Are You Human? Investigating the Perceptions and Evaluations of Virtual Versus Human Instagram Influencers

Anika Nissen
University of Duisburg-Essen
Essen, NRW, Germany
anika.nissen@icb.uni-due.de

Colin Conrad
Dalhousie University
Halifax, Nova Scotia, Canada
colin.conrad@dal.ca

Aaron Newman
Dalhousie University
Halifax, Nova Scotia, Canada
aaron.newman@dal.ca

ABSTRACT

Virtual influencers (VI) are on the rise on Instagram, and companies increasingly cooperate with them for marketing campaigns. This has motivated an increasing number of studies, which investigate our perceptions of these influencers. Most studies propose that VI are often rated lower in perceived trust and higher in uncanniness. Yet, we still lack a deeper understanding as to why this is the case. We conduct 2 studies: 1) a questionnaire with 150 participants to get the general perception for the included influencers, and 2) an electroencephalography (EEG) study to get insights into the underlying neural mechanisms of influencer perception. Our results support findings from related works regarding lower trust and higher uncanniness associated with VI. Interestingly, the EEG components N400 and LPP did not modulate perceived trust, but rather perceived humanness, uncanniness, and intentions to follow recommendations. This provides a fruitful beginning for future research on virtual humans.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

virtual influencers, avatars, social media, trust, uncanny, EEG

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1 INTRODUCTION

Can you tell whether your favorite Instagram influencer is a real person? Driven by increasing computational power and advances in artificial intelligence (AI), it is increasingly common to encounter AI synthesized media such as images, audio, and video [41, 71, 94]. This development has lead to the rise of virtual humans and deepfakes that are largely indistinguishable from actual humans [71]. Today, actual human users and virtual humans interact in a range of ways, from the passive creation and consumption of image or video contents (e.g., on social media), to interactive exchanges using complex simulations (e.g., in medical operations) [93]. Virtual humans can also be found on e-commerce websites, where the placement of avatars in chatbots can increase the perceived trust of the website [6, 49]. Unsurprisingly, there is an increasing trend of social media influencers that are virtual humans, which have been referred to as "virtual influencers" [68]. Such influencers can range from obviously non-human anime characters on YouTube [52], to highly human-like Instagram celebrities such as Lil'Miquela[1] and shudu.gram[2] [68].

Virtual influencers have also created new opportunities for marketers. For instance, Lil'Miquela and shudu.gram, have been contracted for marketing campaigns by high-value, international brands such as Prada and Calvin Klein [12]. As a result, researchers have increasingly focused on how consumers and users perceive these influencers in social media context [14, 33, 40]. Research that has been conducted to date often draws on works related to social robots and avatars, often concerning constructs such as perceived trust, uncanniness, and behavioral intentions towards a virtual influencer [2, 4, 19, 73]. Many of these works assumed that higher human-likeness in the design of social robots and virtual humans does not always lead to higher perceived trust and approach intentions [35, 58, 72]. This is often justified by the uncanny valley effect, which states that trust and positive perception of agents increase with human-likeness until a certain tipping point at which they significantly decrease and therewith, enter a valley [58, 65, 66]. Only when human-likeness is indistinguishable from real humans, the ratings of trustworthiness and positive perception are thought to increase again [58, 65, 66]. In this context, this effect shows that when perceived uncanniness of a virtual human is rated high by users, positive affect and perceived trust are typically rated low.

Yet, the prior named examples of Lil'Miquela and shudu.gram are designed to resemble real humans as closely as possible, suggesting that there is a trend towards designing virtual influencers that become indistinguishable from real humans. Prior work that focused on the reactions of users to human-like virtual influencers show that while they pose a fascinating phenomenon, they are often perceived as uncanny [2], which may also result in lower perceived trust [33, 85]. Still, there remains some debate about why the uncanny valley effect occurs. Some studies suggest that it is the result of a decision conflict as measured by more pronounced neural activity in the human brain [86, 100]. Some have reasoned that this decision conflict is due to a virtual human being originally expected to be human, but on second guess is identified as

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[1] https://www.instagram.com/lilmiquela/
[2] https://www.instagram.com/shudu.gram/

a computer-generated entity, which is perturbing [79]. One study that compared the processing of human versus computer-generated avatar faces identified increased positive emotional processing for human rather than computer-generated faces [80]. The authors investigated this in relation to perceived trust and approach intention, where increased emotional processing in the brain was positively associated with higher perceived trust and approach intentions [80].

While these studies provide promising insights into how we perceive and process virtual humans and suggest a neurophysiological explanation of uncanniness, empirical investigations into the neurophysiological phenomena are still scarce. Some work focused on the uncanny valley effect of social robots [86, 100], others on clearly computer-generated avatars on websites [80], animated virtual humans [69], or computer-generated faces in relation to the uncanny valley [70]. However, all of these studies have in common that the presented virtual humans were directly identifiable as such, and not like deepfakes which might lead to even higher trust perceptions as real humans [71]. We are thus led to question whether the results from these related works generalize to contexts where virtual humans take on the role of Instagram influencers. As virtual influencers, they are designed as deepfakes and may not always be distinguishable from real humans - they may have crossed the uncanny valley proposed in related literature. Furthermore, as some virtual influencers do not disclose themselves as such on Instagram, it is questionable whether users are actually able to distinguish them from real human influencers in image posts, and whether the effects of perceived higher uncanniness and lower trust will still hold true for virtual influencers.

When considering this high human-likeness from an ethical perspective, several concerns may be raised which make it even more important to investigate this phenomenon empirically. Given that some of the virtual influencers do not disclose themselves as artificial, questions arise concerning the values that they represent, their accountability, and about who takes responsibility for their actions [76, 81]. As suggested by prior findings from Nightingale and Farid [71], higher trust in deepfakes might lead to belief in disinformation, which may lead to manipulating decision-making [20]. In such cases, it is difficult to define who is held accountable, and how this will impact general online trust in the long run. Instagram is especially used as a platform to shape perceptions of consumers through means of influencer marketing [88]. Therefore, our research goal is to investigate the perceived trust and uncanniness, behavioral intentions, as well as underlying neural mechanism of highly human-like virtual compared to human Instagram influencers.

To achieve this goal, we conduct two studies: *i)* a questionnaire distributed to 150 participants to get a general impression of the sentiment of social media users about the presented virtual compared to human influencers, and *ii)* an electroencephalography (EEG) neuroimaging experiment in which the Instagram posts from the questionnaire are once again investigated to receive insights in the neural mechanisms which lead to the self-reported perceptions of the influencers. We hypothesized that participants would express decreased reported perceived trust and increased reported uncanniness when presented with images of virtual influencers. We also predicted the that event-related potentials (ERPs; consistent EEG responses time-locked to stimuli) elicited by virtual influencers would differ from those elicited by human influencers. Specifically, based on prior findings related to EEG patterns, uncanniness and virtual humans, we predicted that virtual influencers would elicit increased electrical amplitude in the central region of the scalp 300-500 ms following a picture of a virtual influencer, as well as 600-1200 ms following the onset of the image.

