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# UNREAL INFLUENCE: LEVERAGING AI IN INFLUENCER MARKETING

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## Structured Abstract

**Purpose**: This article examines how consumers respond to social media influencers that are created through artificial intelligence (AI) and compares effects to traditional (human) influencers.

**Design/methodology/approach**: Across two empirical studies we examine the efficacy of AI social media influencers. With study 1, we establish baseline effects for AI influencers and investigate how social psychological distance impacts consumer perceptions. We also investigate the role of an influencer's agency – being autonomous or externally managed - to test the boundaries of our results and determine the interactive effects between influencer type and influencer agency. Study 2 acts as an extension and validation of study 1 whereby we provide generalisability and overlay the role of need for uniqueness as a moderated mediator.

**Findings**: We show that there are similarities and differences in the ways in which consumers view AI and human influencers. Importantly, we find no difference in terms of intention to follow or personalisation. This suggests that consumers are equally open to follow an AI or human influencer, and they perceive the level of personalisation provided by either influencer type as similar. Furthermore, while an AI influencer is generally perceived as having lower source trust, they are more likely to evoke word-of-mouth intentions. In understanding these effects, we show social distance mediates the relationship between influencer type and the outcomes we investigate. Results also show that AI influencers can have a greater effect on consumers who have high need for uniqueness. Finally, we find that a lack of influencer agency has a detrimental effect.

**Research limitations**: Our studies investigate consumers' general response to AI influencers within the context of Instagram, however, future research might examine consumers' response to posts promoting specific products, across a variety of category contexts, and within different social media platforms.

**Practical implications**: We find that in some ways an AI influencer can be as effective as a human influencer. Indeed, we suggest that there may be a spill-over effect from consumer experiences with other AI recommendation systems, meaning that consumers are open to AI influencer recommendations. However, we find consistent evidence that AI influencers are trusted less than traditional influencers, hence we caution brands from rushing to replace human influencers with their AI counterparts.

**Originality/value**: This article offers novel insight into the increasingly prominent phenomenon of the AI influencer. Specifically, it takes initial steps toward developing understanding as to how consumers respond to AI influencers and contrast these effects with human influencers.

**Keywords**: artificial intelligence (AI), social media, influencer marketing, agency

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## 1.0 Introduction

Social media influencers are a dominant force in marketing, having been described as the 'new brand' (Weinswig, 2016). However, recently a new form of social media influencer has risen in prominence – the virtual artificial intelligence (AI) influencer (Leighton, 2019; Thomas and Fowler, 2021). Attesting to the prominence of AI influencers, the World Health Organisation engaged AI influencer Knox Frost during the COVID-19 pandemic. Frost, with more than a million Instagram followers, was engaged to promote public service announcements – including the need to observe lockdown restrictions and maintain good hygiene practices (Chance, 2020). The use of AI influencers is not new either: after dropping the Kardashians as their social media influencers in 2018, French luxury brand Balmain appointed three virtual AI influencers: Shudu, Margot, and Xhi. According to the brand's press release, these influencers were a better reflection of the brands celebration of inclusion (Minton, 2018). Global brands including KFC, LVMH, Mini, Netflix, Nike, and Samsung have all worked with AI influencers (Baklanov, 2019).

Influencer marketing is anticipated to reach US$15 billion in revenue in 2022, up from US$8 billion in 2019 (Schomer, 2019). This increased investment is driven in part by social media influencers being trusted tastemakers in one or several niches (de Veirman et al., 2017). These influencers have become particularly desirable for brands and are often more effective than traditional advertising tactics, due to their higher authenticity and credibility – which results in lower resistance to the message (de Vries et al., 2012). Despite the potential high cost, social media influencers can be effective enough to warrant their prices (Main, 2017a; Main, 2017b). Indeed, brands like clothing label REVOLVE attribute their success to effective influencer marketing (Cheng, 2018).

AI influencers take on many forms. For instance, created in 2016, Lil Miquela (@lilmiquela) is now a prominent AI influencer with more than 3 million Instagram followers in 2021. Promoting themselves as the world's first digital supermodel, Shudu Gramm (@shudu.gramm) is another AI influencer has worked with leading magazines and collaborated with the likes of UK sports apparel brand, Ellesse. Shudu Gramm's influencer account is promoted as an editorial 'model' or something to look at rather than aspire to, whereas Lil Miquela is deliberately curated in a way that makes her appear like a talented '20-something-year-old' in the public eye with a burgeoning music career and someone to aspire to (Hillyer, 2019). However, they craft their personas, they appeal to brands in similar ways compared to their human counterparts.

AI influencers can appeal to brands given their perceived lower cost and their reduced likelihood of being involved in a scandal (Thomas and Fowler, 2021). Like traditional mascots, they may even have meaning that is more stable over time (Wee, 2004). However, despite the potential upside of engaging an AI influencer, there is limited empirical work knowledge about how consumers respond to AI influencers. As such, there is little knowledge of how brands might best leverage AI influencers, or how and why consumers might react differently to them.

This article develops understanding of how consumers react to AI influencers. We do so by testing our hypotheses in two experiments. Our findings develop insight into the underlying mechanisms through which AI influencers work, as well as boundary conditions which limit the efficacy of AI influencers. By examining the differences and similarities between human and AI influencers, this article provides guidance for marketers, developers of AI influencers, and social media influencers themselves.

## 2.0 Theoretical Background

*2.1 The evolution of endorsement*

Traditional brand endorsement is based on the premise that the endorser's qualities transfer – such as expertise, trustworthiness, likability, and attractiveness (Keller, 1993) – and generate desirable brand outcomes (e.g., purchase intentions, positive change in attitude) (Bergkvist and Zhou, 2016; Feick and Higie, 1992; Ohanian, 1991). Three types of traditional endorsers exist, regular consumers (distinguished by similarity), experts (distinguished by credibility) and celebrities (distinguished by familiarity) (Daneshvary and Schwer, 2000). In contrast to consumers and experts, celebrities typically portray attractiveness, status and meaning (Kennedy et al., 2019). As such, celebrities tend to be more effective endorsers as they can penetrate advertising clutter and attract attention (Knoll and Matthes, 2017). Past research outlines how celebrity endorser efficacy operates and explored boundary conditions for positive outcomes related to consumer attitudes, intentions, and behaviours (Bergkvist and Zhou, 2016).

Over the past decade, developments in communication technologies (Campbell et al., 2014; Berthon et al., 2012) have led to the rise in a new type of endorser: the social media influencer. These influencers are individuals that post self-generated content about their lives, experiences, and opinions to social media platforms in exchange for monetary or in-kind compensation (Campbell and Grimm, 2019). Influencers are characterised by having sizeable networks of active followers that can be reached to promote brands, products, or services (de Veirman et al., 2017). While an influencer draws on similar standing and success factors as a celebrity (Breves et al., 2019; Weinswig, 2016), they are also relatable and perceived as authentic in a manner like a regular consumer. Influencers have unique characteristics that define them; they gain fame by successfully branding themselves as experts on social media platforms (Khamis et al., 2017), their reach is generally focused on niche audiences (García-Rapp, 2016), they engage in two-way communication with their audience (Khamis et al., 2016), and they are easy to relate to given they share their personal life and stories (Schau and Gilly, 2003). Importantly, research suggests similar boundary conditions and positive brand outcomes occur with influencers to those of traditional endorsers (Kim and Kim, 2021; Schouten et al., 2020).

*2.2 Rise of the AI influencer*

Recent advancement in AI have led brands to incorporate service delivery through technology (Campbell et al. 2020; Huang and Rust, 2018) and a general trend toward synthetic advertising (Campbell et al., 2021). This has led to the rise of AI conversational interfaces and even the possibility of digital humans in retail environments (Kaplan and Haenlein, 2019; Reis et al., 2020; Wirtz et al., 2018). In the context of social media, AI is now being used to automatically write and respond to messages (Liu, 2019), effectively aiding brands in managing their social media accounts. Within the domain of influencer marketing, AI has led to the emergence of a new kind of influencer – the AI influencer (Leighton, 2019; Thomas and Fowler, 2021). Table 1 presents a summary of existing work on AI influencers and situates our work within this domain.

An AI influencer can have a sizable social network of followers and can be regarded as "a trusted taste-maker in one or several niches" (de Veirman et al., 2017, p. 798). Research on AI and machine learning also points to potential positive effects that can be realised from AI influencers. Specifically, the boundary between human and bot-like behaviour is becoming less distinct, which makes it possible for a bot to acquire significant influence (Ferrara et al., 2016).

