HUMAN VS. MACHINE AS MESSAGE SOURCE IN ADVERTISING: EXAMINING THE PERSUASIVENESS OF BRAND INFLUENCER TYPE AND THE MEDIATING ROLE OF SOURCE CREDIBILITY FOR ADVERTISING EFFECTIVENESS IN SOCIAL MEDIA ADVERTISING

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By

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

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presented by Weilu Zhang

a candidate for the degree of Doctor of Philosophy,
and hereby certify that, in their opinion, it is worthy of acceptance.

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DEDICATION

Dedicated to my parents: Shuyun and Zhenjun.

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At this moment, I am hopeful and grateful. My four years of the Ph.D. journey have come to an end. It feels very short and very long at the same time. I am glad to see the person and the scholar I am turning to be and very excited about what is coming next. Without a doubt, I cannot get to this point without my advisor, mentors, friends, and family rallying around me and providing generous support throughout.

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I love you all.

Sincerely,

Weilu

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ABSTRACT

Message source effects on persuasion of target audiences have been examined for decades by scholars in advertising, consumer behavior, communication, and psychology, among others. Myriads of studies are available on the subject, but in nearly every instance "source" is defined as a human and rarely is source defined as non-human, or machine. The rise of artificial intelligence (AI) as a message source urges scientific inquiry of the validity of those established theories in a new technology context. The focus of this dissertation is on that of the machine as source. By "machine" this study refers broadly to AI agents, defined to mean digitally created artificial beings that can think and perform tasks like a human. The specific AI agent examined here is that of SMIs, defined as AI agents who are associated with fame and perform human tasks using software and algorithms. The context of the study is social media, defined as "digital networked tools or technologies that enable communication, collaboration, and creative expression across social networks" (McMillan & Childers, 2017, p. 52). Influencer marketing is a crucial component of social media marketing, which is projected to become a $10 billion market by 2023 (Tan, 2019). The primary contribution of this study is, therefore, to understand SMIs' effectiveness in social media advertising. Considering that 95 percent of consumer interaction is projected to be powered by AI by the year of

2025 (Finance Digest, 2020), research to understand the impact of this transformation of message source (from human to machine) is urgently needed but rarely conducted to date. The most apparent machine sources, SMIs, are already being put to use in practice without fully understanding their effectiveness and risk, to replace human influencers. Human influencers, here, specifically refer to social media influencers (SMIs) "who have built a sizable social network of people following them and are seen as self-made micro-celebrities" (Shan et al., 2020, p. 2). Indeed, this very notion is reflected in the warnings of the infamous physicist Stephen Hawking who predicted that, someday, machines may even replace humans. As much as this may sound like a futuristic movie, machines are beginning to replace humans in fields as far and wide as medicine, engineering, and transportation. For example, AI is cleaning floors at airports, taking people's temperatures, and even making salad in hospital dining-halls in response to the coronavirus pandemic (Semuels, 2020). In advertising, AI is taking over the work humans have traditionally done, from content matching to advertising creation (Rodgers, 2021). An SMI, Lil Miquela, even takes the spot that is usually reserved for a human and is named as one of *Time's* 25 most influential people on the internet in 2018 (*Time*, 2018). The proposed research is supported by survey results from consumers worldwide that paint a mixed picture – some consumers embrace AI for its potential benefits, whereas others fear that AI will hurt their privacy and ability to control their jobs, lives, and futures (Zhang & Dafoe, 2019), suggesting potential drawbacks of AI technology. This suggests that SMIs could trigger various perceptions among consumers that may lead to different outcomes. The challenge is to know the underlying psychological mechanisms to explain potential positive/negative outcomes, yet studies on the subject are rare but urgently needed. This dissertation investigates this phenomenon, specifically, potential benefits and drawbacks of using SMIs compared to (human) SMIs in social media advertising. Based on established theories of persuasion on advertising and brand endorsers, this dissertation identifies a crucial processing mechanism - source credibility - that is used to explain instances under which influencer type (i.e., AI vs. human) differentially influences advertising outcomes (i.e., attitude toward the advertisement, attitude toward brand, and purchase intentions). Source credibility is the source's truthfulness and believability perceived by the consumers (Roy et al., 2017). The treatment of source credibility as a mediating factor is a unique aspect of the research and that diverges from prior approaches that treat it as a predictor of persuasion. Rather, this research conceptualizes source credibility as dynamic, constantly changing, and not related in a simple way to the persuasiveness of an influencer type. Three dimensions of source credibility - expertise, trustworthiness, and physical attractiveness - are proposed to explain how an AI influencer may perform better/worse than a (human) SMI on advertising outcomes. A review of five decades' of source credibility studies noted several discrepancies regarding three dimensions of source credibility, suggesting gaps or unresolved issues in source credibility that deserve attention (see Pornpitakpan, 2004). Additionally, initial negative/positive dispositions toward the brand influencers, which has hardly been examined (see Pornpitakpan, 2004), will be measured in an effort to assess how much, if any, of a shift is detected in source credibility perceptions. To summarize, this research examines effectiveness of influencer type (artificial intelligence influencer vs. SMI) on persuasion of social media advertising (attitude toward the ad, attitude toward the brand, and purchase intentions). One mediator, source credibility, is proposed to explain the results. This is accomplished with a pilot study and an experimental study conducted in an online setting.

CHAPTER ONE

INTRODUCTION

> The potential benefits (of artificial intelligence) are huge; everything that civilization has to offer is a product of human intelligence; we cannot predict what we might achieve when this intelligence is magnified by the tools AI may provide, but the eradication of war, disease, and poverty would be high on anyone's list. Success in creating AI would be the biggest event in human history. Unfortunately, it might also be the last, unless we learn how to avoid the risks. (Stephen Hawking, Max Tegmark, Stuart Russell, and Frank Wilczek, 2014, para. 3-4)

Attitudes towards artificial intelligence (AI) are complicated. There are many who hope that AI might one day amplify human intelligence and benefit the world. However, the fear of AI taking control of the humans that solicited its support always lurks beneath the surface, a fear evidenced in the warning from great minds like Stephen Hawking, and sensationalized in pop culture works such as *Westworld*. Neither the hopes for AI's potential nor the fear of adverse consequences are far-fetched. Even though AI has not yet managed to eradicate "war, disease, and poverty," it routinely replaces human activity and thought in everyday life and at an unprecedented pace. This pace has only been accelerated by the COVID-19 pandemic (Semuels, 2020). This trend is particularly evident in advertising (Rodgers, 2021). Communication research focused on consumers' reactions to increased reliance on AI are urgently needed (Gunkel, 2012). Armed with such knowledge, researchers and practitioners would be in a better position to minimize the risks associated with AI. This dissertation is one of the few to try to understand the effects of AI on social media advertising.

Artificial intelligence (AI) refers broadly to computers that can think and perform tasks like human subjects via software and algorithms (Kumar et al., 2019). AI is rapidly becoming a prominent technology for digital advertising (Rodgers, 2021). By 2023, spending on global digital advertising is expected to reach $517.51 billion (Enberg, 2019). PwC's annual AI prediction survey in 2020 found that among the 1000 respondents, more than a quarter of the companies reported widespread adoption of AI, and another 54% are heading in that direction (PwC, 2021). As the total spending on influencer marketing is expected to increase by as much as $10 billion by 2023 (Tan, 2019), AI influencers are gaining an increasingly large share of what has traditionally been a marketplace dominated by human activity alone. Influencer marketing is a type of brand communication where commercial brands seek to weave their commercial posts into the daily narratives of SMIs (Breves et al., 2019). Brands are able to benefit from influencer marketing because consumers perceive influencers to be more authentic in this arena (Coco & Eckert, 2020; Kapitan & Silvera 2016). This might initially seem to argue against widespread use of AI in that the "artificial" nature of such influencers would appear to run counter to the authenticity required by consumers, suggesting that AI influencers might be less effective than their human counterparts. Indeed, when programming AI, the goal is generally "to cope not worse than a human" (Dobrev, 2012, p. 2).

In assessing advertising effectiveness, it is the consumer who determines how well an AI performs. Therefore, understanding the effectiveness of the AI influencer from a consumer’s perspective is crucial for both advertising scholars and practitioners. This understanding is the core goal of this dissertation. Specifically, this dissertation aims to determine if AI, as a brand communicator, can perform equally well, or even better, than humans in bringing about favorable brand outcomes with minimized risks to consumers and society.

AI influencers refer to digitally created artificial humans that are able to gain internet fame and perform human-like tasks via software and algorithms (Thomas & Fowler, 2021). One of the most popular AI influencers is a nineteen-year-old model, Lil Miquela, created by a Los Angeles-based startup called Brud (Bradley, 2020). By December 2020, Miquela already had more than 2.8 million followers on Instagram and 248,000 subscribers on YouTube. Miquela has collaborated with a number of high-end brands, such as Prada and Gucci, and she has already demonstrated great financial potential. TechChurch reported that Brud recently closed a $125 million dollar investment round led by Spark Capital in January 2019 (Tiffany, 2019). The skincare brand SK-ii also uses an AI influencer and advisor, Yumi, a skincare expert ready to provide personalized advice (Hawley, 2020). Unlike Miquela, who mostly mimics the way a human influencer would operate in an online environment, Yumi stresses her distinctive “machine” (non-human) features. As Yumi boasted in her debut video (Global Cosmetics News, 2019), she “can tap into the best skincare info to suit every person” because she has a “digital brain,” suggesting that marketers and programmers believe that AI’s ability to find similarities and demonstrate expertise is of a higher caliber than human-sourced efforts.

Indeed, practitioners are lured by this new marketing possibility, even though some continue to express concerns (Bradley, 2020). By merely looking at the attention paid to these AI influencers, like Lil Miquela and Yumi, it appears that replacing human influencers with AI substitutes is a promising initiative. Thanks to technological advancements, such as natural language processing and image recognition, AI influencers are becoming more indistinguishable from humans in appearance and in the language they use in posts and chats, at least in the social media arena (Thomas & Fowler, 2021). Tan (2019) believes that AI influencers could be beneficial to the brand by allowing more control over brand messaging and the endorser's personalities as compared to human influencers. Additionally, AI has stronger computational abilities for accessing and processing numerous digital resources and consumer inputs (Sterne, 2017). This superior capability in dealing with large amounts of multi-dimensional data might make AI-enabled influencers a better source for the dissemination of consumer information. However, as stated above, it is unknown whether the positive features of a human influencer, such as perceived authenticity (Kapitan & Silvera 2016) or expertise on a specific topic (Lou & Yuan, 2019), could be extended to artificial influencers. Additionally, there are ongoing concerns about AI potential to increase online deception and spread misinformation through social media (Bradley, 2020), as well as the implicit bias embedded in the programming of AI agents that might lead to discriminatory decision-making (Dalenberg, 2018; Metz, 2020). Those concerns may hurt the trustworthiness of an AI source and contribute to the risks of AI advertising applications, a topic that is a focus of investigation in our current research.

A comparison between humans and AI communicators is essential when considering whether to replace humans with AI entities if we are to better understand the "promises and perils" of that decision. Industry surveys show that consumers possess mixed feelings about AI in the global marketplace. On the one hand, a survey conducted by Zhang and Dafoe (2019) found that, in general, more Americans support (41%) than oppose (22%) the development of AI. For example, 40 percent of the 6000 participants in Pega's survey believed that AI could improve customer service and interactions. On the other hand, consumers reveal a strong distrust of AI due to its lack of empathy and autonomy. One study shows that 54 percent of the respondents believe that AI will be biased in its decision-making process (Pega, 2019). Pega's (n.d.) survey also found that consumers still prefer to interact with humans rather than an artificially created AI. In short, academic work investigating how consumers perceive AI as a message source would help guide industry, as well as help set policy on the appropriate application of AI influencers.

To addresses those concerns, this dissertation proposes research guided by two broad questions:

RQ1: What are the effects of message sourcing by AI influencers compared with human SMIs?

RQ2: What is the mediating effect of source credibility, i.e., physical attractiveness, trustworthiness, expertise, on the main hypothesized effects?

The rising popularity of AI influencers provides a tangible, humanlike interface to the underlying AI algorithm, thus intersecting with advertising. Further study of the effect an AI's as source will have on the consumer will be beneficial. In this study, advertising refers broadly to brand initiated communication that is intended to have an impact on consumers (Dahlen & Rosengren, 2016). By executing the tasks of human influencers, AI is gradually taking on the role as a message source (as in McGuire, 1969). A message source is defined as an entity that consumers perceive as being responsible for the content in the communication process (Thorson & Rodgers, 2019). Despite several practical developments, there is relatively limited academic research on AI as a message source (Gunkel, 2012). We do not yet fully understand how consumers perceive, process, and evaluate the message/brand that is delivered by an openly AI entity.

AI advertising is "brand communication that uses a range of machine functions that learn to carry out tasks with intent to persuade with input by humans, machines, or both" (Rodgers, 2021, p. 5). AI advertising is usually studied as an "algorithm-mediated" type of brand communication (Li, 2019, p. 333). For example, a special section on computational advertising in the *Journal of Advertising* is focused on AI's underlying computational ability in the advertising process (for a review of these findings, see Huh & Malthouse, 2020). This approach applies to the initiative of using an AI application in advertising where AI performs only a single task with proficiency (referred to as narrow AI, Rodgers, 2021; Sterne, 2017). In this branch of research, AI usually operates in an intangible way. For example, these studies are in contexts where AI tracks consumers' online behaviors through the monitoring of websites or devices (e.g., Hayes et al., 2021; Malthouse et al., 2019). Here, AI serves as a sorting/recommendation system (also known as AI driven interactive recommendation agents, see Kim et al., 2021), and matches the audience with relevant content in the name of other sources (e.g., brand, celebrity, SMIs). Because of the intangible nature of the operation, consumers have a relatively limited awareness of AI's role in the advertised content they encounter every day (Boerman et al., 2017). For example, Zhang and Dafoe (2019) report that only around 30% Americans consider AI powered web functions such as Facebook photo tagging, Google translate, or Netflix recommendation as AI. Therefore, it is usually the "products" of AI, such as personalized content, that corresponds to an individual consumer's preferences (e.g., Boerman et al., 2017) and that are studied as factors that influence a consumer's responses. The consumer-perspective approach of this research is crucial for understanding AI advertising's effectiveness. However, as AI influencers become a more prevalent trend in advertising practices, current results provide limited insights into how AI as a visible entity might shape consumers' perceptions and evaluations of the brand's message. AI related research examines the tension between technology and humanness is considered as one of the five important themes in digital marketing (Schmitt, 2019).

Before discussing further our research, two assumptions undergirding this dissertation need to be stressed. These two assumptions serve as a starting point for understanding consumers' potentially different perceptions and responses towards AI versus human influencers. Firstly, the researcher assumes that the AI source is transparent. In other words, consumers will be informed as to whether an advertisement comes from a human influencer or an AI. Being transparent about the virtual influencers' non-human nature is crucial for ethical advertising practices in order to ensure that brand communication is not based on a deception (Voorveld, 2019). In other words, AI influencers should not pretend to be human with the goal of deceiving or confusing consumers. Both Lil Miquela and Yumi are quite honest about being a creation of AI. Indeed, Kumar and Gupta (2016) argue that transparency should be a default approach for the future if advertising. Therefore, this dissertation focuses on reactions from consumers towards the non-human nature of the influencer they encounter, rather than on the consumers' subjective knowledge for distinguishing AI characters from humans. Second, the researcher assumes that consumers will hold subjective initial dispositions toward AI, whether positive or negative. The AI dispositions record the general positive/negative feelings and beliefs towards AI, as indicated by previously noted mixed survey results. As such, these pre-existing dispositions would assist consumers in coping with persuasion attempts to persuade (Friestad & Wright, 1994) and processing the incoming message from sources labeled as AI.

This dissertation endeavors to further clarify the effectiveness of AI sources relative to humans, and is distinct from prior research in several important ways. First of all, the human source is theorized as a SMI rather than a celebrity influencer, as is the case in Thomas and Fowler's (2021) study. SMIs, which are commonly used by brands in social media advertising, may yield different results for this type of comparison. Researchers have in the past made distinctions between SMIs and celebrities, but not between SMIs and AI influencers, as proposed here. "Celebrity" is defined as individuals who gain public recognition and fame because of their professional talents in fields such as sports or entertainment (Schouten et al., 2020). SMIs, on the other hand, gain public recognition and fame through successfully branding themselves as an expert in some specific area on social media (Schouten et al., 2020). SMIs are perceived by consumers as being more trustworthy than celebrities (Gräve, 2019; Schouten et al., 2020). Thomas and Fowler (2021) also call for further research to compare AI influencers with other human influencer types, further justifying the need for the present research.