Our findings ultimately contribute further knowledge to the social human-robot interaction (HRI) and human-computer interaction (HCI) literature that focuses on social robots, avatars, and virtual humans. Additionally, we also contribute to social media research with focus on how users perceive created content both on a behavioral and a neural level in dependence of the content creator's nature (i.e., human vs. virtual influencer). The results of this work therefore inform both theory and practice, as we add further insights into the neural mechanisms of virtual human perception, as well as provide further insights into virtual influencers as potential marketing channels for companies.

2 RELATED LITERATURE

2.1 Instagram Influencers

Influencers in social media are generally defined as a person who is perceived as popular and has a high amount of followers on a common social media platform [103]. Influencers often "exhibit their personal life through posts to many followers and influence their follower's attitudes and engagement behaviour," especially on the Instagram platform [98]. It has also been suggested that influencers with a higher number of followers are perceived as more likeable, which often leads to perceiving them as opinion leaders [16, 36]. The role of social media influencer has also become kind of a profession for many people, as companies seek to pay influencers for promoting their products, which has in turn lead to an increase of influencer accounts. While this proliferation offers a high range of alternatives for companies that wish to incorporate influencer marketing in their strategy, it also makes it difficult for companies to select the best fitting partners for their campaigns [1]. This has raised questions about how to actually determine the efficiency of marketing through social media influencers [103].

A number of studies have thus been conducted to develop measures of how well influencers promote and advertise a product [1, 103]. Works have considered characteristics of the influencers themselves such as their number of followers, their engagement with their followers, and cooperation with other influencers. For example, one study found that higher numbers of followers and posts was negatively associated with the engagement of the influencers with their followers [95]. Another study identified that specialized influencers who are experts in a specific field (e.g., sports, beauty/cosmetics, or fashion) seem to have generally better engagement for their related product categories, with beauty/cosmetics influencers reaching the highest engagement for product posts [83].

In addition to content, several other factors also impact the success of influencers. For instance, there is evidence which suggests that the physical and social attractiveness, as well as the self-presence of influencers (which is their follower's perception of presence on the social media platform) seems to foster engagement by establishing parasocial relationships between followers and influencers [22]. Another important factor which determines the willingness to view, like, repost, or interact with an influencer's content is the construct of perceived trust. Studies show that increased perceived trust fosters a more positive attitude and greater purchase intention of users towards the presented products and recommendations of the influencers [5, 31, 75]. Furthermore, the prior described follower count can also positively impact the perceived trust of the influencer and the resulting purchase intentions [101]. Given that trust is primarily a social construct, the perceived credibility of the influencer as well as the established parasocial relationships were found to lead to most positive perceptions of influencers and their recommendations [88]. Further studies add that good storytelling throughout posts and stories on Instagram help to establish parasocial relationships, which are further most effective for fostering purchase intentions [21, 23].

While these findings target the behavior and effects of human influencers on Instagram, an increasing number of influencers appeared during the last years that are not human but generated artificially (i.e., virtual influencers). Given that this is a new phenomenon, studies to date have focused on whether and how these virtual influencers are perceived differently from real human ones [14, 33, 85]. Findings to date suggest that virtual influencers are perceived significantly less trustworthy than human influencers [85]. However, examples such as Lil'Miquela show that it is possible for a virtual influencer to establish user engagement and evoke word-of-mouth distribution which is assumed to be due to good storytelling [7, 85]. With the increasing possibilities in AI, virtual influencers are becoming increasingly similar to real humans with regards to visual human-likeness, which leads to users not being able to reliably distinguish virtual from real humans in still image Instagram posts anymore [33]. This raises not only ethical questions [76, 81], but also whether the perceptions of virtual and real humans may be the same when users are not able to reliably identify them as real or not. One study found that images of deepfakes may be rated even higher in perceived trust than those of real humans [71].

This said, the majority of works which focused on the reactions of users to human-like virtual influencers show that while they pose a fascinating phenomenon, they are often perceived as uncanny [2], which results in lower perceived trust [33, 85]. Building on these conclusions, some experts have called for an investigation of the actual effectiveness and perceptions of users of virtual influencers to identify whether they can actually be applied in a company's marketing strategy [68]. This endeavor is becoming increasingly important as companies increasingly use virtual influencers to market their products, even though the perceived trust of users is lower for these influencers [12]. This makes us question whether the often-utilized construct of perceived trust is the appropriate measure for investigating these phenomena. In the following sections, we take a closer look at the concepts of trust and uncanniness, in an effort to better establish theoretical foundations of this research.

2.2 Trust and Uncanniness in Real vs. Virtual Humans

In addition to the literature on virtual influencers on social media, there are application fields for virtual humans such as in educational medical simulations [93], recommender systems on tourism websites [59], or avatars on e-commerce websites broadly [51]. Much of the research on this topic concerns the impacts of trust and the cognitive processes involved in processing information that leads to trust in avatars, such as perceived uncanniness. The actual effects of such applications on user experience were found to be significantly affected by the facial characteristics of the avatars that are deployed in the various contexts [91, 102]. In cases where avatar faces are animated or shown as a larger image, it has to be considered that virtual humans may have subtle facial expressions that have emotional cues, and that they can lead to increased perceived uncanniness [45], and thus, decreased perceived trust.

Studies on trust and uncanniness related to virtual humans and virtual influencers are present in several application fields beyond Instagram such as chatbots on websites or physical assistant robots [35, 56, 58, 72, 90]. These studies have consistently found that uncanniness and trust play a role in shaping our attitudes towards the virtual and robotic agents. Other studies have found that social judgments such as perceived trust are often made based on the visual appearance and human-likeness of the virtual human [91, 105]. For instance, one study shows that the facial width-to-height ratio of the displayed avatar in an online shop significantly impacts the perceived warmth and perceived trust of the whole shop [102]. As a result, there is emerging literature related to perceived trust in virtual humans which provides guidelines on how to foster trust in the technology [11].

But what can actually be understood as trust? Many technology researchers have defined trust in terms of the formation of trusting beliefs [26, 43, 62], which stem from an individual's evaluation of an agent's attributes (e.g., the prior described human-likeness) [43]. Generally, trust in humans and trust in technology rely on different criteria [48, 61]: while humans are typically evaluated along the dimensions of competence, benevolence, and integrity, technology is evaluated along the dimensions of functionality, helpfulness, and reliability. The dimensions used for technology resemble what traditional technology scholarship McKnight et al. [62] understood as cognitive trust. However, research has since found that trust is not only of cognitive nature, but that trusting beliefs of competence, benevolence, and integrity come with an emotional component that incorporate feelings of security and comfort [26, 43], and that these also count for trust in technology, and not only in humans. In this line, it is argued that "the emotion in emotional trust refers to the trustor's feeling toward the behavior of relying on the trustee" [43, p. 944].