**Table 1**
**Positioning this paper relative to AI influencers research**

| Article | Influencer focus | Research focus | Method | Key findings |
|---|---|---|---|---|
| Arsenyan and Mirowska, 2021 | Human vs human-like virtual vs anime-like virtual influencer | Investigates virtual agents' similarity to humans in terms of behaviour and how reactions differ among types of influencers | Data scraping of influencer posts and public comments. | Human-like virtual influencer receive significantly lower positive reactions from consumers |
| Block and Lovegrove, 2021 | AI influencer | Analysis of an AI influencer's communication to identify what makes her so appealing to her audience | Textual and sentiment analysis of public posting | The influencer's identity and messaging effectively integrate into a single strategic communication tool, whereby the influencer is the strategy and the message |
| Thomas and Fowler, 2021 | AI influencer | Investigates the implications of using AI influencers and sets out to provide guidance for when controversies arise from AI influencers | Two experimental studies | AI influencers can produce positive brand benefits like those produced by human celebrity endorsers |
| This article | AI vs human influencer | Investigates how consumers respond to social media influencers that are created through artificial intelligence (AI) and compares effects to traditional (human) influencers. | Two experimental studies | Compares AI and Human influencers to explore consumer perceptions, and finds similarities (following intentions, perceived personalisation) and differences (AI lowers source trust and increases WOM). These effects are mediated by social distance, and moderated by need for uniqueness and influencer agency. |

An AI influencer can look and behave like a human influencer, suggesting AI influencers – like human influencers – might have similar effects to traditional celebrity endorsers. While research is emerging on AI influencers (e.g., Thomas and Fowler, 2021), relatively little is known about how consumers react to them. It's unclear if consumers will – like in other situations (De Bellis and Johar, 2020; Kim et al. 2019) – react to robots less positively than humans, or regard human-looking AI influencers as like any other human influencer. To this end, we investigate three key outcomes – source trust, intention to follow, and WOM intentions. Drawing on existing literature from human-robot interactions and technology mediation service interactions (i.e., Fernandes and Oliveira, 2021), we predict that an AI influencer have lower source trust. However, given the relative novelty of an AI influencer, we predict they have higher levels of intention to follow and WOM intentions. Formally, we predict the following hypothesis:

$H_1$: *Compared to a human influencer, an AI influencer will have less ($H_{1a}$) source trust but more ($H_{1b}$) intention to follow and ($H_{1c}$) WOM intention.*

*2.3 Social psychological distance*

Even less is known about the mechanisms through which AI influencers might operate. Social psychological distance refers to the psychological distance between oneself and others, with the self being the reference point and the target described in terms of being more psychologically removed as social distance increases (Trope and Liberman, 2010). Thus, individuals are perceived as lying on a social distance continuum ranging from near to far. Importantly, information that is received from varying levels of social distance may be processed differently by the receiver. For instance, information received from individuals with less social distance may be perceived as more credible than from individuals with increased social distance (Edwards et al., 2009). Furthermore, individuals prefer to interact with other individuals to whom they perceive to be similar and familiar, and conversely, to a lesser degree with people to whom they perceive they are different and unfamiliar (Edwards et al., 2009). Thus, social distance can regulate individuals' engagement with similar (or dissimilar) and familiar (or unfamiliar) others or objects (Edwards et al., 2009).

The concept of social distance is relevant to the context of influencer marketing (Zhou, Chen, and Su, 2019). Indeed, influencers often are more similar with their followers than traditional celebrities do (Chae, 2018). Mainstream celebrities are often seen as otherworldly; however, influencers are closer to their followers than traditional celebrities (Chae, 2018). Despite followers not necessarily having met influencers in person, they can more readily view the lives through the online connection. Social media influencers fall somewhere between acquaintances and traditional celebrities (Chae, 2018), but it is unknown as to where AI influencers fall on the social distance spectrum.

Drawing on research that investigates human-robot interactions (e.g., Kim et al., 2013; Kim and Mutlu, 2014), it is expected that social distance will also vary between human and AI influencers. For instance, when people associate human-like cues with robots, they are more likely to accept robots as part of their social environment (Halpern and Katz, 2013). The effect of social distance also extends to the acceptance of robots and avatars that display personalities or social characteristics like our own (Nass and Moon, 2000). Indeed, robots are seen as engaging in more meaningful social interaction with humans when a robot is endowed with a degree of anthropomorphic or human-like qualities, such similarity in form or behaviour (Duffy, 2003) or exploit the social cues that humans naturally possess (Breazeal and Scassellat, 1999).

Given human influencers have a physical presence and can directly address followers in their posts, this creates a certain closeness with followers often seeing and trusting them as peers (Erz and Christensen, 2018; Gannon and Prothero, 2018). The ability to comment on influencers' posts and possibility interact also strengthens similarity of the influencer to oneself (Schmidt, 2007). As such, it is expected that human influencers will be perceived as less socially distant compared to an AI influencer, who is expected to exhibit social distance perceptions more akin to those of robots in human-robot interactions. Formally, we predict the following hypothesis:

$H_2$: *An AI influencer will have greater social psychological distance compared to a human influencer.*

Social psychological distance has also been shown to influence a range of consumer evaluations or outcomes. For our study, we are interested in three important outcomes for influencers: source trust, intention to follow, and WOM. In terms of source trust, those that are seen as less distant are typically regarded as more credible or trustworthy (Castillo et al., 2013; Liljander et al., 2015). In online contexts, when a receiver perceives a source as trustworthy, they are typically more open to their messages (Reichelt et al., 2014). Intention to follow is another important outcome in the context of influencer marketing. While users may be inclined to follow an opinion leader, or someone perceived as having product or category knowledge (Thakur et al., 2016), more positive attitudes toward the influencer can also lead to an increase in the intention to follow (Casaló, Flavián, and Ibáñez-Sánchez, 2020). Influencers that are perceived as having less social psychological distance can lead to more positive attitudes. Finally, WOM has received much attention in the context of social media influencers (Casaló, Flavián, and Ibáñez-Sánchez, 2020). WOM has been shown to be influenced by social psychological distance, and strength of association (Wallace et al., 2012). For instance, word-of-mouth referral is more likely when messages are received from a source that is at a close social psychological distance (Brown and Reingen, 1987). Taken together, we expect differences in the effectiveness of human versus AI influencers such that social psychological distance will act as a mediator between influencer type and subsequent outcomes. Formally, we predict the following:

$H_3$: *The relationship between type of influencer (AI or human) and ($H_{3a}$) source trust, ($H_{3b}$) intention to follow, and ($H_{3c}$) WOM will be mediated by social distance, such that increased (vs. decreased) social distance reduces (vs. enhances) these outcomes.*

*2.4 Influencer agency*

An influencer's autonomy is important in the context of influencer marketing (Weismueller et al., 2020). The concept of agency is established within the literature as a form of self- expression (Botti and McGill 2011; Deci and Ryan 1985). In essence, agency relates to an ability to make choices, exert control over the physical and social environment, and take initiative (Baumeister, 1998). In the context of social media influencers, agency extends to the control a brand, sponsor, or manager exerts over the influencer's decisions, such as their posts or choice of which brands work with. Autonomy, or perceived independence, can also impact consumer perception such as source trust, intention to follow, and WOM, given that messages can be seen as originating from sources that are perceived to be independent of commercial influence (Litvin, Goldsmith, and Pan 2008). As such, we expect a social media influencer that is externally managed to have lower levels of source trust, intention to follow, and WOM Intentions. Specifically, we propose:

$H_4$: *Influencer agency will be an important driver of outcomes, such that when an influencer is externally managed ($H_{4a}$) source trust ($H_{4b}$) intention to follow, ($H_{4c}$) WOM intentions will be lower than when the influencer is autonomous.*

While agency intuitively pertains to human choice and expression, theories on mind perception argue that human and nonhuman entities can be perceived as having agency (i.e., the ability to think, plan, and act) (Gray et al., 2007). While humans are seen as having high agency, robots are typically seen as having a more moderate level of agency – but having agency nonetheless (Gray et al., 2007; Gray and Wegner, 2012). The concept of agency in nonhumans has been studied in the context of service robots. Findings have shown that anthropomorphism enables individuals to humanise service robots by imbuing them with agency (Yam et al., 2020). While completely autonomous AI influencers are not yet commonplace; today's AI influencers have some level of behind-the-scenes human intervention (Thomas and Fowler, 2021). However, completely autonomous AI influencers are likely to become prominent on social media platforms (Appel et al., 2020). An autonomous AI influencer could draw on AI elements, such as machine learning or speech recognition, to better understand customer needs (Kietzmann et al., 2018) –

for instance by gathering information from comments or videos that consumers post to social media. Such an AI influencer could be well placed to be attuned to followers' personalities and subsequently use this information to better deliver personalised interactions with their followers. However, if agency was removed – for instance by the AI being commercially managed, then consumer perceptions of personalisation could decrease, while perceptions of commercialisation may increase (Kim and Kim, 2021). To this end, we propose that in the context of social media influencers, agency – having control of your own choices (i.e., the brands you promote) or not – will influence consumer perceptions of the influencer (human or not). Specifically, we propose:

$H_5$: *An AI influencer will be as effective at influencing outcomes [($H_{5a}$) source trust ($H_{5b}$) intention to follow, ($H_{5c}$) WOM, ($H_{5d}$) commercialisation, ($H_{5e}$) personalisation] when the influencer is explicitly managed by an organisation, and not when autonomous.*

*2.5 The moderating role of need for uniqueness*

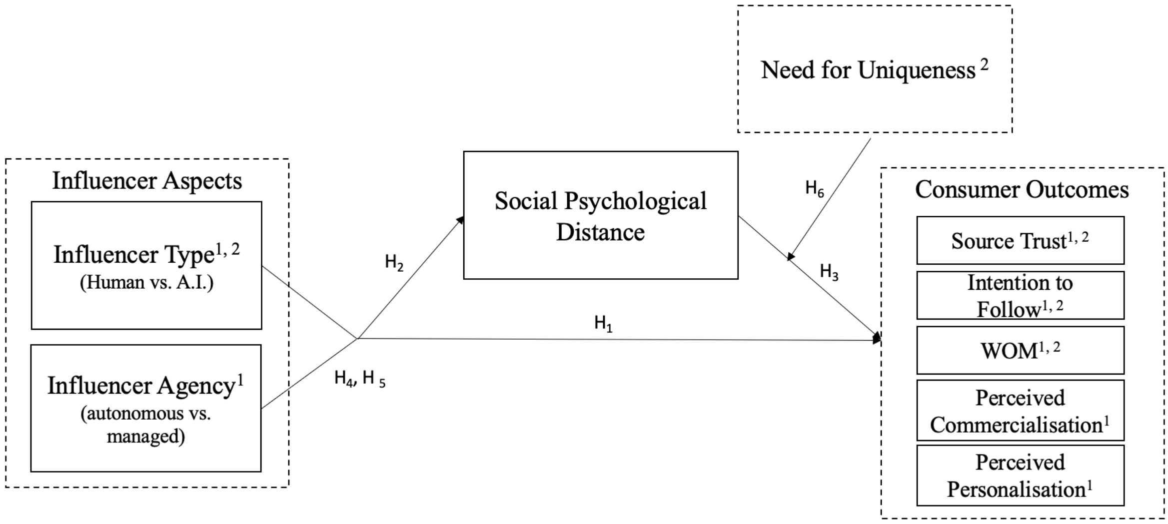
Need for uniqueness is an individual-level trait (Lynn and Harris, 1997; Tian et al., 2001), which leads individuals to desire unique products or experiences to provide differentiation from others (Simonson and Nowlis, 2000). For those with high need for uniqueness, a preference is typically exhibited for distinct features and designs (Bloch, 1995), or attributes that can define them as different to others in a reference group (Snyder and Fromkin, 1980). These consumers exert more effort to own innovative products (Lynn, 1992; Snyder, 1992), and are more likely to choose atypical options (Worchel et al., 1975). Like product experience, it can be expected that interactions with AI influencers will make a person high in uniqueness feel unique (Fisher and Price, 1992), and assist in their expression of identity (Berger and Heath, 2007; Tian et al., 2001). For these reasons we expect need for uniqueness to reduce the negative impact of increased social distance associated with AI influencers. Specifically,

$H_6$: *An individual's need for uniqueness will moderate the mediated relationship between social distance and ($H_{5a}$), source trust ($H_{5b}$), intention to follow ($H_{5c}$), and WOM, such that the negative effect of increased social distance will be dampened for those with high need for uniqueness.*

**3.0 Experimental Studies**

Across two experimental studies, we examine the efficacy of AI influencers compared to their human counterparts. Each study includes a screener that requires respondents to use the Instagram social media platform. Study 1 establishes baseline effects for human versus AI influencers on social psychological distance and subsequent effects on key outcome variables, source trust, intention to follow, and word-of-mouth (WOM). In addition, the impact of influencer agency (autonomous vs. externally managed) is overlayed and the impact on perceived commercialisation and personalisation is investigated. In doing so, we test interactive effects between influencer type and influencer agency. Study 2 extends study 1 in three ways. First, we employ different stimuli to represent the influencer employed in study 1's stimulus material. Second, the role of consumer's need for uniqueness, in addition to social distance, is investigated in a mediated moderation model. And third, we extend our sample to account for potential limitations of generalizability present in study 1. Figure 1 presents a combined conceptual model for both studies.

**Figure 1**
**Conceptual model**




*3.1 Study 1*
Study 1 establishes baseline differences between AI-influencers and their human counterparts on key consumer outcomes, testing $H_1$, to $H_5$. We investigate how influencer type (human vs. AI) impacts our key outcome variables ($H_1$) and consumer perceptions of social psychological distance ($H_2$), as well as the mediating role of social psychological distance between influencer type outcomes ($H_3$). Further, we investigate the role of influencer agency (autonomous versus externally managed) on outcomes ($H_4$ and $H_5$). We conduct a 2 (influencer type: AI vs. human) × 2 (influencer agency: autonomous vs. managed) between-subjects experiment to test our hypotheses.

*3.1.1 Study 1 procedure*
Prolific Academic was again employed to collect data from US respondents via an online survey. Given that our focal influencer is female, and one of our constructs of interest is social psychological distance, we focus on collecting a female sample in study 1. A total sample of 455 respondents completed the survey, with 39 (8.6%) removed for failing two attention checks. A further exclusion criterion was placed at the end of the survey, asking respondents if they recognise the social media influencer shown in the scenario. This led to a further 91 (20%) being removed. This was deemed important as existing knowledge about the influencer would lead to biasing our scenarios that manipulate influencer type and influencer agency. Hence, our final sample comprised 325 respondents (female = 100.0%), with a mean age of 33.26 years (s.d. = 10.50).

Measurement items for source trust are drawn from existing multi-item measurement scales in the literature. Source trust is measured with a five-item scale adapted from Ohanian (1990) to measure the trust individuals' place in influencers. Single-item measures are employed to measure intention to follow the influencer and WOM. Social distance is measured with a three item 7-point semantic differential scale, assessing perceptions of the social media influencers as being: near-far, unapproachable-approachable, unfriendly-friendly. Scales items were also used to measure perceived commercialisation and perceived personalisation. Adapted from Srinivasan et al. (2002), perceived personalisation measures an influencer's ability to tailor recommendations, content, and products to individual customers. Five items were developed to measure perceived commercialisation. All measures display adequate construct reliability and internal consistency. Appendix A1 provides a complete list of variables, factor loadings, and scale reliabilities. Internal reliability tests demonstrate strong Cronbach (1951) alphas, ranging from 0.74 to 0.95. Finally, we test for common method variance (CMV) with the correlation matrix procedure (Bagozzi, Yi, and Phillips, 1991), which assesses the impact of CMV through latent variable correlations. Table 2 presents correlations between our variables. Common method bias is evident when substantially large correlations are found among constructs, however CMV is not an issue given that the correlation among multiple constructs is less than 0.9 (Bagozzi et al., 1991).

We employ a 2 (influencer type: AI vs. human) × 2 (influencer agency: autonomous vs. managed) between-subjects experiment. The experimental scenario combines a written description with visual stimuli to manipulate influencer type (human influencer or an AI influencer) and influencer agency (autonomous or managed). We engaged four experts to aid in developing the scenarios and ensure clarity, relevance, and realism. Minor modifications to phrasing were made to enhance consistency and flow. The scenario descriptions for study 1 is provided in Appendix A2. Respondents were randomly allocated into one of the four conditions. Two scenario manipulation checks were employed toward the end of the survey. First, respondents were asked to recall if the influencer described to them was a human or an AI influencer (94% of the 325 respondents correctly recalled influencer type). Second, respondents were asked to recall if the influencer autonomously operated their own Instagram account or if it was managed by a professional social media team (97% of the 325 respondents were correct in their recall). Taken together, these manipulation checks confirm respondents correctly interpretation and recalled scenario information.

### *3.1.2 Study 1 results*

Hypothesis 1 predicts that compared to a human influencer, an AI influencer will have less source trust but that consumers will report higher intention to follow and WOM intention. We conduct a multivariate analysis of variance (MANOVA) to compare the means for each outcome between two levels of influencer type (AI vs human influencer). For source trust, results reveal a significant main effect ($F = 15.92$, $p \leq 0.001$), with an AI influencer ($M = 2.59$; $S.D. = 1.44$) being perceived less trustworthy than a human influencer ($M = 3.28$; $S.D. = 1.65$). This finding supports $H_{1a}$. For intention to follow, results reveal no main effect ($F = 1.16$, $p = 0.282$), hence providing no support for $H_{1b}$. For WOM intention, results reveal a significant main effect ($F = 6.18$, $p = 0.013$), with an AI influencer ($M = 2.72$; $S.D. = 2.07$) resulting in higher WOM intention compared to a human influencer ($M = 2.20$; $S.D. = 1.64$). This finding supports $H_{1c}$.