Second, the information processing mechanisms of the AI source effect are not fully understood and will be further investigated in this dissertation. Specifically, three dimensions of source credibility of this new technology (i.e., AI influencer) are examined. Source credibility is the consumer's perception of the advertising source's attribution of truthfulness or believability (Roy et al., 2017). In Thomas and Fowler (2021), it was found that AI influencers and celebrity endorsers could be equally effective in prompting favorable brand responses (i.e., attitudes, purchase intentions) among consumers. The explanation for the interchangeability (i.e., serving as exemplars of taste) between AI and human sources is similar to the idea of understanding source effects through the concept of physical attractiveness, which is suitable for the product (i.e., sunglasses) tested in their experiment. Physical attractiveness is the extent to which a source is liked by the consumer (McGuire, 1969). However, the literature on brand endorsers (Amos et al., 2008; Bergkvist & Zhou, 2016; Erdogan, 1999) suggests that physical attractiveness accounts for only one component that determines source effectiveness. The other two dimensions identified by Ohanian (1990) are trustworthiness (i.e., the speaker's intent to convey valid assertions in an honest manner) and perceived expertise (i.e., the entity is a valid source for making such assertions). Considering that consumers demonstrate less trust in AI, as suggested by results in Pega's (2019) survey, trustworthiness may also play a role in differentiating AI sources from humans. Meanwhile, to return to Yumi's example, she emphasizes her "digital brain" when asserting her expertise in skincare. This emphasis suggests that data access and processing abilities in an AI influencer may alter consumers' conventional perceptions of source expertise. Taking all three source credibility dimensions into account could help to differentiate between the information processing of AI and human influencers.

To address the research questions, the researcher proposed a theoretical model as indicated in Figure 1.1. Empirically, one pilot study and a main study were conducted to compare the effectiveness of AI and SMIs and underlying psychological mechanisms in brand endorsement based on proposed advertising outcomes, including the subject's attitude toward the advertisement, attitude toward the brand, and purchase intentions. First, in the pilot study, a three steps dynamitic validation process was conducted to validate the manipulations and measurement instruments. In the main study, a between-subject experiment was conducted to build up validity of the testing of the proposed model with hypothetical brands and influencers within a controlled experiment.

New technologies, especially AI advertising, are changing advertising practices and structures, and by extension, the meaning and scope of advertising research (Kerr & Richards, 2020). This dissertation responds to a call for research by advertising scholars' (e.g., Kumar & Gupta 2016; Voorveld, 2019) to address the changing advertising environment due to technological evaluation. Studying AI from a message source perspective will benefit both advertising theory and practices (Gunkel, 2012; Voorveld, 2019).

Theoretically, this dissertation is among the initial studies on AI source effects in advertising (i.e., AI influencers) and it advances theory-building around evolutionary technology development. Theories and concepts should be reoriented and reconceptualized to accommodate the AI technology (Gunkel, 2012). Message source is a crucial building block for advertising theory (Thorson & Rodgers, 2019). The theories on message source effects can be traced back decades (e.g., McCracken, 1989, Ohanian 1990), to a time when the message source was almost exclusively referred to as a human or a group of humans (e.g., organization) rather than a machine. The use of non-human advertising sources changes the way consumers process and evaluate the message being delivered (Kim & Duhachek, 2020). This is not to say we should ignore former studies on message sources. However, it is important to examine how these earlier theories can be adapted to the AI advertising environment. Therefore, the source effect literature needs to be enriched with empirical work examining this innovative advertising environment, like that proposed by the current research.

By examining AI's influence on message sources, this dissertation provides insights into how consumers' perceptions of AI can influence information processing and message evaluation. Specifically, this dissertation examines how the perceived source credibility (AI vs. human influencer) could help to explain marketing effectiveness. This dissertation also examines the multidimensional model of source credibility, which could add nuance to well-established source credibility research. Additionally, the current empirical studies on message source effects barely examine consumers' initial dispositions towards a brand endorser (Pornpitakpan, 2004). This lacuna may impair the validity of the results, an issue that may be more significant when comparing different types of endorsers. This dissertation focuses on this concern by measuring the positive/negative dispositions of consumers, the results of which not only could provide a baseline for influencer comparisons, but also provide insights into consumers' existing attitudes towards AI sources for advertising use. This would bring to the forefront psychological constructs, such as beliefs and emotions.

Furthermore, this dissertation bridges the well-established advertising theory on message source, psychological theories on associative learning, and the novel applications (e.g., AI influencer) herein. Specifically, this dissertation explores how studies on source credibility could determine the effectiveness of an anthropomorphized non-human AI source. This effort could help us understand how advertising theory adapts and evolves in the relatively new AI advertising environment. Conversely, the research could enrich advertising theories regarding AI. Therefore, it can contribute to the existing body of knowledge.

In advertising practices, with the prevalence of the Internet, consumers are well connected to the world and better informed. Therefore, it is essential that a source be credible if consumers are to be influenced by any branded messages (Kumar & Gupta 2016). This research will, thus help advertising practitioners better prepare for the rise of AI influencers. The results will increase our understanding of what benefits (and risks) AI influencers could bring to the brand so that practitioners can make more informed decisions about how and when to choose AI influencers over humans and vice versa. Additionally, for the designers of AI influencers, this dissertation's results provide insights on what features of AI may be most valuable to the brand in order to boost message effectiveness.

CHAPTER TWO

LITERATURE REVIEW

A. THEORETICAL PERSPECTIVE

Before introducing the primary concepts of this research project, it is important to identify the theoretical frame that helped guide, organize and clarify the concepts and research. The theoretical perspective guiding this research is information processing of advertising (McGuire, 1969, 1978). Information processing is rooted in cognitive psychology and refers broadly to how people perceive and process information. It proposes a series of steps that are to be followed before an individual can be persuaded. Advertising is the type of "information" that we are processing here and there are five components to be considered: message source, content, audience, channel, and effect (McGuire, 1978). McGuire's approach is beneficial for understanding advertising effectiveness. However, this dissertation sees advertising as a distinctive field that is not limited to McGuire's more general communication model. Definitions of advertising are constantly evolving, due primarily to technological advances. However, current discussions revolve around two main components of advertising: a) brand communication; b) persuasive intention (see Dahlen & Rosengren, 2016; Thorson & Rodgers, 2019). Indeed, the field of advertising is based on theoretical perspectives that are founded on the notion that advertising consists of attributes of messages (e.g., message sources). This distinguishes advertising from other forms of communication, such as marketing, public relations, news, etc. (Thorson & Rodgers, 2019).

There is one primary theoretical/practical divide within the field of advertising that provides two possible approaches to the study of advertising: the macro and the micro approach. The macro approach focuses on the big picture in the advertising realm, including advertising industries, “channels” of advertising, and societal and economic impacts, etc. A micro approach focuses on specific influences of advertising on individuals and how these influences affect their attitudes, decision making, purchase behaviors, etc. Although macro/micro perspectives are often viewed as competing perspectives, they are quite complementary and dependent on one another. For example, to understand the impact of advertising on society it is important to understand its impact on individuals, and vice versa. These overlaps notwithstanding, this dissertation is focused primarily on the micro perspective; any mention of the macro perspective is intended to support hypotheses and/or provide background to the micro perspective under review.

Every theoretical perspective is informed by some basic assumptions. It is important to identify these assumptions, as they form the basis of the thinking process even when they are not specifically referenced in the theoretical argument. As noted above, information processing in advertising is the primary theoretical perspective guiding the dissertation. The basic assumptions of information processing theories, in no particular order, are the following: First, the aim of information processing studies is to articulate the processes and structures that comprise cognition. Second, information processing in humans is similar to that of computers. Third, the environment makes information available for processing via multiple systems (e.g., attention, attitude formation, behaviors). Fourth, information can be changed or adapted by these processing systems. Although additional assumptions may arise depending on the theory or theories adopted, these four assumptions form the basis of information processing theories of advertising.

Often, advertising scholars use multiple theoretical perspectives to formulate the principles behind their thinking and to frame the hypotheses, articulate their research design, and provide an analysis of results. Three “types” of theories are identified for the purposes of explaining the main thinking behind this dissertation: 1) assimilation theories (e.g., excitation transfer, social learning); 2) compensatory/contrasting theories (e.g., ELM, HSM, Limited Capacity); and 3) congruity theories (e.g., priming, meaning transfer, self-congruity, identification). The advantage of using these three types of theories is the ability to theorize about different aspects of information processing of advertising. For example, assimilation theories examine how people manage new information and incorporate it into existing knowledge; compensatory or contrasting theories examine how information can persuade people; congruity theories focus on the role of persuasive communication in changing attitudes. While these “subjective categories” do not represent all of the possible types of theories in information processing of advertising, they provide an overview of the primary theoretical trends needed to carry out the present research, as will become clear in later sections of the literature review. The remainder of the dissertation is organized as follows. First, the main concepts of the dissertation are identified and defined. Second, a review of the literature surrounding the proposed theories is provided, and the hypotheses are developed, accordingly. Finally, for purposes of the dissertation proposal, details of the methodology are presented in the next chapter (Chapter 3).

B. CONCEPT DEFINITIONS

The main concepts examined in this research include: 1) advertising; 2) artificial intelligence advertising; 3) influencers (including SMIs and artificial intelligence influencers); 4) persuasion; and 5) source credibility. Each concept is defined below.

1. Advertising.

As noted above, definitions of advertising are evolving, due mainly to technological advancements (Kerr & Richards, 2020). For example, advertising has traditionally been defined as "*paid* message from an *identified sponsor* using *mass media* to *persuade* an audience" (Thorson & Rodgers, 2019, p. 3) In response to technological developments, Kerr and Richards (2020) expand the definition of advertising to include: "paid, owned, and earned mediated communication, activated by an identifiable brand and intent on persuading the consumer to make some cognitive, affective or behavioral change, now or in the future" (p.16). Two main components of advertising are highlighted in recent discussions on the topic: a) brand communication; and b) the intent to persuade (see Dahlen & Rosengren, 2016; Thorson & Rodgers, 2019). This two-part definition, i.e., brand communication with the intend to persuade, is adopted for the purposes of the dissertation.

Crucial Components in Advertising

As a specific type of persuasive communication, advertising possesses features that are similar to and distinct from other forms of communication. Advertising components that are relevant to the theoretical bases of this dissertation are identified below.

Advertising shares the communicative elements and purposes of other forms of persuasive communications, such as public relations or in-person sales. The primary goal of advertising is to change/reinforce consumers' attitudes or behaviors relative to certain products, goals which are also fundamental to other forms of persuasion (Ambler, 2000). Key elements of research in communication (Lasswell, 1948; McGuire,1978), such as source, message, channel, receiver, and effect (both intentional and unintentional) are also deemed crucial in research on today's advertising (Nan & Faber, 2004). Indeed, Thorson and Rodgers (2019) propose an integrated model specifically designed for organizing theories in the advertising field that make reference to McGuire's communication model, commonly summarized by the quote "Who, said what, in which channel, to whom, and with what effect?" The shared elements of communication and advertising studies make McGuire's theories applicable for advertising research and suggest that key factors and the grounding theories of information processing could also contribute to a better understanding of advertising processing. From an information processing perspective, these elements (i.e., source, message, context, etc.) are essential for understanding the interaction between the input of information and information already in memory (i.e., the psychological mechanism of processing) (Eagly & Chaiken, 1984). This dissertation adheres to this paradigm by focusing on the effect a particular message source has on information processing and persuasiveness. Source effects could account for about nine percent of successful persuasive operations, according to a meta-analysis from Wilson and Sherrell (1993).

However, the theoretical perspectives used for understanding advertising in this dissertation are also inspired by specific features found in advertising research, especially developments resulting from technological evolutions. The features that distinguish advertising from other forms of communication concern primarily the (1) brand centered message content; and (2) consumer skepticism. First, as indicated in the above definition, advertising is brand communication. Therefore, the message must contain some form(s) of identifiable brand elements (e.g., brand name/logo, package traits, signage) to trigger consumers' responses (Schultz, 2016). The advertising message is usually crafted based on psychological models that encourage consumers to remember, process, and react to the message, and, in consequence, they will be persuaded to carry out the behaviors being promoted that benefit the brand (Aitken et al., 2008; Schultz, 2016). Second, consumer skepticism is a distinguishing feature that makes advertising distinct from related communication fields (Duff et al., 2019; Nan & Faber, 2004). Consumers have always been skeptical of advertising, not only because of the overt motives of the persuader and the obvious attempt to persuade or manipulate behavior, but also because of an underlying self-serving intent (e.g., the advertiser does not just want to persuade but to profit financially and therefore has no real interest in the consumers) (Duff et al., 2019).

These distinctive features could impact the recipient's information processing mechanisms when encountering an advertising message. Although they follow the same structures as other communication exchanges, the sub-concepts that are enhanced for the purpose of message acceptance in advertising may be different from other forms of communication (for a review of these, see Nan & Faber, 2004). As Nan and Faber (2014) point out, trustworthiness of the source is the most important component in an advertising context, due primarily to the consumer's skepticism. In the field of broadcasting, on the other hand, physical attractiveness has a stronger influence on source receptiveness.

Since the "skepticism" factor highlights the crucial role of trust in advertising, advertisers constantly seek to increase the trustworthiness of the message source in order to neutralize the negative perception of self-serving intentions. An example of this is the practice of using natural endorsements where advertisers place their brands into an influencer's social media everyday narrative in order to better persuade consumers to buy the product (Kim & Kim, 2020; Russell & Rasolofoarison, 2017). Consumers perceive this type of endorsement to be more authentic and less self-serving. Studies on native advertising and influencer marketing usually highlight the importance of having a credible source if persuasion is the ultimate goal (Lou & Yuan, 2019; Russell & Rasolofoarison, 2017).

New Technology and Advertising

New technology plays an important role in reforming advertising practices and reconceptualizing advertising research (Kumar & Gupta, 2016; Voorveld, 2019). To begin, as we noted with advertising's evolving definition, message distribution is no longer limited to mass communication outlets. Rather, any form of mediated communication can fall into the category of advertising (Kerr & Richards, 2020). This dissertation is situated at the intersection of two main types of message distribution "channels." The first is social media, which, when used as an advertising channel, enables brand messages to be distributed through social networks (Voorveld, 2019). Social media is a combination of internet-based technologies that aim to facilitate online users' creation of contact and social interaction (Berthon et al., 2012; Kaplan & Haenlein, 2012). Social media advertising enables consumers "to access, share, engage with, and to co-create" (Alhabash et al., 2017, p. 286) the branded messages. The message source of social media advertising could be the brand itself, the influencers, or online peers. Second, AI technologies allow for a one to one advertising distribution, thus allowing advertisers to address the individual consumer personally (Eisend, 2018).

Second, thanks to recent technological developments, the driving force in the communication model is shifting importance from the brand to the consumers (i.e., advertising is becoming more "consumer-centered," (Li, 2019, p. 333). Consumers are gaining more influence and control over the advertising process (Schultz, 2016), while advertisers are losing theirs (Eisend, 2018). In this context, control refers specifically to the ability to influence the communication components (i.e., source, message, channel, audience, and effect). On the one hand, consumers can actively select what kind of message they are willing to receive by choosing to explicitly follow certain brands or influencers, or by implicitly altering their online profiles or behaviors. Consumers can even co-create the branded content through the practice of commenting or sharing content via social media platforms (Men & Tsai, 2015). Additionally, brand sponsors can barely control the way advertising messages are disseminated across social networks or how their brands are presented in messages conveyed by an influencer or another consumer. By way of example, we can examine the SMI. Hyram, a well-known skincare YouTuber with 4.25 million subscribers usually shares negative product reviews or negative user experiences with his followers in a bid to build trustworthiness and demonstrate his expertise. Clearly, brands have limited power to regulate these kinds of negative information flowing to their consumers. Additionally, because of the opacity of the algorithms, advertisers cannot entirely control which audience members are likely to be reached by the advertisement. For example, the AI targeting function, *Lookalikes,* aims to find an audience that is similar to a specific brand's existing consumers (Bozas & Costantini, 2018). However, advertisers cannot determine how their consumers are defined by Facebook or what characteristics will be taken into account in this process. All they can control is the source audience they provide (Facebook, n.d.). This shift of power control in the communication process causes the brand to find ways to restore some level of control over the process. Adopting AI influencers is a logical way to achieve this goal. For example, AI influencers are less likely to disseminate as much negative brand information as human influencers, who do so without the brand's permission. Also, advertisers carefully design the AI influencer's appearance and persona in order to appeal to the targeted audience.

