, X., Fishburn, F., & Huppert, T. (2018). The NIRS Brain AnalyzIR toolbox. *Algorithms*, *11*(5).

Sato, H., Yahata, N., Funane, T., Takizawa, R., Katura, T., Atsumori, H., Nishimura, Y., Kinoshita, A., Kiguchi, M., Koizumi, H., Fukuda, M., & Kasai, K. (2013). A NIRS-fMRI investigation of prefrontal cortex activity during a working memory task. *NeuroImage*, *83*, 158–73.

Schanke, S., Burtch, G., & Ray, G. (2021). Estimating the impact of “humanizing” customer service chatbots. *Information Systems Research*, *32*(3), 736–751.

Schindler, S., Zell, E., Botsch, M., & Kissler, J. (2017). Differential effects of face-realism and emotion on event-related brain potentials and their implications for the uncanny valley theory. *Scientific Reports*, *7*(February), 1–13.

Scholkmann, F., Kleiser, S., Metz, A. J., Zimmermann, R., Mata Pavia, J., Wolf, U., & Wolf, M. (2014). A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology. *NeuroImage*, *85*, 6–27.

Schreiner, M., Fischer, T., & Riedl, R. (2021). Impact of content characteristics and emotion on behavioral engagement in social media: literature review and research agenda. *Electronic Commerce Research*, *21*(2), 329–345.

Seymour, M., Yuan, L., Dennis, A., & Riemer, K. (2020). Facing the Artificial: Understanding Affinity, Trustworthiness, and Preference for More Realistic Digital Humans. *Proceedings of the 53rd Hawaii International Conference on System Sciences*, *3*, 4673–4683.

Seymour, M., Yuan, L., Dennis, A. R., & Riemer, K. (2021). Have we crossed the uncanny valley? Understanding affinity, trustworthiness, and preference for realistic digital humans in immersive environments. *Journal of the Association for Information Systems*, *22*(3), 591–617.

Shen, Z. (2024). Shall brands create their own virtual influencers? A comprehensive study of 33 virtual influencers on Instagram. *Humanities and Social Sciences Communications*, 11(1), 1–14.

Shin, M., Kim, S. J., & Biocca, F. (2019). The uncanny valley: No need for any further judgments when an avatar looks eerie. *Computers in Human Behavior*, *94*, 100–109.

Sollfrank, T., Kohnen, O., Hilfiker, P., Kegel, L. C., Jokeit, H., Brugger, P., Loertscher, M. L., Rey, A., Mersch, D., Sternagel, J., Weber, M., & Grunwald, T. (2021). The Effects of Dynamic and Static Emotional Facial Expressions of Humans and Their Avatars on the EEG: An ERP and ERD/ERS Study. *Frontiers in Neuroscience*, *15*(April), 1–14.

Šoškić, A., Jovanović, V., Styles, S. J., Kappenman, E. S., & Ković, V. (2021). How to do Better N400 Studies: Reproducibility, Consistency and Adherence to Research Standards in the Existing Literature. *Neuropsychology Review*.

Tinwell, A., Grimshaw, M., Nabi, D. A., & Williams, A. (2011). Facial expression of emotion and perception of the Uncanny Valley in virtual characters. *Computers in Human Behavior*, *27*(2), 741–749.

Tinwell, A., & Sloan, R. J. (2014). Children’s perception of uncanny human-like virtual characters. *Computers in Human Behavior*, *36*, 286–296.

Tremblay, A., & Newman, A. J. (2015). Modeling nonlinear relationships in ERP data using mixed-effects regression with R examples. *Psychophysiology*, *52*(1), 124–139.

Tuch, A. N., Presslaber, E. E., Stöcklin, M., Opwis, K., & Bargas-Avila, J. A. (2012). The role of visual complexity and prototypicality regarding first impression of websites: Working towards understanding aesthetic judgments. *International Journal of Human Computer Studies*, *70*(11), 794–811.

Um, N. (2023). Predictors Affecting Effects of Virtual Influencer Advertising among College Students. *Sustainability* (Switzerland), 15(8).