Hypothesis 2 predicts an AI influencer will have greater social psychological distance compared to a human influencer. We conduct a one-way ANOVA to compare the mean of social psychological distance between two levels of influencer type (AI influencer vs human influencer). Results reveal a significant main effect ($F = 27.47$, $p \leq 0.001$), with the AI influencer ($M = 5.31$; $S.D. = 1.43$) being perceived as more distant than the human influencer ($M = 4.45$; $S.D. = 1.52$). This finding supports $H_2$.

Hypothesis 3 predicts that the relationship between type of influencer and our outcome variables – ($H_{3a}$) source trust, ($H_{3b}$) intention to follow, and ($H_{3c}$) WOM intentions – will be mediated by social distance; such that increased (decreased) social distance reduces (enhances) these outcomes. To test this hypothesis, model 4 of the SPSS PROCESS macro (Hayes, 2017) with 5,000 bootstrap samples was used to assess mediation. Mediation results are presented in Table 3.

**Table 2**
**Study 1 variable correlations**

| Variable | Social psychological distance | Source trust | Intention to follow | WOM |
|---|---|---|---|---|
| Social psychological distance | 1.00 | | | |
| Source trust | 0.76 | 1.00 | | |
| Intention to follow | 0.62 | 0.61 | 1.00 | |
| WOM | 0.44 | 0.46 | 0.68 | 1.00 |

**Table 3**
**Study 1 direct effects, conditional indirect effects and index of moderated mediation**

| | Effect (boot SE) | Lower 95% BCBCI | Upper 95% BCBCI |
|---|---|---|---|
| *Direct Effects (X* = Influencer type: 0=human, 1=AI) | | | |
| X → Source trust | 0.01 (0.59) | -1.15 | 1.17 |
| X → Intention to follow | 0.40 (0.14) | 0.12 | 0.68 |
| X → WOM | 1.07 (0.19) | 0.70 | 1.44 |
| X → Commercialisation | 0.18 (0.46) | -0.73 | 1.09 |
| X → Personalisation | 2.80 (0.59) | 1.64 | 3.96 |
| *Indirect Effects (X* = Influencer type; W = Influencer agency (0=autonomous, 1=managed) *M* = Social distance) | | | |
| X → Social distance → Source trust | | | |
| Autonomous management | -4.85 (1.00) | -6.86 | -2.89 |
| Managed by organisation | -1.17 (0.77) | -2.72 | 0.37 |
| *Index of Moderated Mediation: b = 3.69, boot SE = 1.25, 95% BCBCI [1.22, 6.20])* | | | |
| X → Social distance → Intention to follow | | | |
| Autonomous management | -0.83 (0.18) | -1.19 | -0.50 |
| Managed by organisation | -0.20 (0.13) | -0.46 | 0.05 |
| *Index of Moderated Mediation: b = 0.63, boot SE = 0.22, 95% BCBCI [0.23, 1.08])* | | | |
| X → Social distance → WOM | | | |
| Autonomous management | -0.78 (0.17) | -1.14 | -0.46 |
| Managed by organisation | -0.19 (0.13) | -0.44 | 0.05 |
| *Index of Moderated Mediation: b = 0.60, boot SE = 0.20, 95% BCBCI [0.21, 1.01])* | | | |
| X → Social distance → Commercialisation | | | |
| Autonomous management | 1.74 (0.41) | 0.98 | 2.59 |
| Managed by organisation | 0.42 (0.28) | -0.12 | 0.99 |
| *Index of Moderated Mediation: b = -1.32, boot SE = 0.48, 95% BCBCI [-2.33, -0.43])* | | | |
| X → Social distance → Personalisation | | | |
| Autonomous management | -4.00 (0.78) | -5.54 | -2.49 |
| Managed by organisation | -0.96 (0.64) | -2.28 | 0.26 |
| *Index of Moderated Mediation: b = 3.04, boot SE = 1.01, 95% BCBCI [1.04, 4.98])* | | | |

*Note: Unstandardised regression coefficients are reported*

**Table 4**
**Study 1 scenario condition summary statistics**

| Influencer type | Influencer agency | N | Source trust, Mean (sd) | Intention to follow, Mean (sd) | WOM, Mean (sd) | Commercialisation, Mean (sd) | Personalisation, Mean (sd) |
|---|---|---|---|---|---|---|---|
| Human influencer | Autonomous | 86 | 3.92 (1.63) | 2.53 (1.86) | 2.62 (1.82) | 5.42 (0.94) | 2.81 (1.54) |
| | Managed | 67 | 2.45 (1.27) | 1.49 (0.96) | 1.67 (1.17) | 6.15 (0.81) | 1.81 (0.84) |
| | Overall | 153 | 3.28 (1.65) | 2.08 (1.61) | 2.20 (1.64) | 5.74 (0.95) | 2.37 (1.37) |
| AI influencer | Autonomous | 78 | 2.72 (1.44) | 1.94 (1.63) | 3.01 (2.14) | 5.97 (0.95) | 2.61 (1.48) |
| | Managed | 94 | 2.49 (1.44) | 1.85 (1.47) | 2.48 (1.98) | 6.07 (0.76) | 2.16 (1.33) |
| | Overall | 172 | 2.59 (1.44) | 1.89 (1.54) | 2.72 (2.07) | 6.02 (0.85) | 2.37 (1.42) |

All items measured on 7-point Likert scales, where 1 = strongly disagree and 7 = strongly agree

**Table 5**
**Study 2 variable correlations**

| Variable | Social psychological distance | Need for uniqueness | Source trust | Intention to follow | WOM |
|---|---|---|---|---|---|
| Social psychological distance | 1.00 | | | | |
| Need for uniqueness | 0.46 | 1.00 | | | |
| Source trust | 0.74 | 0.40 | 1.00 | | |
| Intention to follow | 0.73 | 0.51 | 0.70 | 1.00 | |
| WOM | 0.68 | 0.50 | 0.68 | 0.70 | 1.00 |

**Table 6**
**Study 2 direct and indirect effects of influencer type on consumer outcomes**

| Direct Effects | b (SE) | Lower 95% BCBCI | Upper 95% BCBCI |
|---|---|---|---|
| Human vs. AI Influencer → Social Distance | 0.17 (0.08) | 0.07 | 0.32 |
| *Outcome = Source Trust* | | | |
| Human vs. AI Influencer → Source Trust | -0.74 (0.67) | -2.05 | 0.58 |
| Social Distance → Source Trust | 9.02 (1.17) | -11.31 | -6.73 |
| Need for Uniqueness → Source Trust | -0.65 (1.80) | -4.19 | 2.89 |
| Social Distance * Need for Uniqueness → Source Trust | 0.15 (0.27) | -0.38 | 0.69 |
| Outcome = Intention to Follow | | | |
| Human vs. AI Influencer → Intention to Follow | 0.07 (0.15) | -0.23 | 0.36 |
| Social Distance → Intention to Follow | -0.85 (0.28) | -1.40 | -0.30 |
| Need for Uniqueness → Intention to Follow | 1.58 (0.43) | 0.73 | 2.43 |
| Social Distance * Need for Uniqueness → Intention to Follow | -0.19 (0.07) | -0.33 | -0.07 |
| *Outcome = WOM* | | | |
| Human vs. AI Influencer → WOM | 0.16 (0.16) | -0.16 | 0.47 |
| Social Distance → WOM | -0.81 (0.25) | -1.30 | -0.31 |
| Need for Uniqueness → WOM | -1.63 (0.37) | 0.92 | 2.36 |
| Social Distance * Need for Uniqueness → WOM | -0.20 (0.57) | -0.32 | -0.09 |

*Note: Influencer Type: Human = 0, AI = 1; Unstandardized b coefficients (with boot SE within parentheses). BCBCI = bias corrected 5,000 bootstrap confidence intervals.*

**Table 7**
**Study 2 conditional indirect effects and index of moderated mediation**

| Indirect Effects | Effect (boot SE) | Lower 95% BCBCI | Upper 95% BCBCI |
|---|---|---|---|
| *Human vs. AI Influencer → Social Distance → Source Trust* | | | |
| -1 S.D. | -1.46 (0.68) | -2.82 | -0.19 |
| Mean | -1.43 (0.65) | -2.70 | -0.19 |
| +1 S.D. | -1.37 (0.63) | -2.62 | -0.18 |
| Index of Moderated Mediation: b = 0.03, boot SE = 0.05, 95% BCBCI [-0.05, 0.13]) | | | |
| *Human vs. AI Influencer → Social Distance → Intention to Follow* | | | |
| -1 S.D. | -0.22 (0.10) | -0.43 | -0.02 |
| Mean | -0.26 (0.12) | -0.50 | -0.03 |
| +1 S.D. | -0.35 (0.16) | -0.65 | -0.03 |
| Index of Moderated Mediation: b = -0.04, boot SE = 0.02, 95% BCBCI [-0.09, -0.03]) | | | |
| *Human vs. AI Influencer → Social Distance → WOM* | | | |
| -1 S.D. | -0.20 (0.09) | -0.39 | -0.02 |
| Mean | -0.24 (0.11) | -0.46 | -0.03 |
| +1 S.D. | -0.31 (0.15) | -0.62 | -0.04 |
| Index of Moderated Mediation: b = -0.03, boot SE = 0.02, 95% BCBCI [-0.08, -0.01]) | | | |