The last development in advertising to be considered in this section is the increasing knowledge (topic and persuasion knowledge as in Friestad and Wright, 1994) of consumers due to their immediate access to multiple sources of information, including alternative products and opinions (Schultz, 2016). Consumers are better informed and better connected world-wide as a result of the Internet (Kumer & Gupta, 2016). As a result, consumers have a greater ability to access and compare alternative opinions on brands and products. At the same time, increased accessibility to the internet increases the opportunity to encounter branded content. Therefore, a consumers' persuasion knowledge (consumers' theories about persuasion, as in Friestad and Wright, 1994) is enhanced due to their frequent interaction with content on social media sites. In this context, message source plays an increasingly crucial role in the consumer's decision-making process (Schultz, 2016). Consumers "no longer trust advertisements until endorsed by personal or virtual positive word of mouth by credible sources” (Kumer & Gupta, 2016, p. 302).

2. Artificial Intelligence Advertising.

AI advertising is defined as “brand communication that uses a range of machine functions that learn to carry out tasks with intent to persuade with input by humans, machines, or both” (Rodgers, 2021, p. 2) AI advertising is a distinct subfield in advertising research because of its specific focus on applying AI in brand communication (Rodgers, 2021). To understand AI advertising and its possible influence on information processing, this section will begin by defining the two separate terms *artificial* and *intelligence*. Here, AI’s applications in the advertising field will be analyzed according to the types of intelligence contained in the AI technology. Next, the unique features and persuasion role of AI advertising will be explained in light of the communication process (McGuire,1978).

The Meanings of Artificial Intelligence

The term artificial intelligence (AI) is composed of two concepts, *artificial* and *intelligence*. The word *artificial* is used to refer to objects that are “made by humans to imitate nature” (The Merriam-Webster Dictionary, 2016, p. 39). This definition implies that when we call something artificial, it is (1) intentionally mimicking a natural/authentic object, but (2) it is not real. The natural object that AI is mimicking is intelligence, which usually means human intelligence. Therefore, the ultimate goal of an AI agent is to achieve a human-like level of intelligence. In so doing, the intelligence aspect of AI contains three separate but overlapping components (Goel & Davies, 2020): (1) robotics (allowing the embodied AI agent to sense, perceive, and react to the physical world); (2) machine learning (allowing it to process information by detecting and exploiting patterns in data); and (3) exploiting cognitive systems (to ensure AI can perform high-level cognition and interact with the human and social world) (for a review of these components, see figure 25.1 in Goel & Davies, 2020, p. 603). Another typology for assessing the level of machine intelligence is a continuum that places an infantile level of intelligence on one end of the spectrum (i.e., narrow AI or NAI), human intelligence on the other end (i.e., super AI or SAI), and a human adult's level of intelligence, AI referred to as general AI (GAI), in the middle (Rodgers, 2021). The SAI is not yet available for advertising use (Rodgers, 2021).

AI influencers discussed in this dissertation could be considered as having a human adult level of AI (i.e., GAI) but operate in the digital world (i.e., they lack the abilities of sensation and perception). The intelligence possessed by AI influencers is situated at the intersection of machine learning and cognitive systems that are outlined in the three-component model of Goel & Davies' (2020). With these intelligence abilities, AI influencers would be able to deal with the data that is available in the digital world and engage in social interactions with humans on the Internet. However, although the development of robotics is predictably the future direction of AI influencers, at the time of this current research, it is not yet available for advertising practices.

The idea of artificial intelligence was first proposed by Alan Turing as in his "imitation game," which aimed to build a machine that could communicate like a human to such an extent that a human could not tell the difference between the machine and the human (Gunkel, 2012). This idea is embedded in the definitions of AI across disciplines. For example, Kok et al. (2009) define AI as computer programs "imitating intelligent human behavior” (p. 1). Meskó and Görög (2020) consider AI as “machines that mimic cognitive functions” (p. 1). The original design idea of AI is to make a machine that is able to perform like a human but that is not in fact human at all. The intelligence programmed in AI should allow it to demonstrate the ability to think or act rationally (Kok et al., 2009), perform human tasks (Kumar et al., 2019), and ideally have feelings and emotions (Lehman-Wilzig, 1981).

The core belief of AI revolves around the idea that all types of intelligence are a kind of computation and can be mimicked through the use of mathematical models (Goel & Davies, 2020). For example, intelligence is defined as data processing and transformative abilities that provide useful information and that can direct behavior (Paschen et al., 2019). In this sense, AI and cognitive psychology are both based on the assumption that the information processes of humans and computers can both be attributed to cognitive ability. A cognitive system is an essential component of the concept of intelligence and it is a building block of AI intelligence as well (Goel & Davies, 2020). If one understands intelligence to be a computational ability in AI development, it is understandable that AI could be perceived as being smarter than humans in some aspects, particularly as it pertains to logic based reasoning, memory, and computational processing. AI is good at dealing with high-cardinality (i.e., strong uniqueness of elements in a database for an individual, like a phone number) and high-dimensionality (i.e., a large number of attributes belonging to one individual that need to be taken into account) problems (Sterne, 2017). Goel and Davies (2020) suggest that AI is particularly good at figuring out key data to be collected and simulating all possible approaches to solving certain problems. Also, AI is superior in “exploring the benefits and limitations of various ways to represent and organize knowledge in memory" (Goel & Davies, 2020, p. 602). A machine agent is, therefore, can be perceived as more objective and rational than a human (Dijkstra et al., 1998).

However, some aspects of humanity are still difficult for a machine to mimic, at least for the moment. These include the ability to feel emotions (e.g., empathy) and have ethical awareness. These features are the key factors that cause AI to be perceived as different from humans. Sterne (2017) listed the unintended consequences and implicit bias of AI due to its artificial approaches (e.g., the modelling issues) such as overgeneralizing rules based on limited data (i.e., overfitting) and a lack of flexibility. For example, Amazon faced criticism when its AI algorithm failed to offer same-day delivery to Black neighborhoods (Sterne, 2017). Additionally, Alexa's speech recognition works better when interacting with white Americans (Metz, 2020). These mechanical features also influence how consumers perceive and respond to AI. Longoni et al. (2019) found that in a medical setting, consumers tended to resist choosing an AI pharmacist due to the belief that AI would be unable to treat them as a unique individual, something a human is quite capable of doing. Moreover, these perceived "not real" or engineered components reportedly make the machine less trustworthy (Herz & Wiese, 2019; Pega, 2019). Trust is the psychological tendency to accept vulnerability based on the positive behavior/intention of another person (Rousseau et al., 1998). Ameen et al. (2021) found that trust plays a key role in AI-enabled service experiences. The lack of confidence is also related to how intelligence is defined in AI.

The Role of Artificial Intelligence in Advertising Processes

To understand AI within the concept of advertising, this dissertation's focus is on the crucial components of advertising (i.e., source, audience, message, channel, and effect) and I will discuss the role AI plays in every part of the advertising process. Additionally, the dynamic feature that AI advertising adds to the communication process, causing advertising to remain in a constant state of flux as a result of moment-by-moment input from online users will be discussed.

The most common application for advertisers today is to use AI only in message or channel components of advertising, either to generate message content or conduct message delivery (Taylor, 2019). This application is also known as computational advertising. Computational advertising is a data-driven advertising approach that relies on computational capabilities or mathematical models to create and deliver messages (Huh & Malthous, 2020). The examples of computational advertising include predictive targeting (i.e., finding potential customers), rule-based personalization (i.e., providing ad content based on consumer traits), content curation and generation (i.e., assembling elements to create ad content) (Groner, 2020; Hall, 2019), and advertising context matching (i.e., automatically placing an advertisement into an online channel) (Watts & Adriano, 2020). Besides increasing efficiency, this approach largely aims to achieve the advertising goal of sending the right message to the right consumer through the right channel at the right time. The change in advertising from a one-to-many distribution to one-to-one approach relies heavily on the computational algorithm. This application of AI in advertising is quite limited. AI technologies involved in this kind of application are usually NAI and designed to accomplish one task at a time. The intelligence involved in computation advertising involves primarily machine learning. Studies on computational advertising focus on the quality or quantity of the messages that are being distributed by the system or the relationship between human communicators that are established through the AI tool (Gunkel, 2012). For example, these studies focus on how consumer information is delivered or on consumers' information processing and their attitude toward the advertised brand/product (e.g., Boerman et al., 2017).

AI also functions as both sender and receiver of messages in interactions with humans using a combination of intelligence aspects empowered by both machine learning and cognitive systems (Goel & Davies, 2020). Examples of this application include conversational tools, such as Siri and Alexa (Goel & Davies, 2020; Rhee & Chio, 2020), consumer service bots (Leo & Huh, 2020), and AI influencers, the subject of this dissertation. A detailed definition of AI influencers will be provided in the next section. In these cases, consumers can communicate directly with a mechanical entity about a specific brand, rather than just speak through a machine. This AI application is more closely aligned to GAI. Communication studies on AI as a communicator are not well developed (Gunkel, 2012). When we take into account the fact that the intelligence of an AI medium is not similar to other communication technologies, it becomes apparent that studying communication phenomena by minimizing the role of the medium/channel is not a suitable approach for current studies on AI (Gunkel, 2012). Rather, we believe it is more useful to study the persuasive effects of AI when it functions as a message source. Research on message sources from various disciplines, such as cognitive psychology, communication, and advertising shows that some features of the messenger in any message source operation (e.g., credibility) can greatly impact the consumers' information processing, and as a result, affect the persuasion outcomes as well (Eagly &

Chaiken, 1984; Pornpitakpan, 2004). Therefore, understanding consumer's perceptions about AI is crucial for research on how the message source affects advertising outcomes.

3. Influencer.

In this section, I will begin with defining and providing the main types of influencers. I will be particularly concerned with how the meanings and typologies are evolving with technological developments and the concept of advertising. Then, I will summarize the literature on the role the influencer has in information processing and advertising persuasion when functioning as a source. Lastly, I will look at two main types of influencers that are the subject of this dissertation, the AI influencer and the SMI.

The reader will note that the terms "endorser" and "influencer" are used interchangeably in advertising literature. The preferred term in our research, however, is "influencer" and the term "endorser" will be reserved only for instances when the cited literature uses that specific term.

In traditional advertising settings, the role of influencers is usually filled by either a celebrity or non-celebrity endorser who is featured in the brand's commercials. Understanding the features of celebrity and non-celebrity endorsers who benefit the brand in traditional settings is useful for an understanding of the influencer's role in persuading consumers to buy the targeted product. That is because, although existing in a somewhat different form, many of the features and benefits linked to human influencers can be applied to AI influencers as well. A celebrity endorser is defined as "any individual who enjoys public recognition and who uses this recognition on behalf of a consumer good by appearing with it in an advertisement" (McCracken's 1989, p. 310). A non-celebrity endorser is a spokesperson who has no established persona for consumers, but whose character is built specifically for a brand (Erdogan, 1999). Brands can benefit from celebrities' positive features (e.g., credibility, known character traits, likeability) as a result of their endorsement (Kapitan & Silvera, 2016). On the other hand, non-celebrity endorsers might be more malleable, allowing their brand sponsors to better control the messaging (Erdogan, 1999). The ability to control spokespersons means that they are less likely to be involved in some public scandal or engage in transgressive behaviors that might ultimately damage the brand (Bergkvist & Zhou 2016**)**. A non-celebrity endorser can be molded to have a stronger link with the brand than a celebrity (Erdogan, 1999).

With developments in technology, commercials made by advertising executives are no longer the primary way to solicit endorsements. Individuals are now able to communicate messages about brands with their followers on social media accounts. The rise of influencer marketing is an illustration of how decentralized advertising distribution has become, as we noted in the section on changes in contemporary advertising. Influencer marketing refers to the marketing strategy that "uses the influence of key individuals or opinion leaders to drive consumers' brand awareness and/or their purchasing decisions." (Lou & Yuan, 2019, p. 58) These opinion leaders, referred to as influencers, share a number of features with their celebrity endorser counterparts who operate in more traditional settings. For example, they usually enjoy public recognition and have a certain amount of fame (Schouten et al., 2020). Their impact on their followers' opinions or behaviors can be the result of similar processes, such as identification, internalization, or meaning transfer (Kapitan & Silvera, 2016; Thomas & Flower, 2021). Delbaere et al. (2021) consider SMIs as having the status of "micro-celebrity." Additionally, celebrities also own social media accounts and endorse branded products in much the same way as SMIs do (Kim & Kim, 2020). This muddles the line between these two types of influencers.

However, advertising researchers do make distinctions between celebrities and SMIs (Schouten et al., 2020; Shan et al., 2020), and have therefore updated the meaning of celebrity to further delineate these two concepts. In the new terminology, celebrities now refer specifically to individuals who have gained public recognition and fame because of their professional talents; SMIs, on the other hand, gain public recognition and fame through their success at branding themselves as an expert in some specific area on social media sites (see Khamis et al., 2017; Lin et al., 2018). As indicated by the descriptor, SMIs rely heavily on social media platforms to gain recognition (Kim & Kim, 2020). Studies comparing these two types of influencers have found that consumers identify more with SMIs than celebrities and find them to be more trustworthy. They are thus more likely to induce the identification process (Schouten et al., 2020). Gräve (2017) found significant differences in consumers' attitudes toward traditional celebrities and SMIs in terms of self-identification, attractiveness, trustworthiness, likeability, and familiarity.

AI influencers constitute a third type of influencer in the new technology context. The AI influencers mimic and perform the tasks of SMIs in order to exert a social influence. This is the basis for our comparison between the source effect of AI influencers relative to their human SMIs, the subject of this dissertation. Although both social media and AI influencers are relatively new advertising practices, one of the striking differences between these two is to be anticipated. Compared to SMIs who are effectively "self-made micro-celebrities" (Shan et al., 2020, p. 2), AI influencers can be created specifically for a particular brand, such as the earlier example of Yumi who was made for SK-ii. Consequently, among other benefits of AI (such as its computationabilites), AI influencers can be controlled much like non-celebrities found in traditional advertising settings, a feature that is attractive to the brands.

This research examines two main types of influencers, AI and SMIs. They will be defined in more detail in the following sections.

Artificial Intelligence Influencers.

An AI influencer is defined as "a digitally created artificial human who is associated with Internet fame and uses software and algorithms to perform tasks like humans" (Thomas & Fowler, 2021, p. 2). AI influencers are highly anthropomorphic, virtual agents that mimic human influencers in carrying out brand communication tasks. Anthropomorphism is defined as the degree to which a non-human agent exhibits human characteristics (de Visser, 2016). The anthropomorphism of AI influencers is achieved both through having a humanlike appearance and demonstrating intellectual abilities. These humanlike characteristics are the result of a combination of technological innovations (Thomas & Fowler, 2021). The AI influencer is one of the few GAI applications in AI advertising, as indicated in Rodgers' (2021) introduction.

The realistic appearance of an AI influencer is achieved through computer generated imagery (CGI). The computer uses these images to generate a fictional avatar that can be placed into a variety of scenes that are indistinguishable from a human's picture or video in a digital context (McDonald, 2020). As stated, the AI influencer's intellectual abilities are achieved via cognitive systems and machine learning. The general idea of cognitive systems allows the machine to function as if it had a human mind, as indicated by cognitive psychology research that deals with symbolic (i.e., conceptual abstractions of the world) and sub-symbolic (e.g., the weight of an association, the probabilities that a proposition is or is not true) (Goel & Davies, 2020) abstractions. More specifically, through natural language processing, image recognition, and speech recognition, the AI influencers can be made to "understand" (1) the pattern of SMIs' posts and languages; and (2) their audiences' preferences and responses (Goel & Davies, 2020; Kietzmann et al., 2018; Thomas & Fowler, 2021). Machine learning can assist the reasoning process and refine the AI influencer's actions based on the consumers' feedback data (Goel & Davies, 2020; Kietzmann et al., 2018; Thomas & Fowler, 2021). As a result, AI influencers can learn from their highly influential counterparts whose followers are similar to their own target audience and can learn to generate social media content on their own. AI can also learn from behavioral data collected from their followers and communicate with them in the way in which their audience prefers. They can even interact individually with their followers. Consequently, AI influencers can appear, behave, and operate just like a human SMI. AI influencers also possess social capital and could serve as an exemplar of taste and ultimately be admired as if they were real celebrities (Thomas & Fowler, 2021). However, since influencers play multiple roles in the art of persuasion, the ability to serve as exemplars of taste may not paint a complete picture of the AI influencer's effectiveness.

Based on the technological aspects of AI influencers as discussed, we may infer that AI influencers have both strengths and weaknesses. The benefits and drawbacks that relate to the research of this dissertation will now be discussed.