In recent years, there has been an increasing emphasis on a more interpersonal perspective in HCI and HRI research [8, 44, 99], emphasizing a conception of trust that depends on warmth and affect, rather than just on perceived competence [9, 24, 60]. This is supported in a study where the cognitive and emotional trust in an avatar on an e-commerce website was investigated in its impact on purchase intentions [49]. The results of this study revealed that the impact of emotional trust in the avatar on purchase intentions was higher than that of cognitive trust [49].

Human-likeness has been conceptualized as a design factor that elicits more emotional warmth and thus, higher perceived trust and more positive affective reactions [17, 32, 66]. Yet, increased human-likeness also raises the potential uncanny valley effect [65, 66]. In an investigation of robotic to computer-generated to human faces, Mathur and Reichling [57] show that there is a significant negative relationship between uncanniness and positive affect (i.e., likeability), and a negative relationship between uncanniness and perceived trust. Reasons for why a high but not "perfect" human-like design leads to decreased likeability and perceived trust may be found in a lack of conformity to norms [79], because the agent first appears to be human although it is not. This explanation is supported in neuroscientific findings, which reveal that robots that are perceived as highly uncanny elicit neural activity associated with decision conflicts [86]. As a result, a neural investigation of virtual influencers on Instagram might give us more insights into what may be the cause for perceived uncanniness, and associated decreased trust in virtual influencers.

2.3 Towards Potential Neural Mechanisms in EEG of Virtual Influencer Perception

As previously discussed, there have been some neural investigations into social robots, avatars, and virtual humans. These works show how the addition of neuroimaging can help to advice insight about user's reactions that lead to an uncanny valley effect or antecedents to trust formation towards virtual influencers. In studies that employ functional magnetic resonance imaging (fMRI), higher human-like social robots consistently led to higher medial prefrontal cortex (mPFC) activation than lesser human-like robots [10, 64, 82]. In this vein, it was shown that mPFC activation may signal a non-linear function between increasing human-likeness and the associated likeability of the agent, thus reflecting the uncanny valley effect [82]. When comparing the images of real humans and computer-generated faces as avatars, the mPFC also shows activation differences. In this case, the activation of the mPFC was greater for real humans [80]. The authors identified that this was also associated with higher perceived trust, and feelings of social belonging to the human rather than the human-like avatar [80]. As a result, the mPFC may be a key structure that modulates perceptions leading to an uncanny valley effect.

Besides fMRI, electroencephalography (EEG) has also been employed to examine the relationship between trust, uncanniness, and affective processing. For example, one study demonstrated that both computer-generated avatars and humans can trigger empathic processing, as expressed by the suppression of alpha waves, when they express being in pain [39]. Other EEG studies have identified relevant event-related potentials (ERPs; consistent EEG responses time-locked to stimuli), that are associated with perceived trust and uncanniness, pertinent to the study of virtual influencers: the N400 and the LPP.

Researchers have reported negative potentials that onset between 300-500 ms after stimulation as N400, which may be relevant to understand the perception of virtual influencers. The N400 is a well-established component often observed with semantic mismatch in language (e.g. "I take my coffee with milk and dog") and is thought to reflect a conflict between expectations defined by prior semantic context, and an incoming stimulus [46]. The N400 is not only elicited by linguistic stimuli, but it is also seen for semantic mismatches created by pictures [25] or gestures [78]. Recent work has demonstrated that the N400 is also sensitive to emotional facial expressions [50, 67, 104], with larger N400s to emotional expressions that do not match with a context.

Given the association of the N400 with general mismatch between expectations based on context and presented reality, it seems plausible that the N400 is connected to perceived uncanniness. In closely related finding, Mustafa and colleagues associated a larger amplitude of the N400 component with increased uncanniness of virtual characters [69, 70]. Therefore, it may provide an indicator for perceived uncanniness in virtual influencers as well.

The late positive potential (LPP) is a distinct pattern that can be observed starting around 600 ms following the onset of a stimulus. Similarly to the N400, the LPP is well-studied in the context of emotional processing, and has been established to be associated with attentional mechanisms that are triggered with the processing of emotion-inducing images [30, 74]. Much of the research on the LPP has found that EEG amplitudes in the central-parietal regions of the scalp are elevated when participants observe either positive or negative valence images with high degrees of reported arousal, as compared to neutral stimuli [13, 53, 74]. This pattern has been observed in a wide variety of image contexts ranging from smoking advertising [63] to images of cybersecurity notifications [13]. With regard to virtual humans, the LPP seems to be sensitive to the processing of human and virtual avatars in both neutral as well as negative emotional conditions [89]. LPP amplitude has been observed being lower for virtual avatars as compared to humans, independent of the expressed emotion [89]. This suggests that the LPP is sensitive to the human-likeness level independent of the emotional expression of the agent. This is further supported by another study which found that the LPP amplitude has a positive linear relationship with human-likeness of the face (i.e., the LPP is lower for less realistic faces and higher for real faces) [87]. In the context of the prior discussed trust in virtual influencers, the LPP may also be an indicator of perceived trust. That is, two studies found that the LPP signal seems to be higher for trustworthy faces compared to less trustworthy faces [47, 55].

Given that virtual influencers are often found to be rated lower with perceived trust and higher with uncanniness, this leads to the assumption that the LPP might be higher for human compared to virtual influencers, and that it may modulate perceptions of trust and approach intentions. That is, in line with a higher LPP for human and trustworthy faces, the LPP also seems to be higher in situations which are expectancy-confirming in a given social context [77]. In this regard, the LPP seems to provide an indicator for behavioral intentions as it seems to be larger when congruous actions are performed as responses to emotional stimuli, e.g., approaching pleasant stimuli [3, 106]. As a result, modulation of the LPP might not only reflect the perceived trust of influencers, but may also provide an indicator for approach intentions towards the influencers.

Based on this brief overview of related literature, we hypothesized that we would observe a more negative amplitude in the central regions of the scalp between the 300 ms and 500 ms in response to images of virtual influencers, which is expected to be associated to higher uncanniness. The N400 often provides an indicator for a mismatch between expectation and actual information given, which in our case would be influencers that on first sight are expected to be human, although they are computer-generated. We also hypothesized that we would observe an increased positive amplitude in the central regions of the scalp between 600 ms and

1200 ms in response to images of human influencers, corresponding to the LPP. The hypothesized LPP response would be triggered by higher degrees of positive valence and arousal towards human images, which could be related to the perceived trust and humanness of the influencers. Further, the LPP might also provide an indicator for approach intentions towards influencers, such as intention to follow their recommendations, which is assumed to be higher for human influencers.