Vaiciukynaite, E. (2019). Men or Women? Neuro-Marketing study of social media influencers. *Proceedings of the 6th European Conference on Social Media, ECSM 2019*, (June), 280–287.

Vassena, E., Gerrits, R., Demanet, J., Verguts, T., & Siugzdaite, R. (2019). Anticipation of a mentally effortful task recruits Dorsolateral Prefrontal Cortex: An fNIRS validation study. *Neuropsychologia*, *123*(March 2018), 106–115.

vom Brocke, J., Riedl, R., & Léger, P.-M. (2013). Application Strategies for Neuroscience in Information Systems Design Science Research. *Journal of Computer Information Systems*, *53*(3), 1–13.

Waizenegger, L., Seeber, I., Dawson, G., & Desouza, K. C. (2020). Conversational agents Exploring generative mechanisms and second-hand effects of actualized technology affordances. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 5180–5189.

Wang & Benbasat. (2009). Interactive Decision Aids for Consumer Decision Making in E-Commerce: The Influence of Perceived Strategy Restrictiveness. *MIS Quarterly*, *33*(2), 293.

Wang, M.-Y., Lu, F.-M., Hu, Z., Zhang, J., & Yuan, Z. (2018). Optical mapping of prefrontal brain connectivity and activation during emotion anticipation. *Behavioural Brain Research*, 350, 122–128.

Wang, S., Pang, M.-S., & Pavlou, P. (2022). Seeing Is Believing? How Including a Video in Fake News

Influences Users' Reporting of Fake News to Social Media Platforms. *MIS Quarterly*, *45*(3), 1323–1354.

Wang, Y., & Quadflieg, S. (2014). In our own image? Emotional and neural processing differences when observing human-human vs human-robot interactions. *Social Cognitive and Affective Neuroscience*, *10*(11), 1515–1524.

Wooldridge, M., & Jennings, N. R. (1995). Intelligent agents: theory and practice. *The Knowledge Engineering Review*, 10(2), 115–152.

Xie-Carson, L., Benckendorff, P., & Hughes, K. (2023). Keep it #Unreal: Exploring Instagram Users' Engagement With Virtual Influencers in Tourism Contexts User engagement with virtual influencers. *Journal of Hospitality and Tourism Research*.

Xie-Carson, L., Magor, T., Benckendorff, P., & Hughes, K. (2023). All hype or the real deal? Investigating user engagement with virtual influencers in tourism. *Tourism Management*, *99*(April), 104779.

Yang, J., Chuenterawong, P., Lee, H., & Chock, T. M. (2023a). Anthropomorphism in CSR Endorsement: A Comparative Study on Humanlike vs. Cartoonlike Virtual Influencers' Climate Change Messaging. *Journal of Promotion Management*, *29*(5), 705–734.

Yang, J., Chuenterawong, P., Lee, H., Tian, Y., & Chock, T. M. (2023b). Human versus Virtual Influencer: The Effect of Humanness and Interactivity on Persuasive CSR Messaging. *Journal of Interactive Advertising*, *23*(3), 275–292.

Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C., & Wager, T. D. (2011). Large-scale automated synthesis of human functional neuroimaging data. *Nature Methods*, *8*(8), 665–670.

Yorgancigil, E., Yildirim, F., Urgen, B. A., & Erdogan, S. B. (2022). An Exploratory Analysis of the Neural Correlates of Human-Robot Interactions With Functional Near Infrared Spectroscopy. *Frontiers in Human Neuroscience*, *16*(July), 1–12.

You, S., & Robert, L. P. (2018). Emotional attachment, performance, and viability in teams collaborating with embodied physical action (EPA) robots. *Journal of the Association for Information Systems*, *19*(5), 377–407.

Yücel, M. A., Selb, J., Aasted, C. M., Lin, P.-Y., Borsook, D., Becerra, L., & Boas, D. A. (2016). Mayer waves reduce the accuracy of estimated hemodynamic response functions in functional near-infrared spectroscopy. *Biomedical Optics Express*, *7*(8), 3078.