*Note: Influencer Type: Human = 0, AI = 1; Unstandardized b coefficients (with boot SE within parentheses). BCBCI = bias corrected 5,000 bootstrap confidence intervals.*

Results for source trust ($H_{3a}$) show no main effect for influencer type on source trust (b = −0.50, SE = 0.68; 95% CI [−1.83, 0.84]), however we find a significant indirect effect through social distance (b = -2.92, SE = 0.69; 95% CI [-4.26, -1.74]). Thus, $H_{3a}$ is supported. Results for intention to follow ($H_{3b}$) show a main effect for influencer type on intention to follow (b = 0.32, SE = 0.15; 95% CI [0.02, 0.62]) and a significant indirect effect through social distance (b = -0.51, SE = 0.11; 95% CI [-0.75, -0.30]). Thus, $H_{3b}$ is supported. Results for WOM intention ($H_{3c}$) a main effect for influencer type on WOM intention (b = 1.02, SE = 0.19; 95% CI [0.64, 1.40]) and a significant indirect effect through social distance (b = -0.50, SE = 0.12; 95% CI [-0.77, -0.28]). Thus, $H_{3c}$ is supported.

Hypothesis 4 predicts that influencer agency will be an important driver for our outcomes. Specifically, that when an influencer is externally managed ($H_{4a}$) source trust ($H_{4b}$) intention to follow, and ($H_{4c}$) WOM intentions will be lower than when the influencer is autonomous. We conduct a MANOVA to compare the means for each outcome between two levels of influencer agency (autonomous vs externally managed). Significant main effects are found for source trust (F = 28.50, p ≤ 0.001), intention to follow (F = 10.15, p = 0.002), and WOM intentions (F = 10.16, p = 0.002). Together, these finding support $H_{4a}$ to $H_{4c}$. Means for each condition are presented in Table 4.

Finally, hypothesis 5 predicts that there will be differences in influencer type when they are autonomous but not when explicitly managed. To test this, we conduct a 2 (influencer type: Human, AI) × 2 (influencer agency: autonomous, managed) MANOVA. Results reveal significant 2-way interactions for three outcomes; source trust (F = 14.47, p < 0.001), intention to follow (F = 7.34, p = 0.006), and commercialisation (F = 10.57, p < 0.001). A marginally significant interaction effect is identified for personalisation (F = 3.31, p = 0.07) and no significant interaction effect is identified for WOM (F = 0.99, p = 0.32). Interaction effects reveal that when an influencer is autonomous human influencers have higher source trust (autonomous: F = 24.88, p < 0.001, $M_{Human}$ = 3.92, S.D. = 1.63, $M_{AI}$ = 2.72, S.D. = 1.44; Managed: F = 0.32, p = 0.86, $M_{Human}$ = 2.45, S.D. = 1.27, $M_{AI}$ = 2.48, S.D. = 1.44). This result shows a significant difference in influencer type when they are autonomous but not when explicitly managed, supporting $H_{5a}$. Similarly, when an influencer is autonomous human influencers rate higher in intention to follow (autonomous: F = 4.77, p = 0.03, $M_{Human}$ = 2.53, S.D. = 1.86, $M_{AI}$ = 1.94, S.D. = 1.63; managed: F = 3.04, p = 0.08, $M_{Human}$ = 1.49, S.D. = 0.96, $M_{AI}$ = 1.85, S.D. = 1.47). This result shows a significant difference in influencer type when they are autonomous but not when explicitly managed, supporting $H_{5b}$. For commercialisation, interaction effects reveal that when an influencer is autonomous AI influencers are higher (autonomous: F = 13.67, p < 0.001, $M_{Human}$ = 5.42, S.D. = 0.94, $M_{AI}$ = 5.97, S.D. = 0.95; Managed: F = 0.45, p = 0.50, $M_{Human}$ = 6.15, S.D. = 0.81, $M_{AI}$ = 6.07, S.D. = 0.76). This result shows a significant difference in influencer type when they are autonomous but not when explicitly managed, supporting $H_{5d}$. Finally, for personalisation an AI influencer is also higher in terms of personalisation (autonomous: F = 13.67, p < 0.001, $M_{Human}$ = 2.81, S.D. = 1.54, $M_{AI}$ = 2.61, S.D. = 1.48; managed: F = 3.57, p = 0.06, $M_{Human}$ = 1.81, S.D. = 0.84, $M_{AI}$ = 2.16, S.D. = 1.33). This result shows a significant difference in influencer type when they are autonomous but not when explicitly managed, supporting $H_{5e}$.

### *3.1.3 Study 1 discussion*

With this study we identify several differences between human and AI influencers.

First, we find that when exposed to an AI influencer, consumers have higher WOM intentions – which may be driven by novelty (Venkatesh et al., 2016). However, an AI influencer is perceived as less trustworthy. This supports existing research which shows consumers can be hesitant in adopting technology mediated interactions in service encounters (Fernandes and Oliveira, 2021). Interestingly, we find that there is no difference between an AI influencer and human influencer in terms of intention to follow. This suggests that consumers are as likely to follow an AI influencer as a human influencer. Further aligned with these prior findings, we find that an AI influencer is perceived as more social psychologically distant than a human influencer. At face value this may seem intuitive, however modern technology means that AI influencers have increasingly high levels of verisimilitude (Campbell et al., 2021). Regarding social psychologically distance, we find that it acts as a mediator between influencer type and source trust, intention to follow, and WOM intention.

In terms of influencer agency, our results support the prediction that autonomous influencers are preferred to those that are externally managed. When considering the role of agency, we find that there is no difference in perceived personalisation, however that an AI influencer is perceived as more commercial. The fact that there is no difference in personalisation means an AI influencer is seen as being able to personalise content or recommendations in a manner like a human influencer. This is interesting and likely driven by consumers becoming increasingly comfortable with AI recommendation systems (Kim, Giroux, and Lee, 2021), it may be that the perceived efficacy of such systems spills-over to other domains of AI, such as AI influencers. We also find that WOM intentions are higher for an AI influencer regardless of agency. While we find no difference between an AI and human influencer when the influencer is externally managed, our key outcomes are perceived more positively when an AI influencer is seen as autonomous.

*3.2 Study 2*

Study 2 extends study 1 in three ways. First, it employs different influencer stimuli to enhance external validity. In doing so, we investigate how influencer type (human vs. AI) impacts our key outcome variables ($H_1$) and consumer perceptions of social psychological distance ($H_2$) as well as the mediating role of social psychological distance between influencer type outcomes ($H_3$). Second, the role of consumer's need for uniqueness, in addition to social distance, is investigated in a mediated moderation model ($H_6$). We conduct a between-subjects experiment and manipulate influencer type (AI vs. human) to test our hypotheses. Third, we extend our sample to include male respondents in addition to females. This was deemed important to extend the generalizability of results from study 1.

*3.2.1 Study 2 procedure*

The online participant recruitment platform Prolific academic was used to collect data from US respondents via an online survey. Four hundred and three respondents completed the survey, however, 56 (13.9%) were removed for failing two attention checks. The final sample comprised 347 respondents (female = 42.2%) with a mean age of 36 years (s.d. = 9.42).

The same measures for source trust, intention to follow, and WOM as used in study 1 are employed in study 2. Additional measurement items for need for uniqueness are drawn from existing multi-item measurement scales in the literature. Need for uniqueness is measured with a four-item scale adapted from Tian et al. (2001), measuring the extent to which individual's create a unique identity through consumption. Measures displayed adequate construct reliability and internal consistency (see Appendix A1 for factor loadings and scale reliabilities). Internal reliability tests for scales employed demonstrate strong Cronbach (1951) alphas (ranging from 0.75 to 0.97). Again, we test CMV as in study 1. Table 5 presents correlations between variables and shows that CMV is not an issue given that the correlation among multiple constructs is less than 0.9 (Bagozzi et al., 1991).