First, AI influencers are highly efficient, as other types of GAI (Leo & Huh, 2020). They are able to operate multiple accounts centered around different topics all at the same time and they are able to engage simultaneously with different followers. For example, Lil Miquela has social media accounts across various platforms, including but not limited to Facebook, Instagram, SnapChat, YouTube, Twitter, TikTok, Discord. She is able to post content and respond to followers continuously and almost simultaneously, something that is difficult for a human influencer to accomplish. Additionally, the company that created Lil Miquela, Brad, owns a group of AI influencers that can interact with each other. The algorithms behind the various characters are presumably the same. However, this adaptable capability holds potential risks, as indicated by Thomas and Fowler's study (2021) that found that AI influencers are perceived as being interchangeable. This perception is caused by the AI system/algorithms that are used to generate the mechanical influencers. The technology is the same, even though the influencers may have different personas (Thomas & Fowler, 2021).

Second, brands have more control over AI influencers in the brand communication process. For example, they are able to design an avatar that is perfectly suited to their products, and they can try out different advertising strategies using computer simulation. Research found that there is a superior persuasion effect when the influencer is closely aligned with the product (Erdogan, 1999). For example, an attractive influencer works better when promoting a beauty- enhancing product (Kamins, 1990). As stated above, AI designers could collect and analyze massive online data and figure out the optimal features for an attractive influencer, then design one accordingly. However, because of the company's control over the mechanical construct, consumers may perceive an AI agent as having less autonomy, which could lead to a lack of trust (Hertz & Wiese, 2019; Kim & Duhachek, 2020; Leo & Huh, 2020). Although research found that increasing the virtual agent's humanness could lead to a higher level of trust (de Visser et al., 2012; Hertz & Wies, 2019), it is still not comparable to an authentic human. Furthermore, a significant counter effect may occur when a non-human entity is virtually identical to a human being, yet still cannot really be considered as human (Mori, 2012; Waytz et al., 2010). Additionally, there may be ethical concerns to consider, such as creating avatars that reinforce gender or racial stereotypes or that set up unrealistic beauty standards (Złotowski et al., 2015). AI influencers can also achieve tasks that humans cannot achieve due to increased temporal and spatial limitations.

Third, AI could provide more detailed information and instructions for individual audiences (Campbell et al., 2020). Human intelligence has a computational metaphor where intelligence, seen as a processing ability, can be measured by working memory (Cianciolo & Sternberg, 2008). Therefore, it is possible to see the intelligent machine as being smarter and with better cognitive abilities than a human. It has been found that consumers perceive machines to be more accurate and reliable (Hertz & Wiese, 2019), more objective and rational (Dijkstra et al., 1998), and consumers generally prefer the action instructions they receive from a virtual agent (Kim & Duhachek, 2020). However, this may also imply that an AI might be seen as being void of emotions and/or empathy. This assumption could account for the controversy raised when Lil Miquela engaged in social movements such as *Me Too* and *Black Lives Matter*. Additionally, a machine can be manipulated and is not without biases (Strene, 2017). Consumers' unawareness of a machine's potential for biased information may lead to unethical advertising practices.

Social Media Influencers (SMIs).

The definition of a social media influencer varies across studies. Delbaere et al., (2021) listed ten components taken from previous literature that provide a nice snapshot of the meanings contained in the term SMI (for a review of these definitions, see Appendix A in Delbaere et al., 2021). For the purpose of this dissertation, we rely on Delbaere's definition of social media influencers as the "third-party users of social media who have achieved micro-celebrity status in the form of large followings on social media platforms and who have a position of influence on their audience" (Delbaere et al. 2021, p. 2). SMIs are generally found to be credible and an effective source for brand communication (Delbaere et al. 2021; Russell & Rasolofoarison, 2017; Schouten et al., 2020, Shan et al., 2020).

The SMIs relay information on social media platforms in order to gather fame and develop a global reputation. Lou and Yuan (2019) suggested in their study on the SMI value model that content value and an influencer's credibility are two important aspects that affect brand outcomes. SMIs are, first and foremost, content producers (Shan et al., 2020). They have features of both celebrity and non-celebrity endorsers in advertising, but are distinct from both of them. As "micro-celebrities," SMIs have social capital and enjoy fame and popularity. much like traditional celebrities (Kim & Kim, 2020; Lou & Kim, 2019b). Therefore, these two types of influencers can both impact their fans' and followers' attitudes. SMIs are ordinary people who provide in-depth and thoughtful information to their followers (Delbaere et al., 2021). Consumers perceive SMIs as being more similar to themselves than celebrities (Schouten et al., 2020). Schouten et al. (2020) found that consumers identify more strongly with SMIs than celebrities.

SMIs are often perceived to be credible sources by their followers. These influences tend to build up their credibility status using two different methods. One is to portray themselves as ordinary product users and share their everyday experiences with their followers (Russell & Rasolofoarison, 2017). As such, they might be perceived as more authentic (Coco & Eckert, 2020) and trustworthy (Jin et al., 2019) than celebrities. For example, one of the most influential YouTuber, PewDiePie, with 108 million subscribers, is famous for his reaction videos when he plays sponsored games. The experiences of SMIs are perceived as more authentic and objective (Delbaere et al., 2021) than paid consultants. A second way to attract an audience is by successfully branding themselves as an expert in some specific area and building their career upon that expertise (Schouten et al., 2020). For example, Doctor Mike, a SMI with 6.6 million subscribers on YouTube, is a self-identified family medicine doctor. His content is focused on health-related information and he endorses related products such as diet plans and weight loss apps.

However, there are risks to using SMIs in brand endorsements since the brands have relatively low control over what the influencer might say and how they might present their brand. The SMIs have to balance the need to be transparent about their sponsored products and to maintain their own reputation and integrity as they communicate the positive features of the products/brand (Kim & Kim, 2020). Therefore, unanticipated brand messaging may reach the audience from the SMIs. Additionally, a lack of control is also exhibited as a result of the SMIs' tendency to expose details of their personal life that is independent from the brand. This might expose the brand to contradictory messaging. The influencers' personal transgressions and scandals risk tarnishing the brand’s image (Bergkvist & Zhou 2016; Thomas & Fowler, 2021). Both PewDiePie and Doctor Mike have been involved in some sort of scandalous event.

4. Persuasion.

The main focus of the dissertation is the persuasive capability of the influencer. Here, persuasion is defined as “a successful intentional effort at influencing another’s mental state through communication in a circumstance in which the persuadee has some measure of freedom” (O’Keefe, 2016, p. 4). The expression “mental state” is a general term for a state that is a precursor to the desired change of behavior, including the attitude and behavioral intention of the persuadee (O’Keefe, 2016). A successful influence on a subject’s mental state could be an attitudinal/behavioral change (alter the valence) or a reinforcement (increase in strength) of the attitude or behavior (Ambler, 2000). Common independent variables investigated in communication processing theories involve message source, content, channel, or recipients (Eagly & Chaiken, 1984). One of the basic principles in the art of persuasion is that extraneous information can influence an individual's existing attitudes, beliefs, and behaviors (Maio & Haddock, 2007). The extraneous information is a part of “communication” as found in the definition of the word persuasion. Because brand communication is designed to persuade (Thorson & Rodgers, 2019), advertising serves as extraneous information with the intent to influence consumers’ purchase intentions or even the actual purchase behaviors of the promoted product/service (Schultz, 2016). There are three aspects of persuasion examined here: the attitude toward the advertisement, the attitude toward the brand, and the consumer’s purchase intentions. Attitude has been defined as “a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor” (Eagly

& Chaiken, 1993, p. 1). The particular entity could be a person, an object or an issue (Petty & Cacioppo, 1981). Behavioral intention refers to “a motivation to act” (Maio & Haddock, 2019, p. 88).

To understand the way advertising sources persuade consumers in this dissertation, we will apply a processing approach to the communication-persuasion process that was first proposed by McGuire (1968). McGuire proposed that persuasion involves five stages that happen in a chain that includes message presentation, attention, comprehension, yielding, retention, and action. These steps can be simplified and compressed into two broad categories, message reception (i.e., the audience attends to and understands the message) and yielding (i.e., the audience is in agreement with the content). Therefore, persuasion is also considered as a theory of yielding (Eagly & Chaiken, 1984). These stages are not fixed. Evidence shows that people may skip some processing stages or re-order the steps (Maio & Haddock, 2007). For example, the expertise of a source could be a silent feature of the message communicated to the audience and move them from attention to yielding, without paying much attention to shortcuts or heuristics (Chen et al., 1999). Additionally, variables in the communication process may have different effects at different stages of processing (Maio & Haddock, 2007). For example, attention to the message could be more intense because of the influencer’s attractiveness, but the influence might also be a valid source for beauty enhancement products.

Persuasion theories usually separate input information from information that already exists in memory. They provide either verbal or mathematical descriptions of how recipients combine or integrate the various cues and make judgments (Eagly &

Chaiken, 1984). The information (e.g., attitude, beliefs, knowledge) that already exists in memory, referred to as dispositions, is usually linked together and organized around a topic (Eagly & Chaiken, 1984; van Raaij, 1989). For example, individuals may hold general attitudes or beliefs about AI or machines through the use of technology, or by watching fictional representations about AI in movies. These dispositions play a crucial role in how recipients process and evaluate the persuasive message (Kruglanski & Sleeth-Keppler, 2007; Lord & Putrevu, 2009; O'Keefe, 2016; van Raaij, 1989). For example, the incoming information that advocates for a position that is consistent with one's pre-attitude or expectation will be processed more smoothly and have a better chance of acceptance (Shelby, 1986). This means when an individual is presented with an advertisement that is in some way related to AI, he/she will apply existing attitudes (e.g, AI is bad for human society) and beliefs (e.g., AI cannot be trusted) in order to process the incoming information. Then, they will evaluate the message, and either chose to accept the advertised message by strengthening/altering existing attitudes/beliefs, or to reject the attempted persuasion. Although these dispositions are crucial for understanding advertising's effectiveness, it is rarely taken into account in message source research (Pornpitakpan, 2004). This dissertation will take consumer's dispositions into consideration to see how the message source factor (i.e., being human vs. machine) might impact persuasion.

5. Source Credibility.

Source credibility generally refers to "the positive characteristics conveyed by the communicator that subsequently influence the receiver's evaluation of the message" (Lord & Putrevu, 2009, p. 2). The three-dimensional model for credibility is widely accepted and adopted for message source studies (e.g., Amos et al., 2008; Breves et al. 2019; Djafarova & Rushworth, 2016; Erdogan 1999; Ohanian, 1990; Schouten et al., 2020; Shan et al., 2020; Sternthal et al., 1978). The model posits that the attractiveness, trustworthiness, and expertise of the message source are positively related to message effectiveness. Source credibility is an important concept when considering source effect (Pornpitakpan, 2004) in both traditional settings (Bergkvist & Zhou, 2016; Erdogan, 1999) and in a social media context (Delbaere et al., 2021; Lou & Yuan, 2019; Schouten et al., 2020). Amos et al., (2008) conducted a meta-analysis of the effect of celebrity endorsements in advertising efforts, and found that credibility was a primary predictor for effectiveness, one that positively influenced attitudes towards the advertisement and the brand, as well as the viewer's purchase intentions. In this research, source credibility is treated as a mediator rather than a predicator. In other words, source credibility is seen as a perception that could positively impact the influencer's presentation and affect the persuasiveness of the advertisement.

In this dissertation, source credibility is considered as a dynamic perception rather than a static feature, as has been suggested in prior studies (Erdogan, 1999; Hovland et al., 1953; Ohanian, 1990; Roy et al., 2017). Roy et al. (2020) considered source credibility to be the consumer's perception of the advertising source's attribution of truthfulness and believability. Ohanian (1990) refers to credibility as "the extent to which the target audience views the source in order to gain expertise and knowledge in their understanding of the product/service" (p. 3, cited from Ohanian, 1990). This is to say that source credibility is not related simply to the persuasive talents of an influencer type; perception can be altered due to the influencer's manner of presentation. For example, Stubb et al. (2019) found that a sponsorship compensation justification disclosure (i.e., justifying their right to be compensated for their work) could increase consumers' perception of source credibility. It is the perception of the source's expertise, trustworthiness or attractiveness that really has an impact on the source's effectiveness.

Source credibility is a multi-dimensional concept. The most commonly used model of source credibility contains three sub-concepts: trustworthiness, expertise, and attractiveness (Ohanian, 1990). Trustworthiness and expertise are concepts first identified by scholars working in the field of source credibility (Giffin, 1967; Kelman, 1961; Sternthal et al., 1978). These two concepts could also be interpreted as the reliability and validity of a message source, respectively. Ohanian (1990) extracted a third dimension of source credibility: attractiveness. Amos et al. (2008) also found attractiveness to be a sub-dimension of credibility. However, these three sub-concepts may not be influencing information processing and persuasion through the same mechanism. Consumers have been found to weigh these dimensions differently. There is, however, no conclusive results on which to be able to state that one is consistently perceived as more important than the other (Pornpitakpan, 2004).

Trustworthiness is "the honesty, integrity and believability of an endorser" (Erdogan, 1999, p. 297). Usually, when a message source demonstrates no persuasive intention through their communication or shows general concern about the audience, people will perceive the source as being more trustworthy (Pornpitakpan, 2004). This is perhaps because consumers may infer that the influencer truly likes the endorsed product, rather than just complementing the product for financial gain (Kamins & Gupta, 1994). This internal attribution process can increase persuasion (Eagly & Chaiken, 1984) and reduce advertising skepticism (Kamins & Gupta, 1994). Nan and Faber (2014) argue that trustworthiness is a crucial source attribution because of consumer skepticism as it relates to advertising. Perceived source trustworthiness could bring a favorable disposition, acceptance, psychological safety, and it can create a more supportive climate (Amos et al., 2008).

Expertise is defined as "the extent to which a communicator is perceived to be a source of valid assertions" (Erdogan, 1999, p. 298). It is a cognition-based attribute, and depends on the knowledge, experience or skills that an endorser is perceived to possess (Eisend & Langner, 2010). Lord and Putrevu (2009) found that expertise triggers informational processing causing the receiver to evaluate the personal relevance and potential risks of a purchase decision. Expertise is found to have the strongest effect on persuasion when the cognition nature of the message is significant (Wilson & Sherrell, 1993). Source expertise could serve as a heuristic cue to the expert credo and increase the effectiveness of the message directly (Eagly & Chaiken, 1984). Eisend & Langner (2010) found a long-term persuasion effect from an expert source due to the source's ability to activate high level cognitive-based information processing.

Attractiveness is defined as "a source's perceived physical appeal or desirability." (Lou & Kim, 2019, p. 3) Attractive communicators will be liked by the audience and, as a result, have a positive impact on message effectiveness (Erdogan; Shan et al 2020; Till & Busler, 2000). Kelman (1961) argues that attractiveness, the possession of qualities that makes an agent desirable for building a continued relationship, could increase the identification process with the targeted source. Thompson & Malaviya (2013) explain the persuasiveness of source attractiveness through dual-processing models (e.g., ELM, HSM) (Eagly & Chaiken, 1984). Attractiveness could be a heuristic cue that directly increases the message persuasiveness for low involvement consumers (Thompson & Malaviya 2013). Cohen and Golden (1972) and Horai et al. (1974) found that attractiveness could also increase the persuasion effect when the consumers are highly involved. Kapitan and Silvera (2016) suggest that consumers will also use the source attractiveness as an information cue and change their behavior, motivated by the desire to be more like the influencer.

Persuasion theories suggest that attractiveness is a concept that is independent from the other two aspects that influence message effectiveness (Erdogan, 1999; Shelby, 1986) and ought thus to be treated separately (e.g., Nan & Faber, 2004; Schouten et al., 2020; Sternthal et al., 1978). Expertise and trustworthiness can increase persuasiveness through internalization (Kamins & Gupta, 1994; Wilson & Sherrel, 1993). Internalization refers to the acceptance of a source's influence as a result of the source's message content being aligned with one's value system (Kelman, 1961). Attractiveness could be persuasive because adopting an attractive source's behavior/opinion could help establish a satisfying self-defining relationship to the source (i.e., identification) (Kelman, 1961). Lou & Kim (2019) found that attractiveness could influence the consumers' parasocial relationship with the SMI, while trustworthiness and expertise could not. Eisend & Langner (2010) found that endorser's attractiveness is the main impact factor for immediate source effect, while expertise is the primary factor for a delayed effect. They suggest that the effect of attractiveness is related to affective processing that is relatively autonomous. However, information from a perceived expert could be processed more deliberately and increase higher-level cognitions. Without cognitive processing, the results from an affective processing cannot be long lasting.

C. THEORETICAL MODEL

The afore-mentioned concepts form the basis of the theoretical model, shown in Figure 1.1. The underlying assumption of the theoretical model is that AI contributes to a deeper understanding of advertising in several important ways. First, AI advertising can mean many things, and meaning can change over time (i.e., is dynamic) depending on where one wants to lay emphasis. Here, the influencer type is what is emphasized, of which there are primarily two options: artificial intelligence influencer and SMI. This is represented on the left-hand side of the model.