To develop insights into how a broader number of users perceived virtual influencers on Instagram with regard to the identified constructs of perceived trust, uncanniness, and behavioral intentions, we first employed a questionnaire in study 1. Our goal with this study was to provide a larger sample size than could be feasibly obtained in an EEG study. This allowed us to detect potential smaller effects in the questionnaire data, to verify the selected stimuli and scales for study 2, and to run both within- and between-subjects analyses. By cross-referencing the results of both studies, we can be more confident that the EEG results are the product of the mechanisms discovered in the behavioral differences observed. The neural mechanisms discussed in this section are then investigated in study 2 with a smaller sample, and compared to the results gained from the larger sample in study 1.

3 STUDY 1: BEHAVIORAL STUDY

3.1 Method

3.1.1 Participants. The survey was distributed through the Prolific platform to a total of 150 adult participants. One questionnaire was not filled out completely and was excluded from analysis, giving a sample size of $N = 149$ participants. The majority of the sample reported their sex as female (71.8%), with the remaining participants being male (26.8%), non-binary (0.7%), or preferred not to state their sex (0.7%). Average age of the sample is $M = 37.1$ years ($SD = 12.9, Min = 19, Max = 71$). Regarding their education level, about 13.4% have a postgraduate University degree, the majority of the sample holds a University's bachelor degree (43.0%), followed by a college or post-secondary certificate (29.5%), high school or GED (13.4%), and below high school or GED (0.7%).

Given that we investigated the perceptions of Instagram influencers, we asked about their Instagram use. Most of the participants stated that they use Instagram several times per day (40.9%), some of the participants use it even several times per hour (4.0%). The remaining participants stated that they only use it several times per week (27.8%), per month (8.7%), or even less frequent than on a monthly basis (21.5%). Almost half of the sample reported following fewer than 5 influencer accounts on Instagram (47.0%) while 7.4% of the sample reported following more than 5 influencer accounts, 15.4% reported more than 10, 17.4% reported more than 50, and 12.8% stated that they followed more than 100 influencers on Instagram. Regarding the use of different Instagram functions, the majority of the sample reported scrolling the feed every time they open Instagram (64.9%), almost half of the sample also looked at User Stories (47.7%). Other activities such as looking at user profiles, liking or commenting on posts, or writing personal messages through the chat are done by most participants on a less frequent basis. Few reported creating content each time they use Instagram (6.8%). As a final step, we also asked participants about their perception of influencer's impact on them [38]. The self-rated influence was slightly below the 5-point scale average at $M = 2.41$ ($SD = 0.94$). As a result, most participants do consume content created by influencers, however, they believe themselves not to be influenced by it.

All methods were approved by the Dalhousie 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.

3.1.2 Stimuli and Procedure. Stimuli consisted of a collection of 20 images which were manually selected and extracted from Instagram. Ten of the stimuli were from different accounts which self-identified as virtual influencers, and ten that were identified by the research team as likely human. The human influencer stimuli were selected in order to accurately match the dominant colors, poses, and backgrounds of the individual virtual influencer images as closely as possible. To avoid perceived differences due to differently used colors, all posts were presented in black and white to control for color effects. We also calculated the average brightness of each image and ran one-way ANOVA between the two conditions to control for brightness balance between the conditions. Figure 1 illustrates the images used both in this study 1, and also in study 2.

Upon opening the questionnaire, participants were first asked for their informed consent and then welcomed to the research topic of Instagram influencers. After that, they were randomly shown a series of Instagram posts and asked whether they knew the shown influencer or not. To keep the duration of the study reasonable, each participant was presented with a random sequence of 5 human and 5 virtual influencers, selected from the 20 possible stimuli pseudorandomly to ensure even sampling of all stimuli. Upon being shown each Instagram post, participants were asked to rate the perceived trust [42], uncanniness [96], as well as the intention to follow recommendations of the influencer [38], using prior validated multi-item measures with a 5-point Likert scale from 1 = I totally disagree to 5 = I totally agree. Finally, we asked participants to rate perceived humanness of the influencers from 0 (not at all) to 100 (totally) to get a more fine-grained idea of participant's perceptions (humanness question with original scale from [57]).

Participants were sequentially presented with a series of the posts from the 20 different influencers. Given that rating all 20 posts would be too straining for the participants, we randomly selected 5 human influencer posts and 5 virtual influencer posts for each participant. This resulted in an average of $N = 75$ answers for each of the included posts.

Following the presentation of the images, participants were asked for demographic information, as well as their typical Instagram use behavior (reported under Participants). Overall, the whole survey took about 15 minutes to complete, and participants received a compensation of £3.00 for their time.

3.2 Results

We checked whether participants knew the shown influencers or not. Results of a Kruskal-Wallis test show that the majority of the sample was not familiar with the shown influencers, and that there

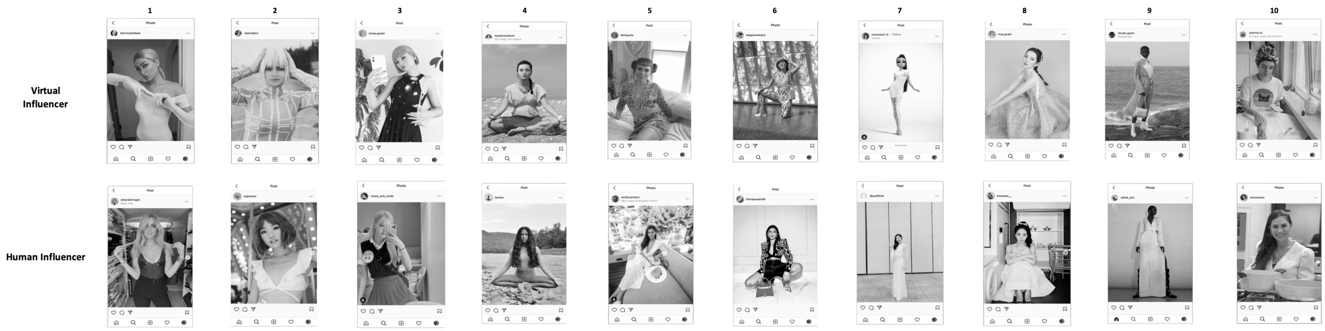

Figure 1: Stimuli observed in both Study 1 and Study 2

were also no significant differences in the familiarity with the included human versus the virtual influencers ($\chi^2(1) = 0.523, p = .469$). Given the structure of the questionnaire, we used linear mixed-effects (LME) models to analyze each of the self-reported data of the measured constructs of perceived trust, uncanniness, and intention to follow recommendations. The model used the influencer type (human, virtual) as fixed effect, and included random intercepts for each participant. We described the significance of our results using the Bonferroni-Holm correction to account for multiple comparisons.