The experimental scenario combines a written description with visual stimuli to manipulate our dependent variable (influencer type) as being either a human influencer or an AI influencer. Again, experts were engaged to aid in developing the scenarios and ensure clarity, relevance, and realism. Minor modifications to phrasing were made to enhance consistency and flow. The scenario descriptions for study 2 are provided in Appendix A3. Respondents were randomly allocated into one of the two influencer type scenario conditions. Scenario manipulation checks assess respondent scenario interpretation and recall. At the end of the survey, respondents were asked to recall if the influencer described to them was a human or an AI influencer, with 90% of respondents correctly identifying the influencer type based on the condition they were allocated into.

*3.2.2 Study 2 results*

First, we again test hypothesis 1 which predicts an AI influencer will have less source trust but higher intention to follow and WOM intention. We conduct a MANOVA to compare the means for each outcome between the two influencer types. For source trust, results reveal a significant main effect ($F = 3.99$, $p = 0.047$), with an AI influencer ($M = 3.68$; S.D. = 1.59) being perceived less trustworthy than a human influencer ($M = 4.03$; S.D. = 1.92). This finding supports $H_{1a}$. For intention to follow ($F = 0.33$, $p = 0.569$) and WOM ($F = 0.13$, $p = 0.908$) intention results reveal no main effect, hence providing no support for $H_{1b}$ again, and neither for $H_{1c}$.

Next, we conduct analysis to assess hypothesis 2 which predicts an AI influencer will have greater social psychological distance compared to a human influencer. Again, a one-way ANOVA is conducted to compare the mean of social psychological distance between two levels of influencer type (AI influencer vs human influencer). Results reveal a marginally significant main effect ($F = 3.44$, $p = 0.06$), with the AI influencer ($M = 4.67$; S.D. = 1.90) being perceived as more distant than the human influencer ($M = 4.34$; S.D. = 1.62). This finding provides additional support for $H_2$.

To test hypothesis 3 and hypothesis 6, Model 14 of the PROCESS macro for SPSS (Hayes, 2017) was used to assess mediation of social psychological distance as moderated by need for uniqueness. Analysis used 5,000 bootstrap samples to estimate the bias corrected bootstrap confidence intervals. Further, the index of moderated mediation was also calculated (Hayes, 2018). The index of moderated mediation is estimated using bootstrap resampling and indicates whether the conditional indirect effect is statistically different at different values of the moderator (Hayes, 2018). Model 14 allows for the indirect effect ($X \rightarrow M \rightarrow Y$) effect to be tested for $H_3$, as well as moderated mediation to test $H_6$. Analysis was conducted for each dependent variable, with results for hypothesis 2 shown in Table 6.

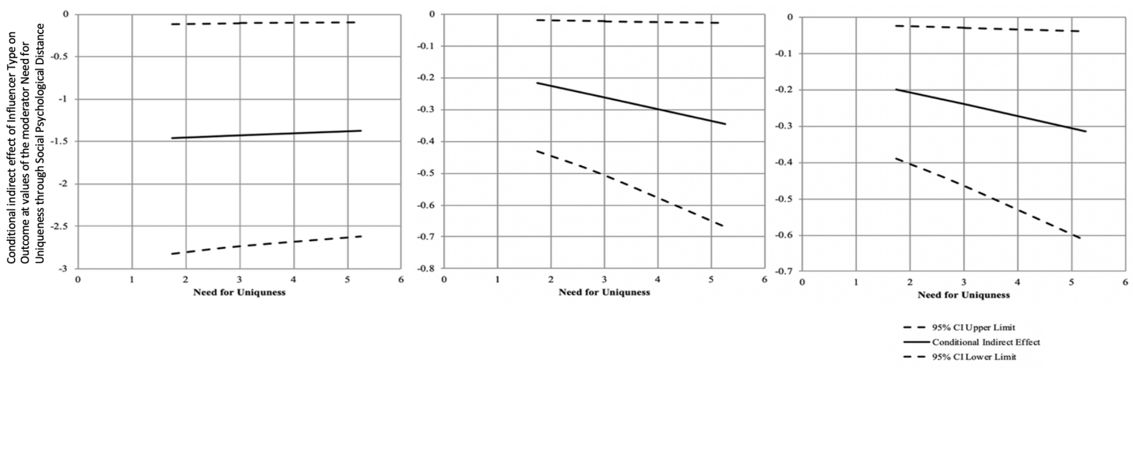
Hypothesis 3 predicts that effects on the outcome variables – ($H_{3a}$) source trust, ($H_{3b}$) intention to follow, and ($H_{3c}$) WOM intention – will be mediated by social psychological distance. Results for source trust ($H_{2a}$) reveal no main effect of influencer type ($b = -0.74$, $SE = 0.67$; 95% CI [−2.05, 0.58]), however, the indirect effect on source trust through social distance is significant ($b = 9.02$, $SE = 1.17$; 95% CI [-11.31, -6.73]. Thus, $H_{3a}$ is supported. For intention to follow ($H_{3b}$), no main effect for influencer type on continue to follow was found ([$b = 0.07$, $SE = 0.15$; 95% CI [−0.23, 0.36]), however, an indirect effect on intention to follow through social distance is significant (b = -0.85, SE = 0.28; 95% CI [-1.40, -0.30]). Thus, $H_{3b}$ is supported. Finally, for WOM ($H_{3c}$), no main effect for influencer type is found (b = 0.16, SE = 0.16; 95% CI [−0.16, 0.47]), however, an indirect effect on WOM through social distance is significant (b = -0.81, SE = 0.25; 95% CI [-1.30, -0.31]. Thus, $H_{3c}$ is supported.

Hypothesis 6 predicts that an individual's need for uniqueness will moderate the mediated relationship between influencer type, social distance, and the dependent variables: ($H_{6a}$) source trust, ($H_{6b}$) intention to follow, and ($H_{6c}$) WOM intention. Results for hypothesis 6, conditional indirect effects, and the respective index of moderated mediation is shown in Table 7.

To test the moderated mediation, the conditional indirect effect of influencer type on each outcome variable through social distance is estimated at varying levels of need for uniqueness. Unstandardised coefficients and bootstrapping with 5,000 resamples to place 95% confidence intervals around estimates of the indirect effects is employed. The index of moderated mediation indicates whether the conditional indirect effect is statistically different at different values of the moderator (Hayes, 2018).

For source trust ($H_{6a}$), conditional indirect effects at different levels of the moderator show significant effects [-1 S.D. (b = -1.46, SE = 0.68, 95% CI [-2.82, -0.19]); Mean (b = -1.43, SE = 0.65, 95% CI [-2.70, -0.19]); +1 S.D. (b = -1.37, SE = 0.63, 95% CI [-2.62, -0.18])]. Bootstrap (5000) results indicated the index of moderated mediation does include zero (b = 0.03 SE = 0.05, 95% CI [-0.05, 0.13]), which does not support $H_{6a}$. For intention to follow ($H_{6b}$), conditional indirect effects at different levels of the moderator show significant effects [-1 S.D. (b = -0.22, SE = 0.10, 95% CI [-0.43, -0.02]); Mean (b = -0.26, SE = 0.12, 95% CI [-0.50, -0.03]); +1 S.D. (b = -0.35, SE = 0.16, 95% CI [-0.65, -0.03)]. Bootstrap (5000) results indicated the index of moderated mediation does not include zero (b = -0.04, SE = 0.02, 95% CI [-0.09, -0.03]), which provides support for $H_{6b}$. Finally, for WOM intention ($H_{6c}$), conditional indirect effects at different levels of the moderator shows significant effects [-1 S.D. (b = -0.20, SE = 0.09, 95% CI [-0.39, -0.02]); Mean (b = -0.24, SE = 0.11, 95% CI [-0.46, -0.03]); +1 S.D. (b = -0.31, SE = 0.15, 95% CI [-0.62, -0.04])]. Bootstrapped (5000) results indicated the index of moderated mediation does not include zero (b = -0.03, SE = 0.02, 95% CI [-0.08, -0.01]), thus results provide support for $H_{6c}$. Figure 2 shows the conditional indirect effects.

**Figure 2**
**Study 2 conditional indirect effects of influence type on consumer outcomes through social distance at values of the need for uniqueness**



*3.2.3 Study 2 discussion*

In terms of the effect of influencer type on our outcome variables, this study provides additional support that an AI influencer is perceived as less trustworthy, again supporting a generalised negative view of technology mediated interactions in service encounters. Again, we also find no difference between an AI influencer and human influencer in terms of intention to follow. However, with this study we also find no difference in terms of WOM intentions. Our results also provide partial support to study 1 in terms of an AI influencer being perceived as more social psychologically distant than a human influencer. While this result was marginally significant in this study, it is possible that the inclusion of male respondents in study 2 had an impact on WOM intention and social psychological distance – with males potentially not perceiving the female influencer the same manner as female respondents.