<Insert Figure 1.1 About Here>

Influencers can shape their followers' attitudes and purchase decisions (Freberg et al., 2011; Lou & Kim, 2019). This persuasion effect is usually understood through a source effect (e.g., Bergkvist & Zhou, 2016; Lou & Kim, 2019). Consumers' perceptions of a source's features, such as trustworthiness, expertise, attractiveness, could positively influence message acceptance (Amos et al., 2008; Wilson & Sherrel, 1993). From an assimilation perspective, influencers can be an exemplar for the advertised product and facilitate consumer's positive attitudes or motivate behavior or product adoption (Bandura, 1999). Influencers also have heuristic value for consumers, allowing them to evaluate the advertising and the brand. The characteristics of the influencer, such as physical attractiveness, can serve as an information cue for either systematic or heuristic processing, thereby inducing the desired attitude or behavior change (Eagly & Chaiken, 1984). Congruity theories suggest that feelings attached to an influencer could be transferred to a brand through product endorsement. Consumers tend to generate positive attitudes or manifest behavioral intentions toward purchase of a brand that communicates meanings that are congruent with consumers' self-definitions (Bergkvist & Zhou, 2016; Erdogan, 1999).

Initial work comparing AI and humans as message sources finds that AI is a good alternative to humans, but not without a caveat. For example, Thomas and Fowler (2021) found that AI influencers and celebrity endorsers could be equally effective in prompting favorable brand responses (i.e., favorable attitudes, purchase intentions) among consumers. Because those AI influencers behave just like humans on social media sites, they could also serve as exemplars of good taste. However, consumers see all AI influencers as fundamentally similar and interchangeable; celebrities, on the other hand, possess individual and independent characteristics (Thomas & Fowler, 2021). This perception could hurt consumers' acceptance of AI influencers when non-distinctiveness is perceived.

From Thomas and Fowler's (2021) results, we can see that consumers have the basic understanding to assist them in responding to AI influencers. Consumers understand that there are fundamental differences between AI entities and humans. In practice, we do see that practitioners intentionally build different functions and personalities into AI influencers. It is therefore difficult to assume that all AI influencers will be perceived in the same way. But consumers may differentiate AI influencers in a way that is distinct from how they differentiate humans. The difference in appearance among AI influencers may not be enough for consumers to view them as independent entities. In order to do so, there should be fundamentally different algorithms that are visible so that variations are visible to consumers. For example, the interchangeability factor may decrease when the AI agents are developed by different companies, such as Siri and Alexa, or are provided with different functions, such as Lil Miquela and Yumi.

To understand how influencer types could impact advertising effects, it is important to emphasize the meanings AI have for consumers. The specific influencer's presentation is expected to change the way consumers interpret and evaluate the advertising messages. Consumers are also expected to have dispositions about AI, which could be established or influenced through the presentation of AI in science fiction (Złotowski et al., 2015) such as *Westworld*, *Black Mirror*, *Her*, or *Avengers,* where AI is portrayed as sometimes beneficial and sometimes dangerous. Or, impressions could be based on everyday experiences involving persuasion episodes (Friestad & Wright, 1994). These episodes include interactions with an AI service bot which are in use in almost every big company's customer service system (e.g., USPS, AT&T), and AI conversational agents. In everyday consumption, there is a wide range of AI advertising applications that can be encountered at every step of the customer's journey, from consumer profiling in the recognition phase, to chatbots supporting a customer's post-purchase behaviors (Kietzmann et al., 2018). Some of the dispositions are the focus of prior research. Thomas and Fowler's (2021) found that AI influencers might be seen as interchangeable (i.e., lacking in independence) in their pilot study. Machines have also been found to be seen as less autonomous (Kim & Duhachek, 2020), less trustworthy than humans (de Visser et al., 2016), less flexible, (Longoni et al., 2019), and more likely to make the same mistakes (Leo & Huh, 2020; Thomas & Fowler, 2021).

Furthermore, from the computational perspective of intelligence, AI elaborates various ways that knowledge can be represented and organized in memory. For example, cognitive psychology has had a long-standing debate about what constitutes "knowledge" and how we know what we know. Two such systems are the symbolic (the ability to process recognizable symbols) and the sub-symbolic (the ability to process beneath the symbol level) (Goel & Davies 2020). For example, a brand name may be represented symbolically (e.g., by the letters that spell "L-O-U-I-S-V-U-I-T-T-O-N") and sub-symbolically (e.g., by specific pixels or dots that make up the letters). Examples of symbolic cognitive processes examined in this dissertation include perception, learning, problem solving, memory, and action. Sub-symbolic cognitive processes can include probability, neural networks, and Bayesian belief networks. Of course, cognitive systems overlap, but both capture a range of processes and both are needed to understand AI advertising. The research contained herein focuses on the symbolic cognitive system, as this is more in line with the theoretical perspective of information processing of advertising.

The various sources of existing attitudes and beliefs regarding AI also suggest that the meaning of AI is not static. The primary words, *artificial* and *intelligence*, represent both the mechanical nature and the humanized features of AI, and these should constitute two of the essential categories of meanings contained in AI. This two-fold meaning could explain the consumers' mixed attitudes towards AI found by the surveys. A specific persuasion episode may trigger a change of meaning process (Werner, 1954) in a consumer's mind who will then make an evaluation based on that specific stimulus. In other words, either the *artificial* or *intelligence* part of AI could be primed in a persuasion episode (i.e., advertising exposure). For example, the design of a machine's human-like appearance (de Visser et al., 2016) or social role (e.g., Rhee & Choi, 2020) if intended to demonstrate learning abilities (Kim & Duhachek, 2020) will emphasize the human-like features of the machine. This change-of-meaning could be explained by the anthropomorphism process. Consumers may associate the humanlike machine with the human schema and understand it accordingly. Złotowski et al., (2015) argue that consumers will perceive the anthropomorphized machines as having truly felt emotions and as having positive intentions. de Visser et al. (2016) also found that an anthropomorphized design will increase consumers' trust toward the machine. However, when the machine is labeled as a robot, the non-human, machine-related artificial parts of meaning will be triggered. According to the uncanny valley hypothesis of anthropomorphism (Mori, 2012), when an object is very close to human but not human, people will experience a relatively strong discomfort level and the positive attitude will drop dramatically.

A SMI labelled as human will symbolically communicate different meanings than a robot influencer. When an influencer is explicitly labelled as a human, the human schema will be relevant when consumers process the messages. The commonalities between the audience and the influencer with human characteristics will enhance the likeability of the influencer, especially when compared to non-human AI influencers. Longoni et al. (2019) found that a human pharmacist is believed to have a better understanding of a human's uniqueness, and therefore will be better accepted than an AI pharmacist. From an assimilation perspective, the commonalities between audience and source are critical if the audience is to be influenced by social learning (Bandura, 1999).

The persuasion effect could also be the result of an identification process. Kelman (1961) proposed that consumers are more likely to accept the message of social influencers if the message comes from a source that aligns with their self-defined relationship to the group (in this case, another human). An authentic human source is crucial if consumers are to accept the branded messages (Coco & Eckert, 2020).

As ordinary people, SMIs are likely to be perceived as authentic counselors who provide unbiased and useful information to the audience (Delbaere et al., 2021). In an advertising context, consumer skepticism runs high (Nan & Faber, 2004). But SMIs who seem sincere and authentic could reduce consumers' skepticism regarding their intentions (Evans et al., 2017; Lou & Yuan, 2019; Russell & Rasolofoarison, 2017). Compared to a celebrity source, Schouten et al., (2020) found that SMIs did a better job increasing perceived similarities between source and consumer and in intensifying wishful identification. The difference in the perceived similarity between consumers and celebrities versus SMIs is one of the reasons for the different persuasion effects due to influencer type. This difference is not identified in Thomas and Fowler's (2021) study but is expected to be found in future studies. Therefore, H1 predicted that compared to AI influencers (i.e., highly anthropomorphized robots), SMIs will result in better attitudes towards the advertisement (Aad) and the brand (Abr), as well provide a higher level of purchase intention (PI), as presented in the right-hand side of figure 1.1. The hypotheses for the current dissertation are summarized in table 2.1.

<Insert Table 1 About Here>

H1. A SMI (vs. AI influencer) leads to higher (a) Aad, (b) Abr, and (c) PI.

On the other hand, there may be no differences in the persuasion outcomes from SMIs and AI influencers, as Thomas and Fowler (2021) found in their research. This null hypothesis will be true in, but not limited to, the following cases. First, when consumers' perceptions of the anthropomorphized AI influencers pass the uncanny valley, the attitude will be restored, and consumers will then treat AI influencers exactly as humans. Second, consumers may not even care about the robot nature of an influencer on social media as long as they can function as humans (e.g., provide relevant, quality information). Especially considering that advertisement is not the primary content consumers are searching for in social media. Alternatively, consumers may generate mixed (i.e., both positive and negative) perceptions for both AI and SMIs and result in parallel overall advertising evaluations. In other words, there may be various underlying information mechanisms that are contradicting with each other and offset the final processing outcomes.

This null hypothesis for H1, if observed, will also be significant for future studies and practices on AI influencers. To name a few, it can serve as a starting point for this and subsequent studies looking into the processing mechanisms for the AI message source. The null finding could also be a baseline of searching for the appropriate anthropomorphizing degree of AI influencers. Additionally, the no difference could also imply the consumers' inabilities to tell the differences between AI and humans in social media even with the discloser. Therefore, sound a warning for the ethical use of AI influencers and could inform related regulations. Thus, the null hypothesis for H1 is also proposed in the current dissertation.

H1$_{null}$. There is no difference on consumer's (a) Aad, (b) Abr, and (c) PI towards the messages delivered by a social media and an AI influencer.

AI can increase the accuracy and efficiency of advertising but can come at a cost, cognitively speaking. This dissertation seeks to understand the value and cost of using AI through the concept of source credibility as a mediator. Specifically, different dimensions of source credibility (i.e., trustworthiness, expertise, and attractiveness), as indicated in the middle of figure 1.1, will be induced by the meanings invested in AI and human influencers and these will impact consumers' attitudes and behavioral intentions accordingly. Although an AI agent may be able to seem as attractive to viewers as a human, and may be seen as having even more expertise than a human, it is unlikely that an AI figure will be considered as trustworthy as a human. To establish the mediation effect, the author will first rationalize the relations between influencer type and the three dimensions of source credibility (i.e., trustworthiness, expertise, and attractiveness). Then, the hypotheses for the impact of source credibility on consumers' attitude and behavioral intentions will be developed.

One of the risks of applying AI to brand endorsing on social media is that the AI entity appears to lack trustworthiness. It is to be anticipated that the dimension of trustworthiness in an influencer has an effect on advertising effectiveness. As stated, trustworthiness is the "honesty, integrity, and believability" of a message source. It is the most important source factor in an advertising context (Nan & Faber, 2004). Trustworthiness could be elevated when consumers perceive the influencers to be internally motivated to recommend the product, a primary advantage of SMIs (Russell & Rasolofoarison, 2017). However, because artificial agents are perceived as more objective (Dijkstra et al., 1998) and less autonomous (Kim & Duhachek, 2020), an external attribution to an AI influencer's brand recommendations may occur. Consumers will consider certain brand recommendations to be the result of external environmental factors, such as the company's requirements, rather than a recommendation made purely in the consumer's best interest. An objective machine could not, it might be assumed, have its own preference for human consumption products. It can only be programmed to do so. This also reflects the downside of a brand's increased control over influencers when it comes to AI versus humans. H2a is stated as below:

H2a. Consumers perceive an AI influencer as lower in source trustworthiness than a SMI.

However, machines do have advantages compared to humans, specifically when it comes to expertise. As stated, there is an intelligence component embedded within the meanings of AI, that allows for the anthropomorphized AI influencer to trigger a positive attitude. When looking into the mechanisms that make an influencer type effective, specific associations linked to intelligence could be helpful in understanding the values and costs for AI for consumers. Human intelligence could be understood through the conveyance of different metaphors (Sternberg, 2020). A computational metaphor sees human's minds as close to computing devices in that they process information much like a computer (Sternberg, 2020). The computational metaphor has been adopted by cognitive psychology and AI research in general. The computational metaphor conceptualizes intelligence as cognitive abilities, such as reasoning, learning, and memory (Cianciolo & Sternberg, 2008). From this perspective, AI agents do have numerous advantages in their ability to elevate advertising accuracy and efficiency

(Sterne, 2017) and could be perceived as being more intellectually capable than humans (Cianciolo & Sternberg, 2008). For example, the chess-playing AI *Deep Blue* that won a chess match against a world class chess champion demonstrates the superior intelligence of AI in a computational sense.

When examining the credibility of a message source, the computational understanding of intelligence could enhance a consumer's perception of AI as a valid message source that could provide useful information on a topic (i.e., be perceived as an expert). The cognitive-based nature of source expertise (Eisend & Langner, 2010) aligns with the computational based intelligence where AI is deemed to perform better. Indeed, compared with humans, AI is able to access and process a richer body of information regarding a specific issue and individual consumers (Campbell et al., 2020). It is also more able to deal with high-cardinality and high-dimensionality problems (Sterne, 2017). SMIs are "grass-roots" celebrities (Lou & Kim, 2019, p. 2) that tend to strengthen a consumer's perceived similarities with the source (Lou & Kim, 2019) and facilitate a para-social relationship (Schouten et al., 2020). However, SMIs may also be perceived as having less expertise than an AI influencer precisely because of this perceived similarity to the consumer. As a product user, a SMI can only provide a unified opinion of brand information based on their individual opinions relative to a product/service to all of their followers. Although SMIs present themselves as experts on certain issues and demonstrate their knowledge and experiences to the consumers (Schouten et al., 2020), in general, it is hard for a human to compete on an intellectual plane with a computer. Therefore, based on the capability of AI and the consumer's possible understanding of its functional abilities, H2b hypothesized that AI influencers will be perceived as possessing a higher level of expertise than a SMI.

H2b. Consumers perceive an AI influencer as higher in source expertise than a SMI.

Thomas and Fowler (2021) found that AI influencers and celebrities could both yield positive brand outcomes for the endorsed brand. This result is explained through the similarity in their possessed social capital and their function of serving as taste exemplars. In this case, the main mechanism is likely a function of the third dimension of source credibility, attractiveness. Prior studies show that the attractiveness of message sources serves as a useful heuristic (Thompson & Malaviya, 2013), and may even enhance the quality of the argument, especially if the message deals with beauty enhancement products (Kamins, 1990). Therefore, attractiveness may be the primary factor for the success of a tested product such as sunglasses, as reported in Thomas and Fowler's study. Indeed, the appearance of an AI influencer in a photo is almost indistinguishable from a real human, especially when one takes into account the fact the human's photos are usually heavily edited with software and thus appear somewhat unrealistic. The CGI technology ensures that AI influencers could have the same appearance as their human counterparts. Additionally, AI or robot entities do not always communicate meanings that have any rapport with the entity's appearance. Due to the content of human-like advertising content, consumers could evaluate the effectiveness of AI influencers based on their similarity to human models due to the anthropomorphism process. AI influencers could in this case certainly be perceived as just as attractive as humans. Therefore, it is possible that a consumer will see no difference in attractiveness in different types of influencers.

However, it is also possible that people will have different standards of beauty for AI and humans when evaluating attractiveness. This is because of the *artificial* nature of an AI's appearance. When the influencer is labelled a robot, people may have a higher expectation regarding their beauty/attractiveness because an AI's appearance is artificial and can be manipulated to look like whatever it was designed for. Therefore, even though an AI influencer looks exactly the same as a human, they may be perceived as less attractive due to the higher expectations of the viewer. Therefore, RQ1 is stated as below:

RQ1. Is there a perceived difference in attractiveness between AI and SMIs?

Source credibility is able to influence the persuasiveness of the advertising, something that is demonstrated by the ability to heighten the advertising/brand evaluation and enhance purchase intention. The positive effect of source credibility is well established in prior research (Pornpitakpan, 2004). The effectiveness of source credibility could be explained through internalization and identification processes of social influence (Kamins & Gupta, 1994; Kapitan & Silvera, 2016).

The internalization process of persuasion is based on the contrast perspective, focusing on how people process and accept incoming information. Internalization happens when an individual accepts the social influence from others because it aligns with his/her value system; in this case, the content of the influencer's attitude or behavior is internally rewarding (Kelman, 1961). During this process, people will generate their own argument or counterargument relative to the advertising content (Kapitan & Silvera, 2016). The information from a trustworthy and/or expert source could inhibit the retrieval of counterarguments from long-term memory, thus increasing message persuasiveness (Sternthal et al., 1978).