The results show significantly different fixed effects between virtual versus human influencers in all of the included constructs. The virtual influencers were rated significantly lower in perceived trust ($\beta = -0.337$, $t(1340) = -10.4$, $p_{Holm} < .001$), intention to follow recommendations ($\beta = -0.337$, $t(1340) = -10.4$, $p_{Holm} < .001$), and humanness ($\beta = -33.8$, $t(1340) = -24.8$, $p_{Holm} < .001$). On the other hand, virtual influencers were rated significantly higher in perceived uncanniness compared to the included human influencers ($\beta = 1.10$, $t(1340) = 21.6$, $p_{Holm} < .001$).

4 STUDY 2: EEG STUDY

4.1 Method

4.1.1 Participants. For the EEG experiment, 22 participants were recruited from our University population. The sex of the participants were nearly balanced (54.5% female, 45.5% male) and average age was $M = 28.2$ years ($SD = 9.37, Min = 18, Max = 49$). Handedness of the sample showed that the majority was right-handed (2 were left-handed, $LQ = 75.9$). Almost half of the sample has a postgraduate degree at University level (45.5%), with the remaining having either a bachelor's degree (31.8%) or a high school/ GED education level (22.7%).

Regarding their Instagram use, 72.7% reported using the app several times per day. Some participants suggested they use it several times per week (9.1%), or at least once per month (4.5%), and some participants use it less than monthly (13.6%). 22.7% claim that they 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. The general self-rated disposition towards influencers indicating how much participants value and rely on recommendations made by influencers is on the lower medium of the 5-point Likert scale ($M = 2.61, SD = 0.746$).

All methods were approved by Dalhousie 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.

4.1.2 Study Design and Procedure. We employed the same image stimuli as described in Study 1. To begin, 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 of CAD $20, the participant was asked to fill out a questionnaire including the same demographic and Instagram use behavior questions as described in Study 1. In addition, we also assessed the handedness of participants, using the laterality quotient (LQ) [27, 84].

After participants finished the 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 electrooculograms (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 s 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 humanness ("The shown influencer is a human."), each on a 5-point Likert scale from 1 = I totally disagree to 5 = I totally agree. A fixation cross jittered between 2-3 s was then presented, after which followed the next trial. Trials proceeded in random order until each Instagram post was shown with each question, resulting in each post being shown 4 times to the participants. As we are interested in the condition “influencer type” (10 virtual, 10 human), and not in the individual

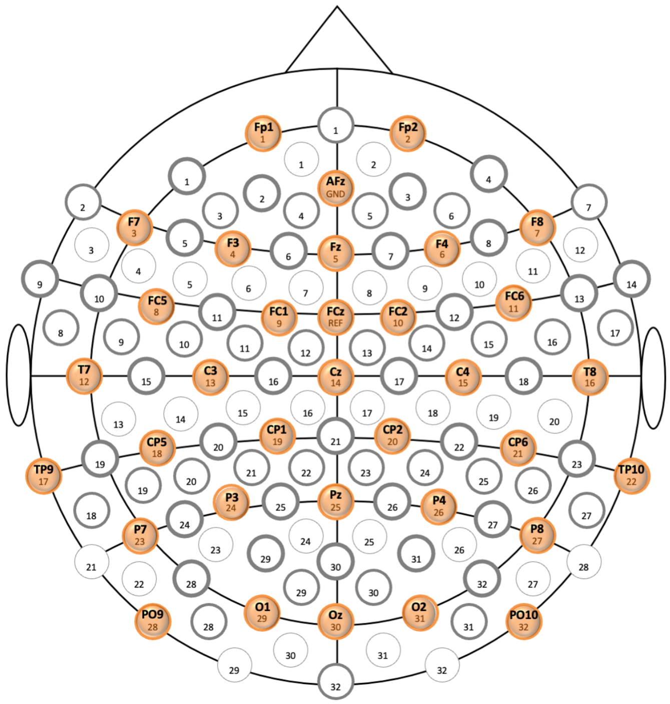

Figure 2: 32-channel EEG montage

influencers, this design resulted in 40 repetitions per condition (i.e., 4 questions per 10 virtual influencers). This procedure lasted about 15-20 minutes, following which the EEG cap was removed from the participant. They were then debriefed on the study by thanking them for their participation and showing which of the presented influencers was human and which was virtual.

4.1.3 *Data Preprocessing and Analyses.*

Behavioral Data. The behavioral data from the self-reported perceived trust, uncanniness, and intention to follow recommendations were each analyzed using LME models, using the influencer types as a fixed effect, and the intercepts per participant as random effects.

EEG Data. To import the data into the MNE Python library [28, 29] for preprocessing and analysis, the raw data were converted from the ASAlab to the EEGlab format [18]. Data were preprocessed using functions in the *MNE* (v. 0.23.0) and *autoreject* (v. 0.2.2; [37]) Python libraries using an automated script run in a Jupyter notebook. The first series of steps was performed to apply independent components analysis (ICA) to identify and remove ocular artifacts. For this, the continuous EEG data were bandpass filtered from 1-40 Hz, then segmented into contiguous 1 s epochs. These were passed through the *ransac* routine in *autoreject* to identify and mark any bad channels to be ignored by ICA. ICA was then fit to the data using the *fastica* algorithm [34] with a stopping criterion of explaining 99.5% of the variance in the data. Independent components containing ocular artifacts were identified automatically using an adaptive algorithm that started by identifying any components whose correlation with either EOG channel exceeded $z > 3.0$, and stepped down this threshold in 0.2 increments until at least two components were identified as correlated with the EOG channels (based on the expectation that all participants would exhibit some blinks and horizontal eye movements during the study). Visualizations of the ICA components for each participant were also saved as image files and manually inspected after the first run of the preprocessing script by the author with the most experience using ICA with EEG. If any additional components were manually identified which appeared artifactual, they were noted and added to the script for removal and the preprocessing script was run again. This helped ensure that the manual process did not miss any significant ocular artifacts that could contaminate the data; additional components were manually removed in this manner for 12 participants.

Following ICA, components flagged as artifactual were marked as such. The raw data were then filtered using a 0.1-40 Hz bandpass and segmented timelocked to the onset of each Instagram post image, from 200 ms prior to onset to 2000 ms post (the entire duration of the stimulation). Any channels identified as bad earlier in the preprocessing stream were also marked as such in these epochs, and then the ICA decomposition was applied to remove the artifactual components from the data. Data from any bad channels was then repaced using spherical spline interpolation, and then the *autoreject* algorithm was used to identify and remove any trials containing residual excessive noise. Finally, the segments were re-referenced to the mastoids (electrodes TP9 and TP10) and saved for visualization and analysis.