We further investigate social psychological distance and its role in mediating the relationship between influencer type and our outcomes. Again, findings show that an AI influencer is perceived as significantly more socially distant than a human influencer. Our mediation analysis reveals that the effects for AI (vs. human) influencers – in terms of intention to follow, WOM, and source trust – are fully mediated by social distance. Finally, with this study we overlay the role of an individual's need for uniqueness. Our results show that need for uniqueness acts to influence reactions to an AI influencer – in that AI influencers can have a greater effect on consumers who have high need for uniqueness. We find this effect for wishful identification, continue to follow, and WOM.

**4.0 General Discussion**

Recent years have seen an increased prevalence of influencer marketing (de Veirman et al., 2017) and an increased desire for marketers to leverage AI (Campbell et al., 2020). Virtual AI influencers sit at the intersection of influencer marketing and the use of AI in marketing –providing novel insight into the increasingly prominent phenomenon of the AI influencer. With this research, important first steps are made towards in providing marketers, brands, advertisers, and social media managers an understanding as to the effect AI influencers can have. At a basic level, our results show that AI influencers can play a similar role to human influencers. In fact, they can have a larger positive effect when consumers have high need for uniqueness, and they are buffered from the negative effect of having no agency – or being externally managed. In sum, we offer implications for theory and managers, as well as outline limitations and future research directions to develop understanding for AI influencers.

*4.1 Theoretical implications*

With this research, we broaden the scope of influencer marketing to include the role of AI influencers. We contribute to theory in several ways. First and foremost, this article provides an understanding of how consumers respond to AI influencers. While our results show that an AI influencer is seen as less trustworthy, we do find that for some outcomes there is no difference between an AI and human influencer. Specifically, we find that consumers are as likely to follow either influencer type, and (in our first study) that consumers report higher WOM intentions for an AI influencer. We also find that there is no difference in perceptions of personalisation, meaning that an AI influencer is perceived as being as able to personalise – content or recommendations – as a human influencer. We propose that this is a spill-over effect from consumers becoming increasingly comfortable with AI recommendation systems (Kim, Giroux, and Lee, 2021), as in the case of Netflix, which are seen as being able to learn from behaviour and make intelligent recommendations. It may be that developers of AI influencers need to play up this element as a key competitive advantage of AI influencers.

Taken together, our findings advance research on influencers and open a new stream of research into AI influencer marketing. Importantly, this study suggests that existing theory and knowledge help explain how consumers respond to AI influencers. First, this study shows that consumers who are high on need for uniqueness are more receptive to AI influencers. It is likely that given AI influencers are so niche, these consumers seek AI influencer interactions to feel unique (Fisher and Price, 1992) and assist in their identify expression (Berger and Heath, 2007; Tian et al., 2001). It is also likely that as AI influencers become more mainstream that these consumers will divert their attention from AI influencers and seek out other unique and identify defining experiences. However, it is somewhat interesting that need for uniqueness does not moderate the effect of influencers on source trust.

Second, this research lends support to an emerging research stream showing that parasocial interaction is a driver of an influencer's effectiveness (Shan et al., 2019). Parasocial interaction refers to an imagined one-way relationship between a spectator and a performer (Horton and Wohl, 1956) that results in an illusion of intimacy like a 'real' interpersonal relationship (Dibble et al., 2015). We find that AI influencers are seen by consumers to be more socially distant than human influencers – suggesting that consumers may have challenges relating to an AI influencer, in much the same way they do inanimate objects (Hancock et al., 2011; Turkle, 2007). Results show that as social distance decreases, an influencer can have more positive effects. This supports the rising interest in micro influencers (Main, 2017b), with theory suggesting that influencers are perceived as 'closer' (compared to celebrities) and thus lead to stronger positive effects.

Finally, this work unites the literature on social media influencers and freedom of choice. Just as agency is fundamental to virtue (Berman and Small 2012), our results indicate that perceived agency is a key factor in the way consumers view influencers and impacts their resultant attitudinal and behavioural responses. First, we show that agency plays an important role in the way in which consumers view influencers. However, importantly, we show that there is a differential effect for agency depending on influencer type. Contrary to expectation, we show that an AI influencer can act to buffer the negative effect a lack of agency can have for an influencer.

### *4.2 Managerial implications*

This research has several implications for marketing and advertising practice. First, managers are provided with insight into the efficacy of AI influencers. From a practical standpoint, this research shows that AI influencer can be as effective as a human influencer but can result in negative effects in terms of source trust– hence, cautions a rush to replace human influencers with their AI counterparts. Nonetheless, our findings provide brands with licence to experiment and complement their existing influencer marketing programs with virtual AI influencers as brand ambassadors. This may prove particularly fruitful in campaigns aimed at spreading WOM as a goal. We illustrate that AI influencers can have higher WOM, which provides support for the WHO decision to engage AI influencer Knox Frost in its COVID-19 campaign. If AI influencers can result in higher spread of WOM, there may be implications for their use in similar campaigns or public service announcements.

Our findings suggest that it is feasible to leverage AI influencers and their ability to quickly leverage social media trends. There is no doubt that working with human creatives takes time – from figuring mutual availability to creating, editing, and releasing content. However, the content creation process can be more rapid when working with AI influencers to develop messaging and capitalise and respond to social trends in real time. Beyond content creation, AI influencers can mitigate the risks of dealing with celebrities and human influencers, including the expense, risk of ageing out of a demographic profile, or even offending consumers by saying or doing something inappropriate or wrong.

A further benefit of AI influencers is that they potentially enable an infinite number of micro-targeted – or even entirely personalised – influencers to be rapidly created by a brand. At the extreme, all consumers could be targeted with their own personalised influencer bots. These personalised influencers might learn consumer desires and tailor offers in a hyper-personal manner, even showing consumers their own aspirational version of themselves. In much the same way that the app Zeekit allows consumers to virtually "try on" fashions before buying online or trying on in-store by virtually seeing items on their actual body. From a practical standpoint, hyper-personalised AI influencers may have benefits such as reducing return rates by providing better targeted product suggestions to consumers (Parisi, 2021).

This research shows that less social distance between the consumer and the influencer drives positive outcomes. This finding suggests that influencers who are more relatable may be more successful. This provides support to engaging micro-influencers, or influencers with relatively small numbers of followers who are assumed to connect more strongly with their audience.

Finally, a consumer's level of need for uniqueness influences how they respond to AI influencers. The study shows that as consumers' need for uniqueness increases, so to do the positive effects of an AI influencer. Thus, for brands that are designing products, services, or experiences for people who are striving to be unique, using an AI influencer will work well. For instance, brands creating products aimed at hipsters, or other unique sub-cultures, that strive to consume to stand out may well benefit from AI influencer engagement. However, source trust is unaffected by differences in need for uniqueness. This indicates that for products that rely more on trust, human influencers are effective across a wider range of consumers.

### *4.3 Limitations and future research*

This research, like all, is subject to some limitations. First, the scenario description of the products the AI and human influencer promoted were intentionally vague. The influencer was described as promoting a luxurious and fashion-forward category (i.e., working with top brands, in exotic settings). It is fair to assume that results may differ for an influencer that is instead known for their expertise (e.g., cooking, technology) or for categories where close social distance might be preferable to far social distance (e.g., everyday restaurants, experiences that align with those of the consumer). To this end, it would be fruitful to extend this study across a variety of different product and experience categories. Regarding the scenario descriptions, it also worth noting that while we combine written and visual elements, that our written scenario in study 1 was long. While we attempted to account for this by spreading the written text across survey blocks, it is possible that confounding effects may be present.

There are important considerations for the dark side of social media also (Sands et al., 2019). Extending researching into illicit consumption is an example where there may be benefits for engaging AI influencers. For instance, in the adult entertainment industry the company YouPorn has announced the introduction of an AI brand ambassador, Jedy Vales (Silver, 2019). This raises the question about the efficacy of influencer marketing regarding stigmatized product categories.

Given that consumers may experience feelings of embarrassment in seeking advice or purchase in such categories (Dahl et al., 2001), AI influencers may be better suited to stigmatized product categories. It is possible that interacting with an AI influencer may reduce consumers fear of negative evaluation, or the "apprehension about others' evaluations, distress over their negative evaluations, avoidance of evaluative situations, and the expectation that others would evaluate oneself negatively" (Watson and Friend, 1969, p. 449).

Second, Instagram was the focal social media platform in this study. However, the effects found may vary by social media platform. Influencers in the context of YouTube, or even emerging platforms like TikTok, may result in different effects. Investigating different social media platforms, and even non-social platforms, is important as there is a move toward AI 'influencers' being embedded into a variety of consumer interfaces. In 2019, it was announced that the China state-run press agency, Xinhua, unveiled an AI news anchor, with digital composites created from footage of human hosts that read the news using synthesized voices.