Identification is a helpful tool to explain the positive impact attractiveness has on persuasion (Cohen & Golden, 1972; Erdogan, 1999). Identification happens when an individual accepts the social influence from a message source because of their desire to identify with the endorser (Kamins & Gupta, 1994). The influencer that audiences identify with have qualities that are admired by the audience; imitating their attitude or behavior is a way to build a satisfying self-defining relationship with the influencer or the influencer's group (Kelman, 1961). An attractive source could be an information cue that triggers a desire to identify with the influencer. Therefore, perceived attractiveness of the source is likely to increase the persuasion factor.

In short, a consumer's perception of the three dimensions of source credibility could facilitate persuasion.

As noted, persuasion outcomes specifically refer to the changes in affective (attitude towards the advertisement and the brand) and conative (i.e., purchase intentions) aspects of a consumer's cognition. Attitude and behavioral changes are central concerns in persuasion theory (O'Keefe, 2016), especially as they relate to advertising outcomes (Ambler, 2000). Attitude is the general evaluation of a particular entity. The visual and verbal components of an advertisement could influence attitudes toward the advertisement (Mitchell, 1986). A consumer's favorable affective responses (i.e., attitude) is a good indicator that the receiver will respond favorably to the message source's social influence (Kelman, 1961). Therefore, H3 is proposed as follow:

H3. The source's perceived (a) expertise, (b) trustworthiness, and (c) physical attractiveness is positively related to the receiver's attitude toward advertising messages.

Attitude toward the brand is the second persuasion outcome that can be favorably affected by source credibility. Brand related persuasion outcomes could be more profound, causing credibility to be a highly desired trait for marketers. Mitchell (1986) suggests that although attitudes formed in an advertising context toward the advertisement and the brand are related, they are different constructs. Therefore, these two concepts are measured as separate affective aspects of consumers' cognition in this dissertation. H4 is stated as follow:

H4. The source's perceived (a) expertise, (b) trustworthiness, and (c) physical attractiveness correlates positively with the attitude toward the brand.

Behavioral outcomes are measured by purchases. The ultimate goal of an advertisement is to encourage consumers to execute the promoted behaviors that benefit the brand (Schultz, 2016). Behavioral intentions, which could be defined as the degree to which a consumer is motivated to purchase the endorsed product, is an immediate antecedent of behavior that is easily measured (Ajzen & Fishbein, 1972). Bergkvist and Zhou (2016) suggest that endorsements have a positive effect on brand sales. Additionally, research has also established the strong impact that attitudes towards the advertisement and brand have on purchase intentions (Gresham & Shimp, 1985; Shimp,1981). Thus, H5 is proposed as below:

H5. The source's perceived (a) expertise, (b) trustworthiness, and (c) physical attractiveness is positively related to purchase intention.

Finally, given the links among source credibility, the influencer type, and advertising outcomes stated above, source credibility could serve as a mediator in the model for the current dissertation, as indicated in figure 1.1. The majority of studies on source credibility use credibility as a predictor of persuasion. As noted, in this dissertation, source credibility is seen as a dynamic perception that could be influenced by the nature of the influencer, whether a human or robot. Studying credibility as a mediator is necessary, especially in the initial stage of AI advertising research. AI as a compound concept that has multiple meanings in the minds of consumers. Broadly speaking, it can be seen as an artificial machine or a humanized form of intelligence. Consumers' perceptions could change based on how the message source is perceived moment by moment as put forth by AI and humans.

H6. Source credibility mediates the effect of influencer type on (a) Aad, (b) Abr, and (c) PI.

As a multiple dimensional concept, different influencer types would highlight different aspects of source credibility. Specifically, as specified in H2a and H2b, SMIs will be perceived as more trustworthy; AI influencers, on the other hand, will be perceived as having more expertise. These source credibility perceptions induced by influencer types will affect consumers' attitudes towards the advertising, the brand, and purchase intentions. Specifically, a SMI will be perceived as lower in source expertise compared to an AI influencer. This perceived lack of expertise in human SMIs will lower the consumers' attitude towards the advertisement and brand, as well as lower purchase intention. Therefore, H6a is as follows:

H6a. Perceived expertise postively mediates the relation between influencer type and (a) Aad, (b) Abr, and (c) PI.

On the other hand, a SMI will be seen as more trustworthy than an AI influencer, and this leads to higher opinion of the advertisement and the brand, and therefore increases purchase intentions. Thus, H6b is proposed as follows:

H6b. Perceived trustworthiness negatively mediates the relation between influencer type and (a) Aad, (b) Abr, and (c) PI.

Lastly, the mediation effect of attractiveness will also be examined. Attractiveness is expected to positively influence persuasion outcomes (i.e., Aad, Abr, and PI) in this study. However, since the relation between influencer type and perceived attractiveness is not yet established, as stated in RQ1, RQ2 is proposed as follow:

RQ2. Does perceived attractiveness mediate the relations between influencer type and advertising outcomes (i.e., Aad, Abr, and PI)?

CHAPTER THREE

METHOD

A. OVERVIEW

The goal of this dissertation was to examine (a) the causal relationships between influencer types and persuasion outcomes, including attitude towards the advertisement (Aad), attitude towards the brand (Abr), and purchase intentions (PI), in social media advertising and (b) the mediation roles of three source credibility dimensions on those effects. According to Chang (2017), an experiment is an appropriate research method that attempts to establish causal relationships. An experimental design allows for maximum control by reducing the influence of extraneous variables, thereby eliminating to the greatest extent possible alternative explanations for the causal relationships (Chang, 2017). To test the hypotheses proposed in the model and answer the research questions (see Table 2.1), one pilot study and one main experiment were conducted. The research was approval by the Institutional Review Board (IRB) at the University of Missouri.

The pilot study aimed to validate the instruments to be used in the main study and to test the viability of the experiments in order to establish validity. The main study tested the effect the type of influencer has on consumers' Aad, Abr, and PI, as well as probes the mechanisms that weaken or strengthen a source's capacity to influence behavior (e.g., product involvement, subjective knowledge). Specifically, the main study examined how perceived source's credibility (i.e., trustworthiness, expertise, and attractiveness) affect credibility and the relationship between influencer type and persuasion outcomes (i.e., Aad, Abr, PI) with a maximized experiential control and manipulation.

B. STIMULI

1. Social Media Context

The social media platform selected for this dissertation was Instagram. This selection was based on multiple considerations. First, Instagram is one of the most popular, yet understudied social media sites (Voorveld, 2019). In the U.S. alone, there are 140 million users and more than 25 million businesses on Instagram (Statista, 2020). Because of these statistics, Voorveld (2019) called for a research focus on platforms other than Facebook. Moreover, Instagram is widely used in influencer marketing (Arnold, 2018). Both SMIs and AI influencers are quite active on Instagram: by 2019, the active Instagram influencers reached 500,000 (Droesch, 2019). 34% of active Instagram users have reportedly purchased products based on an influencer/blogger recommendation, a higher figure than for other common social media sites such as Facebook or YouTube (Augustine, 2019). Therefore, choosing Instagram as a platform could increase the external validity of this research. Third, the visual-centered advertising presentation on Instagram could provide a relatively objective anchor (i.e., the influencer's physical appearance) for consumers' perception and maximize the anthropomorphized manipulation of AI influencers. Additionally, unlike video contents on platforms such as YouTube, static pictures on Instagram are easier to be manipulated and controlled in the experimental condition. Therefore, the internal validity could be verified.

However, the limitations of the selection of Instagram as our platform are also acknowledged by the author. First, according to Statista, by 2021, the U.S. Instagram users' demographics are skewed towards females (57.9%) and younger groups (57.1% among 18-34). Therefore, their perceptions towards AI influencers might not be generalizable to the wider, more heterogeneous group of social media users across various platforms. A second limitation is that the advertising contents on Instagram are largely limited to static pictures. Compared with video-based social media sites, such as YouTube and TikTok, it is harder for consumers to make a thorough evaluation of a source's credibility based on the more static image provided.

2. Influencer Type

Two types of influencers were studied: (human) SMIs and AI influencers. A screenshot of the influencer introduction post containing descriptions of the influencer's human vs. robotic natures were provided as a stimulus to trigger any change in attitude. Verbal cues were provided to specify the influencer type. The description of the influencer was revised and adapted from the profile of a virtual influencer imma (Instagram ID: imma.gram) generated by ModelingCafe and Brud's Lil Miquela (Instagram ID: lilmiquela) to ensure external validity.

To design the influencers, the copyright free human model pictures downloaded from *Depositphoto* were used for the main manipulation materials. The selected model was a non-celebrity White female young adult. The model shown in all the stimuli (including the introduction posts and product ads) was the same person to hold the appearance as a constant and reduce any variation caused by gender/ethnicity. The selected model was a White female young adult with the considerations of (1) the ethnicity distribution in the U.S. (with 76.3% of White) (U.S. Census Bureau, 2021) and (2) the demographics of Instagram users (57.1% of them are between the age 18-34 and 57.9% of them are females) (Statista, 2021). One thing to noted is that this dissertation did not sample only White female young adults. This choice was to reduce the silence of the model's demographics in the Instagram setting for U.S. users. The measure of the participants' ethnicity was also added to control the potential confounding effects. This dissertation acknowledges that in real life, the most popular AI influencers were usually set as females of color. For example, Lil Miquela is a brown girl, Shudu is a black woman, Yumi and imma are Asian girls. Further study was conducted to delve into the impact of race and gender on consumers' perceptions and persuasion outcomes if the initial gender and racial differences were observed.

To manipulate influencer type, the author wrote the initial posts and asked two English native Instagram users to proofread and copyedit the contents and three expertise to ensure the content and construct validity. The final version was settled after several round of manipulation checks with student and MTurk samples and revises described in chapter 4, B (see figure 3.1 for the manipulation). The SMI was portrayed the influencer as an everyday person enjoyed sharing her life and with offline friends. The text read "As a person who enjoys sharing my everyday life experiences, when I first decided to be an influencer, not even my friends could've imagined how many of you would be willing to follow ME;" and "I will continue to share my thoughts and knowledge on various products with you from my PERSONAL EXPERIENCES!" The AI influencer was portrayed as a computer created program only existed online. The introduction text read "As a robot that only exists digitally as a computer program, when I first came online, not even my creators could've imagined how many of you would be willing to follow an Artificial Intelligence account;" and "I will continue to share my thoughts and knowledge on various products with you using my DIGITAL BRAIN!" Non-verbal emoji cues (robot vs. human) were also used to increase the manipulation strength. The pictures of the two types of influencers were identical so as to underscore the anthropomorphic features of the AI influencers.

The pictures of the influencers were selected and processed to be able to be interpreted as either human or robot. The author manipulated the original picture of a real human using Photoshop to achieve flawless skin quality. Additionally, to ensure the influencer's social influence was recognizable to the participants, the number of followers were specified in the introduction post as: "Today, I've officially reached 1 million followers!" The likes and comments of the introduction post was also manipulated as relatively high to show the social influence (47,999 likes and 398 comments). The influencers online activities were also to meet the definition of social media/AI influencer by the words "I will continue to share my life, thoughts, and knowledge with you… Great insights on various products to come!"

To determine whether the participants' perceived influencer type was consistent with the manipulation one multiple choice question was asked: "You were randomly assigned into one of the two influencer types (i.e., human vs. artificial intelligence), which of the condition you were in? Three choices were provided: (a) "a person"; (b) "a computer program/artificial intelligent"; (c) "cannot tell for sure."

3. Advertising Messages

The advertising messages were displayed a series of posts from the influencer's account listing #sponsored, #ad, and # [brand name]. The Instagram post was the most widely used and effective content format for influencer marketing (MediaKix, 2019). Four social media advertisements featuring two types of products were designed for use as experimental advertising messages. Products were broadly divided into experiential and material products (Dai et al., 2020). Experiential products are those purchased by the consumers with the intention of acquiring some sort of enriching life experience, while material products are purchased to acquire and keep in one's possession the tangible objects purchased (Van Boven & Gilovich, 2003). Examples of material products are shoes, electronics, and beauty products, while examples of experiential products include the purchase of video streaming services, art objects, DVD's of movies and TV programs (Dai et al., 2020). The material products that used in the current study were from a health care and wellness brand (i.e., vitamin supplements) and a fashion brand (i.e., sunglasses). While the experiential products were from a travel and lifestyle brand (i.e., hotel) and a service brand (i.e., food delivery). The selections were the results from the multiple considerations of the industries that (1) traditionally applied and benefits from influencer marketing, and (2) adopted or could adopt AI influencers. Additionally, sunglasses were selected as one of the material products to replicate the findings in Thomas and Fowler (2021).

Four hypothetical brands (two experiential and two material products) for different product categories were designed for endorsement either by SMI or AI influencers. The use of hypothetical brands in an experiment could avoid the potentially confounding effects of previous exposure (Geuens & De Pelsmacker, 2017). Hypothetical brands could eliminate the influence a consumer's beliefs and attitudes towards existing brands might have on the study (Geuens & De Pelsmacker, 2017). The advertising messages in the experimental materials (see Figure 3.2) were tested and validated in the first stage of the pilot study described in Chapter 4.

C. MEASUREMENTS

Three dependent variables (i.e., Aad, Abr, and PI) and one mediator (i.e., source credibility) were measured. To rule out other explanations and potential confounding effects (Geuens & De Pelsmacker, 2017), two control variables, product involvement, and participants' subjective knowledge about the marketing use of AI along with demographic variables (e.g., gender and race), were also be measured in the studies. The same measurement instrument for each concept were used across all studies in this dissertation.

Measurement instruments used in the current dissertation were well-developed scales adopted from existing research. Using developed and validated measurements found in prior studies was crucial for ensuring the validity of the research results and contributing to the accumulated knowledge for the advertising field at large (Bergkvist & Langner, 2017). For example, the dependent variables, including attitude towards the advertisement (Aad), attitude towards the brand (Abr), and purchase intentions (PI), are adopted primarily from Thomas and Fowler (2021) in order to maintain consistency to make it possible for the results found in this research to be compared to prior related studies (Bergkvist & Langner, 2017).

Attitude towards the Advertisement (Aad)

The attitude toward an advertisement (Aad) was measured by six items using a 7-point semantic differential scale. Four items were from Thomas & Fowler's (2021) measurement of Abr (good/bad, unappealing/appealing, negative/positive, and unfavorable/favorable). These adjectives were also used to measure Aad (Bergkvist & Langner, 2017). Two other items commonly used by advertising scholars to measure Aad (pleasant/unpleasant and smoothing/irritating) were also added (Bergkvist & Langner, 2017). These additional two items could capture more aspects of Aad.

Attitude toward the Brand (Abr)

Attitudes toward the brand (Abr) were also measured by six items using a 7-point semantic differential scale. Four items were from Thomas & Fowler (2021): good/bad, unappealing/appealing, negative/positive, and unfavorable/favorable. Two items (high-quality/poor-quality, valuable/not valuable) commonly used by advertising scholars to measure Abr (Bergkvist & Langner, 2017) were also added to capture more aspects of Abr.

Purchase Intentions (PI)

Purchase Intentions (PI) were measured by four items, two of which were from Thomas & Fowler (2021). These questions asked participants to rate the likelihood of purchasing the endorsed product using a 7-point scale: likely/unlikely, would definitely, definitely would not. The other two are 7-point Likert items from Bergkvist & Langner (2017): "I will recommend the product to others," and "I will consider buying the advertised product."

Source Credibility

Source credibility was defined as "a communicator's positive characteristics that affect the receiver's acceptance of a message" (Ohanian 1990, p. 41). The credibility assessment was composed of three components, namely, trustworthiness, attractiveness, and perceived expertise. Ten items using a 7-point semantic differential scale revised and adopted from Ohanian (1990) were used to measure the perceived credibility of AI and SMIs for each product. Originally, all fifteen-items developed by Ohanian (1990) were used in the pilot study. Trustworthiness was measured using five pairs of adjectives: dependable/undependable, honest/dishonest, reliable/unreliable, sincere/insincere, trustworthy/untrustworthy. Expertise was measured using the following pairings: expert/not an expert, experienced/inexperienced, knowledgeable/unknowledgeable, qualified/unqualified, skilled/unskilled. Finally, attractiveness was measured by the groupings of attractive/unattractive, classy-not/classy, handsome(beautiful)/ugly, elegant-plain, and sexy/not sexy. The scale was reduced to ten items according to the empirical results for validity and practical reasons (see details in Chapter four). Five items (i.e., dependable/undependable, reliable/unreliable, qualified/unqualified, classy-not/classy, elegant-plain) were deleted in the main experiment. The same set of items was used to measure the source credibility of the specific influencer for each of the advertised products.

Product Involvement

Product involvement was defined as "a person's perceived relevance of the object based on inherent needs, values, and interests" (Zaichkowsky, 1985, p. 342). Product involvement was measured based on five items using a 7-point semantic differential adapted from Zaichkowsky (1985) and Mittal (1995). The four item items were: important/unimportant; of concern to me/of no concern to me; means a lot to me/means nothing to me; matters to me/does not matter to me; and significant/insignificant.