To analyze the EEG data on a group level, the mean amplitude was computed for each trial and electrode between 300 − 500 ms post stimulus onset for the N400 component, and between 600 − 1200 ms for the LPP. In accordance to utilized electrodes and scalp locations in related literature, we used the electrodes at Cz, CP1, CP2, and Pz for both the LPP [13, 54] and the N400 [92]. Data of the selected electrodes were analyzed on a group level using LME [15, 97], with the influencer type (human, virtual) treated as a fixed effect. The random intercepts for participants, random slopes for electrode by participant, as well as random slopes for influencer by participant, were taken into account as random effects.

4.2 Results

4.2.1 *Behavioral Results.* We find significant effects in all of the included self-reported constructs. The virtual influencers were rated significantly lower in perceived trust ($\beta = -1.3$, $t(21) = -10.1$, $p_{Holm} < .001$), humanness ($\beta = -1.96$, $t(21) = -12.4$, $p_{Holm} < .001$), and intention to follow recommendations ($\beta = -1.00$, $t(21) = -8.35$, $p_{Holm} < .001$). Virtual influencers were also rated significantly higher in perceived uncanniness compared to human influencers ($\beta = 1.4$, $t(21) = 8.69$, $p_{Holm} < .001$).

The histograms in Figure 3 show the distribution of the self-reported ratings for each of the conditions. While there is some overlap between virtual and human influencer, we can also see some significant differences in the distributions. In accordance to the LME results presented above, virtual influencers were much more often rated with 1 as answer to perceived trust, humanness, and intention to follow their recommendations. For uncanniness, a lot more participants rated virtual influencers with 5 as being uncanny.

4.2.2 EEG Results. The EEG waveforms for each condition are plotted at the midline electrodes in Figure 4. The waveform over the occipital lobe (electrode Oz) shows the expected P1-N1-P2 complex characteristic of visual stimulus onset. The ERP responses to human and virtual influencers is highly similar for the first few hundred milliseconds, and begins to diverge around 400 ms with more positive amplitude for human influencers, and 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 in Figure 4).

These differences are highlighted in the difference wave shown in Figure 5, created by subtracting the virtual influencer waveform from the human influencer one, and averaged across the electrodes in our ROI. The scalp topographical maps in Figure 6 confirm that this effect was maximal over the electrodes in and around our chosen ROI.

The timing and scalp topography of this difference is consistent with both the predicted N400 and LPP effects. For the N400, we predicted greater negativity for virtual than human influencers over the vertex from approximately 300–600 ms; the direction of the subtraction here (human-virtual) makes this difference appear positive but a greater positivity for humans corresponds to a greater negativity for virtual influencers. The results are consistent with the LPP insofar as the effect is, as predicted, more positive for human influencers from 600–1200 ms over the vertex. The results of LME modeling confirmed these observations. The N400 was analyzed over the electrodes in the ROI from 300–500 ms, where electrical potential was significantly more negative in response to virtual than human influencers ($\beta = -1.13$, $t = -2.46$, $p = .014$). In the LPP time window (600–1200 ms), the signal was significantly more positive for human compared to virtual influencers ($\beta = -1.244$, $t = -2.40$, $p = .016$).

4.2.3 Integrated Behavioral and EEG Results. To better understand the relationship between the self-reported behavioral data and the

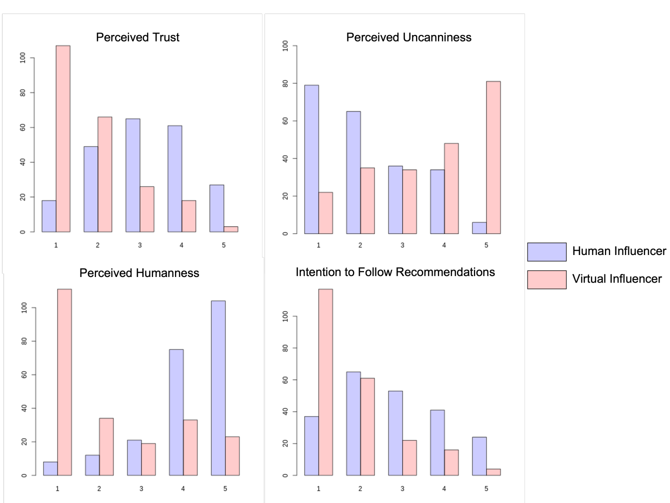

Figure 3: Histograms of the Self-reported Ratings of Virtual and Human Influencer

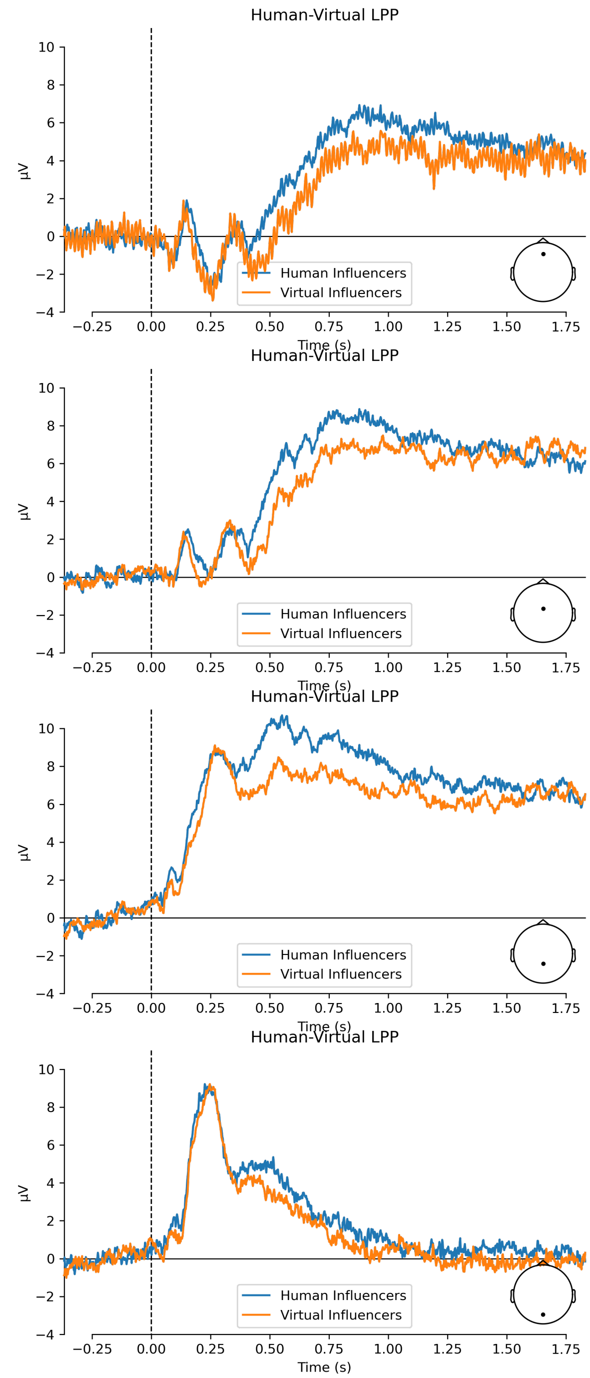

Figure 4: EEG grand average amplitudes at electrodes Fz, Cz, Pz, Oz for conditions