Zhang, Y., Du, D., & Ge, J. (2023). When Virtual Influencers are Used as Endorsers: Will Match-Up and Attractiveness Affect Consumer Purchase Intention? (Vol. 14038 LNCS). Springer Nature Switzerland.

Zhao, T., Ran, Y., Wu, B., Lynette Wang, V., Zhou, L., & Lu Wang, C. (2024). Virtual versus human: Unraveling consumer reactions to service failures through influencer types. *Journal of Business Research*, *178*(May), 114657.

Zhou, L., & Xue, F. (2021). Show products or show people: an eye-tracking study of visual branding strategy on Instagram. *Journal of Research in Interactive Marketing*, *15*(4), 729–749.

Zhou, Q., Li, B., Li, H., & Lei, Y. (2024a). Mere copycat? The effects of human versus human-like virtual influencers on brand endorsement effectiveness: A moderated serial-mediation model. *Journal of Retailing and Consumer Services*, *76*(April 2023), 103610.

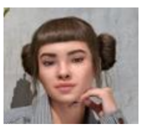
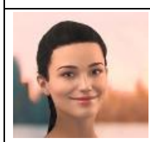
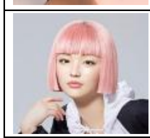
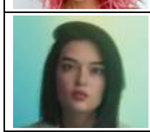
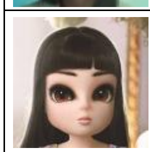
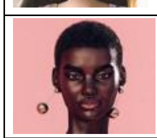
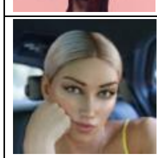
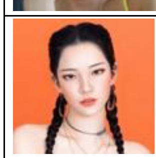
Zhou, X., Yan, X., & Jiang, Y. (2024b). EXPRESS: Making Sense? The Sensory-Specific Nature of Virtual Influencer Effectiveness. *Journal of Marketing*.

Zijlmans, E. A., Tijmstra, J., van der Ark, L. A., & Sijtsma, K. (2018). Item-Score Reliability in Empirical-Data Sets and Its Relationship With Other Item Indices. *Educational and Psychological Measurement*, 78(6), 998–1020.

Appendix A: Top 15 Virtual Influencers on Instagram as of 2024

The top 15 list of female virtual influencers with high human-likeness was created based on synthesizing the lists from seven top listed blog websites. These websites used metrics such as number of followers, user engagement (i.e., like, commments, shares), content quality, and advertisement cooperations. The virtual influencers are presented in order of the number of followers they have on Instagram. Please note that the depicted annual revenue are estimations we derived from several websites. Given that these are no validated numbers from official revenue statements of the media companies that run the virtual influencer profiles, these numbers must be treated with caution.

Table A1. Top 15 Virtual Influencers on Instagram as of 2024

Influencer photo	**Influencer name**	**Followers (on 8/16/24)**	**Social media platforms**	**Est. Annual revenue**	**Marketing cooperations**	**Country**
	Lu du Magalu*	7.1M	Instagram, Youtube	$16,200,000.00	Running partnerships with Samsung, Microsoft, and Intel Past cooperations with Vogue and L'Oreal	Brasil
	Lil Miquela*	2.6M	Instagram, TikTok	$11,000,000.00	Past and running cooperations with Prada, Calvin Klein, Alexander McQueen, Hugo Boss, BMW, Red Bull Primarily collaborates with fashion brands.	US
	Leya Love*	555k	Instagram	$150,000.00	No collaborations, goal is to advocate sustainability	Planet Earth
	Imma gram*	389k	Instagram	$147,000.00	Collaborations with Coach, Apple, Guess and more.	Japan
	Aitana Lopez	325k	Instagram	$40,000.00	Cooperation with Nike and smaller spanish brands	Spain
	Kyra	265k	Instagram	$200,000.00	Collaborates with technology companies, L'Oreal India, and Indian cricket.	India
	Noonouri*	247k	Instagram	$2,600,000.00	Primarily topics of haute couture, NFTs, Metaverse Cooperations with Versace and Warner Bros, among others.	Germany/ France
	Shudu gram*	239k	Instagram	$96,000.00	Luxury fashion brands like Versace, Lanvin, and Vogue and more.	US
	Bermuda*	228k	Instagram	$440,000.00	n/a	US
	Rozy*	170k	Instagram	$2,000,000.00	Collaborations with Cider, and most with Korean fashion brands.	South Korea

Note: * also included in the studies in this paper, the other accounts were started on Instagram during the time of data collection for Study 1.