Third, there are limitations associated with the method of data collection employed in this study. While internal validity was a focus for running an experiment, this necessarily comes at the expense of external validity. Field experiments are encouraged to compare AI influencers to human influencers with similar profiles. Such extensions should also seek to assess purchase as an outcome of interest. Further, the focus on a US sample is a limitation, with results potentially varying with other consumers or in other cultural contexts (i.e., individual vs. collective cultures).

Finally, a narrow set of outcome variables focused on intentions were investigated. While effects are found based on social distance and need for uniqueness, there could be other mechanisms at play too. Important mechanisms to focus on in future research include the consumers level of expertise and perceived authenticity of the influencer. In terms of outcomes, a focus on actual behavioural linked to brands is important to understand. It would be useful for research to extend these findings and investigate alternative mechanisms and behavioural outcomes. These mechanisms and outcomes should be focused to more deeply on how AI influencers may be a means for marketers to reach consumers with information about their products – rather than our primary focus, which has been on variables that focus on how influencers can boost their own influencer brand.

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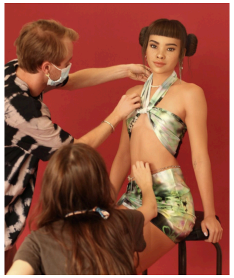
# APPENDICES

## Appendix A1
## List of variables, factor loadings and scale reliabilities

| Item | Study 1 | Study 2 |
|---|---|---|
| *Source Trust (Study 1: alpha = 0.95; % variance explained = 85%; Study 2: alpha = 0.97; % variance explained = 56%)* | | |
| Product recommendations from the influencer Adriana Garcia would be... | | |
| Insincere-sincere | 0.80 | 0.81 |
| Undependable-dependable | 0.86 | 0.87 |
| Dishonest-honest | 0.84 | 0.85 |
| Unreliable-reliable | 0.85 | 0.89 |
| Untrustworthy-trustworthy | 0.89 | 0.87 |
| *Need for uniqueness (Study 1: NA; Study 2: alpha = 0.91; % variance explained = 77%)* | | |
| To what extent do you agree or disagree with the following statements about yourself? | | |
| I actively seek to develop my personal uniqueness by buying special products or brands. | - | 0.84 |
| I often look for one-of-a-kind products or brands so that I create a style that is all on my own. | - | 0.85 |
| The more commonplace a product or brand is among the general population, the less interested I am in buying it. | - | 0.87 |
| When a product I own becomes popular among the general population, I begin using it less. | - | 0.87 |
| *Social psychological distance (Study 1: alpha = 0.93; % variance explained = 82%; Study 2: alpha = 0.92; % variance explained = 75%)* | | |
| The influencer Adriana Garcia feels... | | |
| Far - Near | 0.85 | 0.77 |
| Unapproachable - Approachable | 0.87 | 0.78 |
| Unfriendly - Friendly | 0.83 | 0.66 |
| *Commercialisation (Study 1: alpha = 0.81; % variance explained = 80%; Study 2: NA)* | | |
| To what extent do you agree with the following statements? | | |
| Adriana Garcia feels commercialised | 0.82 | - |
| It seems that a lot of companies sponsor Andrea Garcia | 0.80 | - |
| Many companies probably pay to get their products promoted by Andrea Garcia | 0.81 | - |
| I thought it was obvious that brands are included in her posts just to persuade viewers | 0.75 | - |
| Andrea Garcia's Instagram feels like one big commercial | 0.84 | - |
| *Personalisation (Study 1: alpha = 0.95; % variance explained = 82%; Study 2: NA)* | | |
| To what extent do you agree or disagree with the following statements about the social media influencer Adriana Garcia? | | |
| This influencer would be able to make recommendations that match my needs | 0.94 | - |
| I think that this influencer would enable me to order products that are tailor-made for me | 0.90 | - |
| Overall, this influencer would post content tailored to my needs | 0.93 | - |
| This influencer would make me feel that I am a unique follower | 0.85 | - |
| I believe that this influencer's content would be customised to my needs | 0.93 | - |

Notes: all items measured on 7-point scales, except Intention to follow (if you could, how likely would you be to follow Adriana Garcia?) and WOM (how likely would you be to tell others about the social media influencer Adriana Garcia?) measured with single-items.

**Appendix A2**
**Study 1 scenario conditions manipulation of influencer type (human versus AI) and influencer agency (autonomous versus managed)**

| Influencer type | Influencer agency | Scenario description | Scenario image |
|---|---|---|---|
| Human influencer | Autonomous | Adriana Garcia is a social media influencer. She has been an influencer for 5 years and has a few hundred thousand followers. As an influencer, Adriana promotes a range of products and works with many top brands. She works with a lot of brands to promote products and experiences with followers. She was named one of the Top 50 Emerging Social Media Influencers of 2020. Adriana Garcia started her career as an influencer on her own, and still runs her Instagram account herself. Adriana started out as influencer when she began posting about products and brands, she loved in her first Instagram account. Adriana decides what she posts and how her posts look. She reads her own DMs and comments and chooses which brands she works with. She promotes brands she thinks will be of interest to her followers. Adriana is constantly looking out for the latest trends and popular products to promote. Everything Adriana does as an influencer is decided autonomously by herself. |  |
| AI Influencer | Autonomous | Adriana Garcia is a social media influencer powered by artificial intelligence (AI), which means that she is a virtual entity. Adriana has been an influencer for 5 years and has a few hundred thousand followers. As an influencer, Adriana promotes a range of products and works with many top brands. Adriana works with a lot of brands to promote products and experiences with followers. She was named one of the Top 50 Emerging Social Media Influencers of 2020. Adriana Garcia started her career as an influencer when a programmer created her and the AI algorithm that still runs the Instagram account. Adriana started out as influencer when a programmer created an AI algorithm that defined her look, personality, and digital self. The algorithm decides what Adriana posts and how posts look. The AI algorithm reads DMs, responds to comments, and chooses which brands to work with. The AI algorithm that runs her is designed to promote brands it thinks will be of interest to its followers. The algorithm is constantly looking out for the latest trends and popular products to promote. Everything Adriana does as an influencer is decided autonomously by the algorithm. | |
| Human influencer | Managed | Adriana Garcia is a social media influencer. She has been an influencer for 5 years and has a few hundred thousand followers. As an influencer, Adriana promotes a range of products and works with many top brands. She works with a lot of brands to promote products and experiences with followers. She was named one of the Top 50 Emerging Social Media Influencers of 2020. Adriana Garcia owes her career to a professional social media management team that created her from nothing. They still direct her every move. Adriana started out as influencer when she was hired by a professional social media management company to be the public face of an account they had designed. The team that manages Adriana decides what she posts and how her posts look. The team reads her DMs and comments and chooses which brands she works with. The team has her promote brands they think will be of interest to her followers. Adriana Garcia is a social media influencer powered by artificial intelligence (AI), which means that she is a virtual entity. Adriana has been an influencer for 5 years and has a few hundred thousand followers. As an influencer, Adriana promotes a range of products and works with many top brands. Adriana works with a lot of brands to promote products and experiences with followers. She was named one of the Top 50 Emerging Social Media Influencers of 2020. The team that manages her is constantly looking out for the latest trends and popular products to promote. Everything Adriana does as an influencer is decided by the management team. |  |
| AI Influencer | Managed | Adriana Garcia started her career as an influencer when a professional social media management team created her AI algorithm from nothing. They still direct her every move. Adriana started out as influencer when a professional social media management company created an AI algorithm that defined her look. They manage Adriana's personality and digital self. The team decides what she posts and how her posts look. The team reads her DMs and comments and chooses which brands she works with. The team uses AI to create posts promoting brands they think will be of interest to her followers. The team that manages her is constantly looking out for the latest trends and popular products to promote. Everything Adriana does as an influencer is decided by the management team. | |

Note: scenario text is compressed in this table to save space but within the survey was presented across multiple survey blocks with text spaced out.

## Appendix A3
## Study 2 scenario condition manipulation of influencer type (human versus AI)

| Influencer type | Scenario description | Scenario image |
|---|---|---|
| Human Influencer | Adriana Garcia is a social media influencer. Adriana has been an influencer for 5 years and has a few hundred thousand followers. As an influencer, Adriana promotes a range of products and works with many top brands. Adriana is offered a lot of free products and experiences to share with followers. She is constantly looking out for the latest trends and popular products to share and is known for inspirational and creative posts in exotic settings. She was named one of the Top 50 Emerging Social Media Influencers of 2019. |  |
| AI Influencer | Adriana Garcia is a social media influencer powered by artificial intelligence (AI), which means that Adriana is a virtual entity. Adriana has been an influencer for 5 years and has a few hundred thousand followers. As an influencer, Adriana promotes a range of products and works with many top brands. Adriana is offered a lot of free products and experiences to share. Adriana is constantly looking out for the latest trends and popular products to share and is known for inspirational and creative posts in exotic settings. Adriana was named one of the Top 50 Emerging Social Media Influencers of 2019. | |