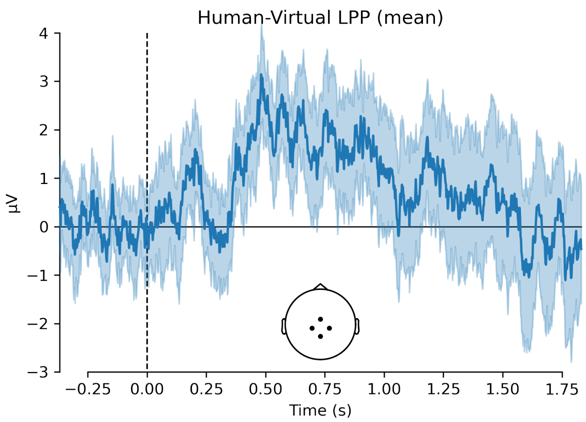

Figure 5: EEG grand average amplitudes at electrodes Cz, CP1, CP2, Pz for conditions

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, humanness, and intention to follow recommendations. That is, for each component (N400 and LPP), we ran four 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 ($\beta = 0.694$, $t = 3.41$, $p < .001$, $p_{Holm} = .003$). ERP amplitude in the N400 time window might be positively related to ratings of perceived humanness ($\beta = 0.339$, $t = 2.3$, $p = .021$, $p_{Holm} = .064$), as well as negatively to uncanniness ($\beta = -0.334$, $t = -2.05$, $p = .04$, $p_{Holm} = .08$) of influencers (i.e. greater negativity at the N400 window for higher uncanny ratings). A note of caution needs to be taken here, as after correcting p for multiple comparisons, both relationships to humanness and uncanniness are only marginally significant ($.05 < p_{Holm} < .10$). However, it does not seem to be related to ratings of perceived trust of influencers ($\beta = 0.248$, $t = 1.26$, $p_{Holm} = .208$).

Similar to the N400 results, the results of the LME models with the LPP data show a significant positive association between LPP and intentions to follow the influencer's recommendations ($\beta = 0.704$, $t = 3.06$, $p = .002$, $p_{Holm} = .009$). Further, a positive relationship between the LPP and self-rated perceived humanness of the influencers was also found, yet it does not hold true after correcting for multiple comparisons ($\beta = 0.33$, $t = 1.98$, $p = .048$, $p_{Holm} = .144$). 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 ($\beta = -0.277$, $t = -1.24$, $p_{Holm} = .302$). Finally, also the LPP does not seem to be related to perceived trust ratings of influencers ($\beta = 0.318$, $t = 1.44$, $p_{Holm} = .302$).

5 DISCUSSION

We observed consistent self-reported responses in the questionnaires towards virtual and human influencers in the two studies. In both studies, the participants rated the virtual influencers with lower humanness and greater uncanniness than the human influencers. We also observed a consistently lower perceived trust among the virtual influencer stimuli, as well as a lower intention to follow recommendations. These findings demonstrate that human observers are sensitive to differences in Instagram posts between human and virtual influencers. Our behavioral results are consistent with past literature on virtual influencers which suggest that virtual influencers exhibit greater uncanniness and lower perceived trust when compared to human influencers [2, 33, 85]. In a broader context, the findings support results from literature on virtual humans [56, 58], avatars [80], and social HRI [35, 72] which similarly found uncanniness and trust to significantly shape reported perceptions, attitudes, and judgments. Virtual influencers may thus seem like a new phenomenon, however, these results suggest that prior findings from related literature that deal with other forms of virtual agents such as avatars on websites, or with physically embodied social robots may be highly relevant to the topic.

The ERP results from this study were partly consistent with our prior predictions, showing differences in ERP waveforms elicited by human versus virtual influencers that were consistent with both the predicted N400 and LPP components. With respect to the N400, the waveforms were more negative for virtual than human influencers over the vertex of the scalp in the 300ms – 500ms time window as assumed based on related literature, although visual inspection of the data suggest this effect did not start until closer to 400 ms in this data set. The timing of the N400 is somewhat variable depending on task and stimulus type [46], and so this difference from our predictions is not unreasonable given the literature. These results are thus consistent with those of Mustafa and colleagues [69, 70], who found increased N400 amplitude for more uncanny virtual characters. The fact that we observed decreased N400 amplitude in the context of virtual influencers further suggests that the N400 may be a reliable indicator of differences in processing among virtual and human characters generally.

Our integrated analyses of the N400 time window reveals further implications along this line of reasoning. The behavioral data revealed that the amplitude at the 300ms–500ms window seems to be significantly negatively related to perceived uncanniness of influencers. It was also positively associated with the perceived humanness and intentions to follow the influencer's recommendations. Therefore, while our results support its association with uncanniness, the N400 may also provide an indicator for general perceived humanness, and especially for intentions to follow recommendations and perhaps also approach intentions more generally. This, when interpreted with the past observations of the N400 in other contexts [69, 70], provides evidence that the N400 is potentially the result of the processing of an observed mismatch in virtual humans. This has practical implications for marketing activities, as companies who consider using virtual influencers as a marketing

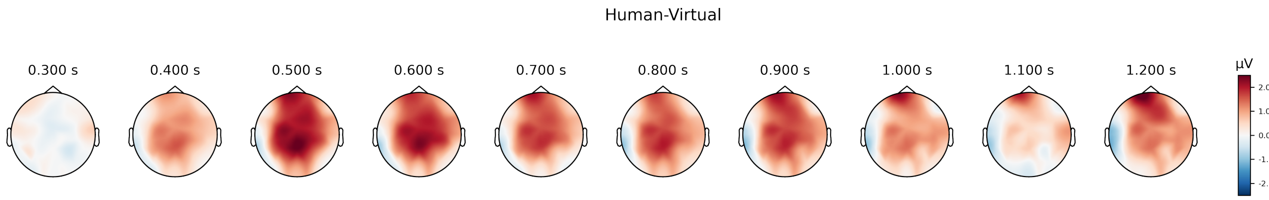

Figure 6: EEG results on topographic maps of average activation across the time frames of the N400 (300 - 500ms) and the LPP (600-1,200ms)

tool could use the N400 as an indicator and test with a smaller sample if the selected influencer is a good fit for their goals. Given its positive association with intention to follow an influencer's recommendation, the N400 may also be used as indicator for approach intentions in general influencer marketing strategies of companies, and is thereby not limited to the utilization of virtual influencers.