Appendix B: Study 3: Reliability and Validity of Included Measures

The items of all constructs were shown in randomized order. All of the used items, the composite reliability (CR) of scales and the average variance extracted (AVE) are shown in Table B1. All reflective indicators reached the conventional thresholds of $CR >= .8$ and $AVE > .5$ (Fornell & Larcker, 1981; Nunnally, 1978). Expectancy violation was measured as formative indicator along the dimensions of the violation itself (ExpVio), the valence of the violation (ExpVal), and the impact of the violation on certainty in behavior prediction (ExpCer). The correlations between items (ExpVio, ExpVal, ExpCer) ranged between $.211 < r < .400$, all of which are smaller than the suggested threshold of $r = .70$ and thereby showing sufficient low correlation in the formative measure. Further, the variance inflation factor (VIF) is below the threshold of 3.33 for expectancy violation (Cenfetelli & Bassellier, 2009; Diamantopoulos & Winklhofer, 2001). Therefore, multicollinearity is not present in this indicator. The item-rest correlations of all included items are > .3 and therefore have sufficient internal consistency to be kept in the analysis (Nunnally, 1978; Zijlmans et al., 2018).

Table B1. Questionnaire Items for Study 3

Item	Question	Item-rest correlation
Expectancy Violation (CR = .629, AVE = .339)		
Exp1	I completely expected this (type of) influencer and post.	.367
Exp2	I'd like to see more posts of this influencer.	.35
Exp3	*This type of influencer and post surprised me a great deal.*	*removed*
Exp4	This influencer made me feel a lot more confident in my predictions of her future behavior.	.504
Emotion (CR = .901, AVE = .647)		
PL1	I feel joyful when looking at this influencer post.	.806
PL2	Looking at this influencer post gives me pleasure.	.829
PL3	I feel gratified when looking at this influencer post.	.789
AR1	I think looking at this influencer post is very exciting.	.775
AR2	Looking at this influencer post makes me feel very aroused.	.563
Perceived Effort (CR =.873 , AVE = .696)		
PE1	It took too much time to form an impression of the influencer.	.762
PE2	Forming an impression about the shown influencer required too much effort.	.757
PE3	Forming an impression about the shown influencer was too complex.	.749
Perceived Trust (CR = .864, AVE = .615)		
Trust1	The influencer can be relied upon on her content.	.683
Trust2	I believe what this influencer says and that she would not try to take advantage of the followers.	.747
Trust3	The influencer is straightforward and honest even though her self-interests are involved	.735
Trust4	The influencer would not tell a lie even if she could gain by it.	.684
Perceived Distrust (CR = .838, AVE= .632)		
Distrust1	I feel cautious about characterizing this influencer as honest.	.732
Distrust2	I am worried that this influencer would not be truthful in her posts with me.	.714
Distrust3	It is uncertain whether this influencer would keep her promises and commitments.	.65

Perceived Uncanniness (CR = .893, AVE = .68)		
Uncanny1	I perceived the influencer as eerie.	.797
Uncanny2	I perceived the influencer as inhuman-like.	.753
Uncanny3	I perceived the influencer as strange.	.826
Uncanny4	I perceived the influencer as unappealing.	.664
Perceived Humanlikeness		
HL1	The shown influencer is a human being.	
Intention to Follow Recommendations (CR = .94, AVE = .841)		
Use1	I would purchase a brand product based on the advice I am given by the shown influencers.	.855
Use2	I would follow brand recommendations from the shown influencers.	.864
Use3	In the future, I would purchase the products of brands recommended by the shown influencers.	.902
Note: CR = Composite Reliability, AVE = Average Variance Extracted		

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