Subjective Knowledge

Subjective knowledge was also known as perceived knowledge, defined as consumers' belief about the state of their knowledge regarding certain issues (Moorman et al., 2004). To measure participants' subject knowledge about AI, this dissertation used three 7-point Likert items (1 = much less, 4 = average, 7 = much more) that were adopted from Moorman et al. (2004). The three items were: compared to the average consumer, (1) “how do you rate your knowledge of artificial intelligence in advertising?” (2) “how do you rate your confidence in effectively interacting with an artificial intelligence to get useful product information?” and (3) “how do you rate your ability to comprehend how artificial intelligence is used by marketers?”

Demographics

Three demographic variables were measured as control variables: gender and ethnicity/race. Gender was measured through a multiple-choice item providing three options: a) female, male, b) non-binary, and c) prefer not to say. Ethnicity was measured through one nominal question: “what race/ethnicity do you most identify with?” with five options a) White, b) Black or African American, c) Asian, d) Native Hawaiian or Pacific Islander, and e) other.

CHAPTER FOUR

PILOT STUDY

A. OVERVIEW

A pilot study is a crucial element in social science research (van Teijlingen & Hundley, 2001). The purposes of this pilot study were two-fold. First, the pilot study aimed to test the validity and reliability of the experiment's manipulations and measurement instruments to be used in the primary studies. The pilot study contained three parts, (a) a validation for the stimuli's elements (picture and text), (b) a manipulation-check to test the validity of the stimuli, and (c) a trial run of the main study.

In the first part, manipulation checks for our main independent variable, the influencer type (i.e., SMI vs. AI influencer), and the invariance of the advertising quality among the repeated factors (i.e., product type) were conducted. A manipulation check would help ensure that the stimuli in the experimental condition have the intended effect (Aronow et al., 2019). Conducting manipulation checks in the pilot study could also reduce concerns regarding the confounding effects of manipulation check items on the results (Hauser et al., 2018). The selection of influencer image and product type were validated in the pilot study in order to ensure internal (i.e., minimize the differences among the selected brands/products) and external validity (i.e., ensure the influencer and brand in the study represent real life advertising practices).

Secondly a trial run of the entire experiment with the same structure as the main study were conducted to assess the feasibility of the proposed full-scale study (van Teijlingen & Hundley, 2001). To meet this goal, a full-length survey was be conducted to ensure the questions' clarity, and to estimate the amount of time it would take to complete the study. The same measures for each concept used in the man study, provided no problematic issues surface after the pilot study. Additionally, the measurement instrument that used in the main studies were validated in the pilot study.

The pilot study used a convenient sampling strategy to recruiting undergraduate students and MTurk samples. Student samples were easier to access and MTurk samples could provide quick turnaround times in the event any adjustment in stimulus or measurement was required. Additionally, it was easier to obtain qualitative feedback from undergraduate students which will allow us to determine if there is any lack of clarity in the process. The results collected from the pilot study also informed the reliability of the main study.

B. STIMULI VALIDATION

To test the validity of the designed messages, the author conducted a pre-test for the message elements (i.e., text and picture) with a small amount of convenient sample composing graduate and undergraduate students (N = 19). Participants were asking to (1) rate the credibility, general attitudes, and perceptions of the influencer's nature (i.e., human vs. AI) towards pictures, (2) rate their perceived credibility and attitude to each sentence that to be used in advertising messages, and (3) report their general perceived credibility and their attitude toward ad, brand, and influencer to the entire posts. The measures used in this pre-test are the same as in pilot and main study, but on 5-point scales, the reliability of each scale indicated by Cronbach's α was satisfactory (all above 0.8).

To ensure the anthropomorphism of the influencer, four items were asked (5-point semantic differential questions, fake/nature; machinelike/humanlike;

unconscious/conscious; artificial/lifelike, Bartneck et al., 2009). From the picture, the influencers were generally perceived neither too artificial nor too humanlike (M = 3.03, SD = 1.23). The most humanlike picture was from the introduction post (3.94), while the most artificial picture was for food delivery (2.35). Perceived credibility score of photos ranges from 3.53 (introduction) to 2.51 (food delivery) with M = 2.9, SD = 0.81. The results from the multi-level regression models also indicated that the picture for the food delivery service was perceived significantly more artificial and less credible compared with others. The author adjected the pictures for the food delivery services and hotel to make it more nature.

The advertising message text was also tested sentence by sentence. The mean of perceived source credibility is 3.15 (SD = 1.03). The advertising message for vitamin supplement product got the lowest average score (M = 2.8, SD = 1.18), while food delivery service got the highest average score (M = 3.5, SD = 0.94). The results of multilevel regression showed that the source credibility of the designed advertising copy for sunglasses (t (283.99) = -4.019, p < .01) and vitamin supplements (t (284.01) = -5.243, p < .01) were significantly lower than those for food delivery service. When examined the score for each sentence, the fourth sentence in the vitamin supplement "Your body's ultra-protection!" rated the lowest in source credibility (M = 2.28, SD = 1.06).

The mean of attitude toward the advertisement for each sentence was 3.49 (SD = 1.04). The advertising message for vitamin supplement product got the lowest average score (M = 3.14, SD = 1.18), while food delivery service got the highest average score (M = 3.82, SD = 0.94). Similarly, participants' attitude towards the designed advertising copy for sunglasses (t (283.99) = -3.854, $p < .01$) and vitamin supplements (t (284.01) = -5.257, $p < .01$) were significantly lower than those for food delivery service.

For the entire post, the participants only rated for the four the advertising messages. The perceived source credibility was relatively low with an overall average of 1.82 (SD = 1.4). When investigate the different dimensions of source credibility, the mean of trustworthiness was M = 1.48 (SD = 1.53). The sunglasses post received the highest score in trustworthiness (M = 1.76), while the food delivery post received the lowest trustworthiness score (M = 1.18). The average score of source expertise was 1.56 (SD = 1.43). Similarly, the sunglasses post scored the highest (M = 1.78), and the food delivery post got the lowest score (M = 1.17). As for attractiveness, the influencer got a higher average score (M = 2.42, SD = 1.52) and range from 1.58 (sunglasses) to 1.16 (food delivery). The author also fitted a series of multilevel regression models to examine the potential impacts of advertising messages on various concerned variables (i.e., trustworthiness, expertise, attractiveness, source credibility, and attitude towards advertisement, brand and influencers). None of the models showed significant differences due to the variance in advertising messages.

Adjustment

According to the validation results, the picture for food delivery scored significantly worse than other condition. Therefore, the author made some adjustments to the picture after consulting colleague with photo production profession, to increase the photos' quality. The adjustments including a) increased the color/pixel consistency between the background and the influencer, and b) cropped the picture into a more appropriate size. Although the introduction picture performed better than pictures for advertising messages, it was less of the author's concern because the introduction picture was used as a manipulation for influencer type and has a different function with other pictures. Additionally, one sentence from vitamin supplement advertisement that scored the lowest was also deleted to keep a) the length of each post as the same, and b) increase the overall credibility and attitude score of the vitamin supplement post. The overall perceived source credibility and attitude score for each advertisement post was not significantly different as stated above, therefore, the author only made a few minor adjustments to the posts.

C. MANIPULATION CHECK AND TRAIL RUN OF THE STUDY

Sampling

The pilot study was a dynamic process contained a total three stages to achieve a sufficient confident ensuring the validity of the stimuli and measurements used in the main study. A total $N = 297$ student samples and $N = 291$ were recruited into the pilot studies in different stages. The participants were assigned randomly and evenly across each test condition through the Qualtrics survey system. Student samples were granted extra credit in coursework, and MTurk samples were provide monetary rewards matched with the Missouri state's minimal wage as the compensation for their time and participation.

Design and Procedure

The pilot study contained several stages serving the two purposes of the polit study. It involved several rounds of manipulation checks, trail runs, and re-examines after revises until a sufficient level of confidence on the instrument validity and reliability achieved. The pilot study uses a two-group randomized experimental design. The influencer type was between-subject factor. The manipulation check pilot was conducted by presenting the participants with only the main stimulus (introduction posts with AI/social media influencer featured) and two manipulation check questions to isolate the effect from the manipulation.

The trail run of the main study were conducted in a similar procedure as in main study according to the following steps suggested by Geuens and De Pelsmacker (2017). Besides the influencer type, each individual viewed four advertisements featuring two product types (experiential vs. material product). Product type was a massage replication factor using within-subject design. The mixed design was to maximize the explaining power with the same number of participants. However, it was possible that a repeating exposure to different product types may have a confounding effect with source credibility. For example, participants might consider the influencer was more credible recommending one product over others, or less credible because their involvement in multiple products. And it was unknown whether this impact will be equally influencing AI and social media influencers. Therefore, source credibility was measured in different spots to control this confounding effect and to rule it out in the pilot study to make sure a valid design in the main studies.

The procedure of the pilot study was described as below. After the introduction and the agreement signature page, two pre-test variables were measured. The participants were asked to respond to items measuring their general attitude and perceived source credibility toward AI and social media influencers. Then, all of the participants were randomly assigned into one of the two categories determined by the Qualtrics system, where each participant was exposed to one of the influencer's Instagram introduction posts (i.e., social media vs. AI influencers). The introduction post was followed by items for the manipulation check. A series (i.e., four) of advertisements featured four different products as stated above were presented to each subject in a random order. Each advertisement was followed by the measurement of Aad, Abr, PI, source credibility and product involvement. The influence of repeated measure on the results were also controlled through statistical analysis. The other measurements were provided in the following order: a) control variables (i.e., subjective knowledge of AI, and product involvement); and b) socio-demographics (i.e., gender, race, education, and income). Then, participants were asked to complete an open-ended question to allow them to offer any suggestions about the study or measures. Finally, they received a debriefing message.

D. RESULTS

To validate the stimuli and measurement instruments, a pilot study contain three sub-studies were conducted.

Pilot Study Stage One

In the first pilot study, 93 undergraduate students respond to the online experimental survey. 7 responses were screened out by the screening questions. Another 12 respondents were deleted due to a different level of missing values. Thus, a total 74 respondents were included into the data analysis. A total 37 of the participants were assigned in each of the groups (i.e., AI influencer vs. SMI).

Average time: after deleting the respondents ($N = 9$) who spend over one hour on the survey site, the average time consumption for this survey among 65 participants is 15.12 minutes.

Manipulation Check

A total 7 respondents failed the comprehension check, two of them were in the AI influencer group, and five of them were in SMI group. They were excluded from the manipulation check to ensure the validity. The number of total participants in the SMI condition was 32, and 35 in the AI influencer condition.

For the categorical manipulation check, the Chi-square test was not significant (χ^2 (2) = 0.10, $p > .05$). Participants were in general more likely to consider the influencer in the material as AI rather than human. In the AI condition, 31 of the participants thought the influencer is an AI (86.5%), and four (13.5%) selected cannot tell for sure. While in the human condition, 22 out of the 32 participants (70.3%) still considered the influencer as an AI, only three believed the influencer was an authentic human (8.1%), another seven participants could not tell for sure (21.6%). Therefore, the manipulation of influencer type in the first pilot study was not successful. A revise and reexamine of the manipulation were needed.

For the four anthropomorphism items, the Omega analysis with 500 bootstrapping resampling shows a good reliability of the scale (*est.* = 0.91, *se* = 0.02, 95% CI [0.86, 0.94]). The *t*-test for influencer type group on the manipulation check was not significant (t (64.935) = 0.103, $M_{\text{AI}} = 2.67$, $M_{\text{Human}} = 2.65$). Specifically, AI influencer was rated higher on item 2 (Humanlike) and 4 (Lifelike), while SMI was rated higher on item 1 (natural) and 3 (conscious). However, none of the differences were significant.

Measurement Instrument

To ensure the measurement reliability, Omega analyses for each of the main variables were with 500 bootstrapping resampling. Omega was considered a more valid alternative in evaluating scale reliability than Cronbach alpha (Hayes & Coutts, 2020).

Omega does not assume each of the items the multi-item instrument is interchangeable and takes the multi-dimensional feature consideration. Omega values for all main research variables except product involvement are above 0.7, a cutoff value for an acceptable instrument (Lance et al., 2006).

For the multi-dimensional variables, including source credibility (pre- and post-test), emotional response and engagement, four confirmatory factor analyses (CFA) were conducted. Neither the CFA models for pre-credibility (χ^2 (87) = 196.40, CFI = 0.785, TLI = 0.741, RSMEA = 0.130 [0.109, 0.155], SRMR = 0.106) nor for post-credibility (χ^2 (87) = 221.27, CFI = 0.789, TLI = 0.746, RSMEA = 0.144 [0.121, 0.168], SRMR = 0.109) had a satisfactory global fit. To further identify the problem, two exploratory factor analyses were conducted. EFA results shows six problematic source credibility items (either load to the wrong dimension nor more than one dimension) across the two models. The items contained two trustworthiness items (dependable/undependable; reliable/unreliable), two expertise items (experienced/inexperienced; qualified/unqualified), and two attractiveness items (classy/not classy, elegant-plain).

When examining the individual question, these items were found could not fit to the current social media/AI influencer smoothly. For example, the meaning for dependable and reliable were slightly different in the context of human versus AI. These two items loaded to the dimension of expertise instead of trustworthiness in the current models. The items for expertise, “experienced” and qualified were loaded as a measure for trustworthiness instead in the pre-credibility test, which could indicate that these two adjectives may be interpreted differently in the social media context. Classy and elegant may not appropriate to measure attractiveness of the grass-root influencers. After deleting these six questions, the model fit for pre-credibility (χ^2 (24) = 287.295, CFI = 0.992, TLI = 0.988, RSMEA = 0.033 [0.000, 0.102], SRMR = 0.050) and post-credibility (χ^2 (24) = 314.238, CFI = 0.974, TLI = 0.961, RSMEA = 0.064 [0.000, 0.121], SRMR = 0.060) were both acceptable.

After excluding the six questionable items, the measurement invariance for source credibility measure through structural equation modeling (SEM) (Gordon et al., 2009) was performed to examine whether the position of source credibility measure impacted the measurement performance. The measurement invariance examination was conducted through three steps. First, the CFA model for source credibility was fitted for the two groups of participants filling it in different position separately (χ^2 (48) = 71.820, CFI = 0.924, TLI = 0.899, RSMEA = 0.113 90% CI [0.052, 0.165], SRMR = 0.094). Second, the weak (i.e., loading) invariance was tested by constricting the loadings of the two group as the same (χ^2 (54) = 77.696, CFI = 0.924, TLI = 0.887, RSMEA = 0.107 [0.045, 0.157], SRMR = 0.091). Since change of CFI was not larger than 0.01, the loading invariance passed, which implied that the each of the items contained the same meaning to the latent variable across different groups. Last, the strong (interception) invariance was tested by constricting the latent means of the two groups as the same (χ^2 (60) = 94.738, CFI = 0.890, TLI = 0.868, RSMEA = 0.125 [0.073, 0.172], SRMR = 0.102). Therefore, the interception invariance did not pass. The position of source credibility measure could impact the validity of the scales. Additionally, the post credibility group reported a significantly lower in expertise and attractiveness, however slightly higher in trustworthiness (meaning the exposure of a series of sponsored post could decrease credibility). Further revises on the items' wording were made to distinguish these two dimensions and validate the measurement instrument.

Adjustment

The author conducted a MTurk survey to look for possible adjustment. In this manipulation check, only manipulation check questions are asked without any pre-tests or descriptions. A total 90 participants filled in the survey. After cleaning up the data by deleting any incomplete surveys and possible bots' responses. A sample of 80 subjects were enrolled into the manipulation check, 35 of them were assigned in the human influencer group, and 45 of them were in the AI influencer group. In the AI influencer condition, 17 of the participants (37.7%) considered the influencer was an AI influencer, 25 considered the influencer as an authentic human (55.6%), and 3 of the participants selected unsure (6.7%). In the human influencer condition, only 3 participants considered the influencer an AI (8.6%), 32 participants agreed that the influencer was an authentic human (91.4%). The Chi-square test was significant (χ^2 (2) = 12.607, p < .01).

For the measurement instrument, according to the Omega and CFA results, items for engagement and product involvement were reworded. Since the sample size for this pilot study was relatively small, the items for source credibility were kept in the next stage for further examination. Meanwhile, source credibility was tested both before and after the advertising posts to further make sure the sources of the measurement variance.