To strengthen the implications for companies, future research should be conducted to replicate this finding in additional contexts. For example, researchers can build on past work related to facial features of robots and virtual assistants [58, 90] to better understand the uncanny valley. While these findings are exploratory, future research can explore whether these findings generalize and can further refine the relationship between N400 and the degree of uncanniness. For example, a future experiment can incorporate a wider variety of virtual human stimuli with a greater range of perceived humanness. Such an experiment can determine whether the N400 represents the presence of a mismatch, or whether it represents a degree. As we accounted for individual differences between participants only through the random effects of participants, future research may also investigate whether specific demographics or culture has a significant effect on virtual influencer perception, as well as the N400 component.

In addition to the N400, we also investigated the LPP as potential indicator for perceived trust and approach intentions of influencers. The LPP has been well-established to be associated with attentional processes elicited by images that are reported to be highly pleasing and generate a high degree of arousal [30, 74]. Prior work further established a relationship between the trustworthiness of the faces and LPP responses [47, 55], as well as a relationship between decreased LPP amplitude and responses to virtual avatars [89]. Furthermore, related literature suggests that the LPP may also provide an indicator for approach intentions [3, 106].

Building on these past findings, we interpret our results to suggest that our participants associated human influencers with a higher degree of positive valence and arousal. While we observed greater amplitudes in response to human influencers, the integrated analysis of the behavioral and EEG results suggest that the LPP was also associated with a higher intention to follow the influencer's recommendation. Past work on approach intentions [3, 106] suggested that a willingness to follow an influencer is associated with positive perceptions of the influencer's brand image or communications. Our observation is consistent with this explanation; participants likely elicited a greater LPP response to images that they perceived positively and exciting, and likely reported those images as influencers they were more likely to follow. Similarly to the N400, the results of the LPP as indicator for positive affect and approach intentions may provide a useful tool for marketing research. Companies that use influencer marketing can thereby use the LPP as indicator for initial perceptions of the influencer and product presentation. Connecting these findings to broader literature, this signal may also be used as indicator for positive affect and approach intentions toward avatars or chatbots on e-commerce websites. Furthermore, while we accounted for individual differences through our mixed-effects models, it needs to be planned and investigated for potential demographic or cultural differences and if they impact the LPP as an indicator for the given research context.

Curiously, our observation does not support the assumption that the LPP may be an indicator for perceived trust, which is something that we might expect to be associated with positive perceptions. We identify two possible explanations for this. First, it is possible that perceived trust, as understood in the context of virtual influencers, is distinct from positive affect and arousal. The perceived trust towards virtual influencers in the context of this study may be a reflection not of how much one enjoys or is likely to follow a recommendation, but instead on the degree of feelings of mismatch experienced. This could explain why an association was observed with the N400 but not the LPP. Future work may benefit by exploring this observation further, as a replicated study may find evidence that positive perceptions of an influencer are a better indicator of a willingness to follow than perceived trust. Alternatively, this may be a limitation of the single-item measure employed to measure perceived trust. As a complex and multidimensional construct, elements of perceived trust may not have been accurately captured in our observation. Yet, as we observed the N400 and LPP as innovative measures for virtual influencer perception, we selected scales that were validated in prior research to have a comparable basis.

Future work on this topic could benefit by observing elements of trust in the context of virtual humans or influencers to better understand whether trust is associated with similar cognitive processes as willingness to follow recommendations. Drawing back to the increasing call of a more interpersonal perspective on trust from related social HRI literature [9, 24], future research may benefit by developing new trust scales that better capture the nature of trust in virtual influencers. For example, social aspects of trust may be highly pertinent, as the establishment of parasocial relations with followers is a crucial success factor in influencer marketing [20, 88]. Through these relationships, influencers are often seen as opinion leaders [16, 36], making this a topic of ethical concern regarding accountability, moral responsibility, and transparency [81]. Consequently, despite redefining our understanding of trust and its role in virtual influencers, future research also needs to tackle these ethical considerations and may develop policies to which agencies of virtual influencer profiles need to adhere to.

Another point of consideration for these results is whether or not there are indeed separable N400 and LPP effects. While both of these components were predicted a priori on the basis of the literature, and were supported by both visual inspection and statistical analysis, careful inspection of the waveforms and topographic maps does not provide any sense that there is a clear delineation between the two effects. ERP components are typically defined by their timing, polarity, scalp distribution, and eliciting conditions [53]. In the present data, the ERP waveforms for the two conditions begin to diverge around 400 ms and this difference is maintained until 1200 ms, but within this time range the scalp distribution of the difference is quite consistent. The polarity of the difference is the same as well; it is simply a matter of convention that the N400 is typically represented as being more negative for less semantically congruous stimuli, whereas the LPP is represented as more positive for more congruous/affectively arousing stimuli. In other words, this could simply be a single, protracted effect. This would be more consistent with past reports of the LPP than the N400, insofar as the N400 typically only lasts for approximately 200 ms and rarely extends later than 600 ms [46]. In the present case, we do not have evidence to adjudicate between the interpretations of two versus one component. However, given the literature and our resulting a priori hypotheses regarding both components, we have chosen to treat them as distinct here; future work however should aim to clarify whether the contrast between virtual and human influencers indeed elicits two distinct ERP components, or whether there is a single ERP component and if so, what processes it represents.

6 CONCLUSION

As we move into a world that blurs the lines between physical and virtual, it is increasingly important to understand how humans interpret nuances. The phenomenon of virtual influencers is fascinating, and raises questions about whether we reliably disentangle the virtual and physical worlds on social media. Our findings suggest that social media users often (but not always) can distinguish virtual influencers from humans, which is reflected in self-reported responses to humanness, as well as perceived trust, uncanniness, and behavioral intentions towards the influencer. The perceptual differences between human and virtual influencers are also measurable by brain activity potentials in the N400 and LPP signals. Associations between these signals and reported experiences also provide new insights into the factors that drive critical behaviors, such as willingness to follow recommendations of an influencer.

Our findings have implications for future research on virtual influencers as well as virtual humans in general. We corroborated past findings which suggest that the N400 and LPP signals can differentiate the processing of virtual and human actors, and add evidence that this generalizes in the case of virtual influencers. Furthermore, our observations demonstrate how these signals can reveal new insights into perceptions that lead us to accept virtual humans, such as perceived uncanniness, humanness, and intention to follow recommendations through the N400 and LPP components. The N400 was associated with uncanniness, possibly due to a perceived mismatch with expectations. The LPP response observed suggests that the intention to follow recommendations may be driven by affective responses to an influencer, rather than perceived trust. Together, the observations provide the foundation for future inquiry into the relationship between emotional experiences and virtual humans, and provide the foundation for passive measures of uncanniness, perceived trust and willingness to follow. Future work may yet find that it does not matter whether you can tell if your favorite Instagram influencer is a real person. What may matter most is whether you are comfortable not knowing.

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