Pilot Study Stage Two

The author conducted a second pilot study with 204 student sample respondents that different from the previous one with a few adjustments: (1) rephased the Survey recruitment advertising and title from "AI vs. Human influencer" to neural "Instagram influencer," and (2) measured post source credibility twice at the survey (right after the introduction post and after all the advertisement post). 33 of the respondents were disqualified by the screener or due to not finished the questionnaire. A total 171 students were included into the data analysis. The average time of completing the survey is 15.76 minutes (excluding one outliner finished in 26 hours).

Manipulation Check

The Chi-square test for the manipulation check of the second polit study was significant (χ^2 (2) = 13.31, $p < .01$). However, in general participants were still more likely to consider the influencer in the material as AI rather than human. In the AI condition, 69 of the participants think the influencer is an AI (82.14%), and four (4.76%) think the influencer was human, and 11 (13.10%) selected cannot tell for sure. While in the human condition, 50 out of the 87 participants (57.47%) still think the influencer was an AI, only 16 believed the influencer was an authentic human (18.39%), another 21 participants selected cannot tell for sure (24.14%). Although the Chi-square results indicated a certain level of effectiveness of the manipulation, the percentage of the participants correctly answer the manipulation check question was still low. Therefore, the stimuli were further revised, and a third pilot study was conducted.

Measurement Instrument

Similar as in the first stage, both Cronbach alpha and Omega analyses (with 500 bootstrapping resampling) for each of the main variables were conducted. Omega values for all main research variables except product involvement were above 0.8, a cutoff value for an acceptable instrument (Lance et al., 2006).

For the multi-dimensional variables, including source credibility (pre-test, and pre- & post- advertising posts), emotional response and engagement, five confirmatory factor analyses (CFA) were conducted. Pre-credibility did not have a good model fit (χ^2 (87) = 273.575, CFI = 0.879, TLI = 0.854, RSMEA = 0.112 [0.097, 0.127], SRMR = 0.134). However, after deleting the six problematic questions identified in the first pilot study, the model fit was significantly improved (χ^2 (24) = 273.575, CFI = 0.985, TLI = 0.977, RSMEA = 0.057 [0.013, 0.097], SRMR = 0.47). For the first post-credibility test positioned right after the introduction post but before the advertising posts, the CFA model fit is acceptable (χ^2 (87) = 37.529, CFI = 0.944, TLI = 0.933, RSMEA = 0.081 [0.065, 0.097], SRMR = 0.079). But still, the model fit could be improved by deleting the six items (χ^2 (24) = 38.966, CFI = 0.981, TLI = 0.971, RSMEA = 0.060 [0.020, 0.090], SRMR = 0.040). Similarly, for the second post-credibility test positioned after the four advertising posts, the CFA model fit is acceptable (χ^2 (87) = 271.104, CFI = 0.912, TLI = 0.893, RSMEA = 0.111 [0.096, 0.126], SRMR = 0.105), but could be improved by deleting the six items (χ^2 (24) = 46.026, CFI = 0.978, TLI = 0.967, RSMEA = 0.073 [0.040, 0.105], SRMR = 0.043).

The measurement invariance was tested for as in the polit study stage one through nested model comparison through three steps to see whether the positioning of source credibility (after the introduction post versus after the advertising posts) measure could impact the measurement validity. The pretest source credibility was not examined because (a) the poor measurement model fit stated previously, and (b) it was not included in the next stage to avoid a contamination of the manipulation.

The loading invariance and intercept invariance were examined for all 15 source credibility indicators first. First, a CFA was fitted with six latent a CFA model with six latent variables for the three dimensions of source credibility measure after the introduction post and the advertising posts separately. Each latent variables contained five indicators. The same worded items' covariances were allowed to be freely estimated. Therefore, each of the six latent variables contained three indicators. The same worded items' covariances were allowed to be freely estimated. Results demonstrated a good model fit (χ^2 (376) = 683.663, CFI = 0.916, TLI = 0.903, RSMEA = 0.074 [0.065, 0.083], SRMR = 0.089). For the loading invariance, the loading for the same indicator with different positioning were constricted as the same. The change of CFI was not larger than 0.01 (χ^2 (390) = 702.156, CFI = 0.916, TLI = 0.906, RSMEA = 0.073 [0.064, 0.082], SRMR = 0.106), implying the loading invariance passed. Last, the intercept invariance was also passed (χ^2 (402) = 722.233, CFI = 0.914, TLI = 0.907, RSMEA = 0.073 [0.064, 0.081], SRMR = 0.106). Intercept invariance was tested by restricting the intercepts of the same indicator toward a latent variable with different positioning as the same. To ensure the model identifiable, the latent mean of trustworthiness, expertise, and attractiveness measured after the advertising posts were freely estimated rather than fixed to zero. A decrease of the three dimensions of source credibility were observed ($\Delta M_{\text{trustworthiness}}$ = -0.136, $\Delta M_{\text{expertise}}$ = -0.317; $\Delta M_{\text{attractiveness}}$ = -0.122).

The same steps were taken after excluding the six questionable items. Therefore, each of the six latent variables contained three indicators. The same worded items' covariances were allowed to be freely estimated. Results demonstrated a great model fit (χ^2 (111) = 156.292, CFI = 0.975, TLI = 0.965, RSMEA = 0.052 [0.031, 0.071], SRMR =

0.038). Next, the loading invariance was tested through restrict the loadings of the same indicators toward a latent variable with different positioning as the same. Other aspects of the model were the same as the previous one. Results showed a less than 0.01 CFI change (χ^2 (120) = 166.465, CFI = 0.974, TLI = 0.967, RSMEA = 0.051 [0.030, 0.068], SRMR = 0.050), implying the loading invariance passed. Last, the intercept invariance was tested through restricting the intercepts of the same indicator toward a latent variable with different positioning as the same. To ensure the model was identifiable, the latent mean of trustworthiness, expertise, and attractiveness measured after the advertising posts were freely estimated rather than fixed to zero. The intercept invariance was also passed (χ^2 (126) = 172.156, CFI = 0.975, TLI = 0.969, RSMEA = 0.049 [0.029, 0.067], SRMR = 0.050). Again, a decrease of the three dimensions of source credibility were observed ($\Delta M_{\text{trustworthiness}}$ = -0.165, $\Delta M_{\text{expertise}}$ = -0.343; $\Delta M_{\text{attractiveness}}$ = -0.086)

Adjustment

Due to the unsatisfactory results from the manipulation check, the manipulation for influencer type were significantly refined. Additionally, the description, comprehension and pretest items were found influencing the effectiveness of the main manipulation and were not directly related to the hypotheses being tested. Therefore, they were excluded from the third stage of the pilot study. Source credibility was measured with only nine items and was measured after each of the posts to (a) identify the source credibility for each of the product types, and (b) random out the accumulate effect of the measure.

Pilot Study Stage Three

After revising the manipulation and refining the procedure, a simple manipulation check (i.e., only present the stimuli and the manipulation check) with 135 respondents through MTurk were conducted first. After excluding the speeders who had viewed the post for less than or equal to 5 seconds (11.85%, more than one SD quicker than the average), a total of 119 individuals were included in the manipulation check. Fifty-five of them were assigned to the AI group, and 64 were assigned to the human group. Within the AI group, 44 of the participants were considered the influencer as AI (80%), 10 considered the influencer as human (18%), and one could not tell for sure (2%). Within the human group, 57 of the participants were considered the influencer as human (89%), and seven reported cannot tell for sure. The Chi-square test for the crossable showed the experimental condition was significantly related to participants' perception (human vs. AI) ($\chi^2(2) = 81.254$, $p < 0.00$).

Additionally, participants in the AI condition perceived the influencer as more machinelike ($M_{\text{AI}} = 4.05$, $M_{\text{human}} = 3.25$, $t\ (110.01) = 2.18$, $p < 0.05$) and unconscious ($M_{\text{AI}} = 3.82$, $M_{\text{human}} = 3.13$, $t\ (105.46) = 2.03$, $p < 0.05$). However, the differences on the scale of Nature/Fake, Lifelike/artificial were not significant.

Besides this manipulation check, a full-length survey with 66 MTurk samples were also conducted. This pilot was conducted to reexamine the measurement reliability and estimate the time. After deleting the speeders ($N = 25$) finished the survey under 5 minutes, the trail run shows that the experiment took an average of 7 minutes to finish (ranged from 5.1 min-14.6 min). For the manipulation check, 65% of participants answered correctly in the AI group, while 95% answered correctly in the human group. The reliability for one control variable with a reversed item - product/service involvement

– was still not acceptable. A different scale for product involvement were adopted for the main study as reported in Chapter 3.

E. CONCLUSION

After the pilot study, the stimuli, experiment procedure, and measurement instrument were refined for the main experiment. Specifically, four main adapts were made for the main study: (a) the stimuli (pictures and texts) was updated and passed the manipulation check as stated above; (b) the scale for product involvement was replaced due to the low Omega value; (c) the measure for source credibility were shortened according to the confirmatory factor analysis results; and (d) the source credibility was measured repeatedly at the end of every product advertising post to control the confounding effects.

CHAPTER FIVE

MAIN STUDY

A. OVERVIEW

The purpose of the main study was to test the research model (i.e., main effects of influencer types on persuasion outcomes (i.e., Aad, Abr, PI) and the mediator role of source credibility). The main study was a 2 (influencer type: human vs. AI) * 4 (replicated ads) mixed design, where influencer type was a between subject factor and ad replication was a within subject factor. Between-subject design was beneficial in this context to reduce any time-based influences that might affect the results (e.g., a heightened performance level due to practice; or decreased performance due to fatigue) (Campbell & Stanley, 1963; Reeves & Geiger, 1994). However, the effect could also be constricted through the design (e.g., counterbalance presentation order, Reeves & Geiger, 1994) and further statistical analysis (e.g., longitudinal SEM, Little, 2013). Within subject design had a better control over the impact of the individual-level variances on the treatment effects and reduce the *N* of subjects. Additionally, since message variance was built into the dissertation design, it was important to ensure that the appearances of the SMI and AI influencers were identical, and the message was consistent across two influencer type conditions. Therefore, a mixed design allowed to use exactly the same messages to reduce background noise and provided a clearer picture of the treatment effect (Reeves & Geiger, 1994). The stimuli and measurement instrument used in the main study was described in detailed in Chapter 3 and validate through the pilot study described in Chapter 4.

B. SAMPLING

A total $N = 514$ (59.53% female) were included in the finial data analysis determined by the power analysis ahead of the study and the data cleaning process after data collection. The socio-demographic and social media use information of the 514 respondents were shown in Table 5.1. Three quota criteria were applied to ensure the data quality and representation. The participants should be 1) an Instagram user, 2) at the age of 18 or above, and 3) living in the U.S. to be qualified for the research. Additionally, the gender ratio was restricted as 58% females and 42% males to meet the demographics of the Instagram users in the U.S. (Statista, 2021) and ensure representation.

A total $N = 480$ sample size was decided by a power analysis before the experiment to achieve a satisfactory ability to detect the significance of a specific parameter and determine whether the model was acceptable according to Little (2013). Specifically, a sample size of 400 could ensure 100 samples for each experimental condition with the precaution of any influences from product types (i.e., material vs. experiential) on the overall evaluation to ensure sufficient power. An additional 20% participants (i.e., $N = 480$) were recruited as remaining for data cleaning and quality control. This sample size could also ensure that every condition has an equal number of participants.

Neither the power analysis either for parameters or for the entire model yielded a need for a larger required sample size than 480. Specifically, the results of power analysis with Gpower software showed that at least 141 individuals should be sampled to achieve at least 0.95 power with 0.2 effect size for the proposed multiple regression model. At least 77 individuals should be sampled to achieve at least 0.95 power with 0.05 effect size for the measure of RMSEA (df = 708). This predicted model for the main study included one independent variable (i.e., influencer type), three mediators (i.e., expertise, trustworthiness, and attractiveness), two control variables (i.e., product involvement, and subjective knowledge), and three demographic variables (i.e., gender and race).

The online survey was outsourced via Qualtrics, which recruited an online panel of respondents based on the researchers' stringent criteria. Qualtrics panels are reliable for providing a balanced and representative sample pool and high-quality data (Boas et al., 2018). The researcher paid $5 each of the 480 planed participants to Qualtrics. Data were collected in early December 2021. A soft launch was conducted on December 6 with 50 initial participants to ensure the viability of the process and time estimation. The full launch was conducted in December 8-14. A total of 765 U.S. Instagram users accepted the research invitation.

To ensure data quality, the researcher implemented three steps of data clarifications. First, speeders and individuals who failed the attention check were automatically recorded as incomplete data and excluded from the dataset. Speeders were identified by the time estimation in the soft launch. Participants who spent less than one half of the time of the median in the soft launch ($Median_{\text{Time}}$ = 480s) were marked as speeder (i.e., $Time$ < 240s). One attention check question was inserted into the survey and present to the participants in a random order with the questions for the Vitamin message. Participants who failed the attention check question were disqualified and directed to the end of the survey. A total of 153 (19.6%) participants were screened out at this stage. In total, 612 individuals complete the survey. Second, the data quality of the 612 participants was checked through a data scrubbing service provided by Qualtrics. A total

73 of the participants were deleted due to profane responses, non-sensical, duplicate responses, relevant ID check, bots, and straight-line responses. Third, the author manually checked again for any repeated ID ($N = 5$), straight-line responder ($N = 19$), and suspicious geographic coordinate (e.g., location that is not in the U.S, $N = 1$). After the quality check process, 514 individuals (306 females, 59.33%, 200 males, 38.91%, and 8 non-binary participants, 1.56%) were included into the data analysis.

Stimuli and Measurement

As described in Chapter 3, the stimuli used in the main study were validated in the pilot study. As in the pilot study, the social media platform was Instagram, and two influencer types were manipulated using a descriptor that identifies them as either AI or human in the influencers' introduction posts.

Advertising messages were be presented as a screenshot of the influencer's post with (fictional) branded information on Instagram. The ad nature was revealed to the participants through hashtags (i.e., sponsor and brand name) as if it were a typical advertisement on Instagram. The branded messages for four different types of products (two experiential and two material) were designed and serve as a replicate variable.

Procedures

The study was conducted online using Qualtrics software. The main study was conducted using a procedure refined by the pilot study with necessary modifications. The specific procedure for the main study is as follows. After being presented with the introduction and consent form pages, participants were qualified through two screener questions in order to reduce sample frame error, which occurs when the wrong sub-population was sampled (Sax et al., 2003). Next, the participants were randomly assigned into one of the two influencer type conditions (i.e., social media/human vs. AI) to read the influencer's introduction post. The exposure duration was timed using the Qualtrics function. The average time of reading through the introduction post was 18.16s (*Median* = 11.64s). Then, four replicated ads within two categories (i.e., experiential vs. material) were assigned to the participants in a random order. After being exposed to each of the advertisement, the participants responded to a sequence of measurements, including Aad, Abr, PI, source credibility evaluation for each product, and product involvement. Next, manipulation check question followed by thee control variable (i.e., subjective knowledge, Instagram usage) and demographics (i.e., gender, race/ethnicity, household income, and education) were asked. Finally, the debriefing statement was provided. The average time of finishing the entire survey was 707.3s (*Median* = 563.0s).

The manipulation check question was moved to the end of the survey compared to the trial run in the pilot study. This modification was due to the different purposes driving the pilot study and the main study. One of the primary goals for the pilot study was to check the viability of the manipulations; manipulation check items were provided as a main measurement to be assessed first (Geuens & De Pelsmacker, 2017). However, the manipulation check should not be provided before presenting the main variables so that any potential contamination could be reduced (Geuens & De Pelsmacker, 2017).

C. RESULTS

Overview

The statistical analysis was performed through R 4.0.1. The proposed model was tested through longitude structural equation modeling (SEM) with steps including confirmatory factor analyses, measurement invariance analyses, nested model comparisons, bootstrapping, and path analyses (e.g., Brown, 2015, Little, 2013). Compared to other viable methods, such as ANOVA or multiple regression, the advantages of this approach are limited to fewer assumptions, eliminated measurement errors, and more flexibility (Brown, 2015). For example, ANOVA requires balanced data from each group and assumes that factor effects are additive. A normal distribution with any dependent variables. ANOVA also has limited ability to test complicated mediation and moderation models. Regression is not able to test the model as a whole. Also, similar to path analysis, a regression cannot rule out the residual errors unless the errors are truly randomized (Coaley, 2014). Longitude structural equation modeling (SEM) could deal with the experimental data with mixed design, constraining the individual level of measurement errors (Little, 2013). This method can also test assumptions, like measurement invariance, to get more sound data analyses results.

The rest of the results were organized as below. First, the descriptive statistics of the main variables, including the mean, standard division (SD), reliability (Alpha and Omega), confirmatory factor analysis results, were reported. Second, the manipulation results were reported. Next, the measurement invariance results were presented to confirm the validity of the measurement instruments before conducting the main analyses testing the hypotheses. Then, the hypotheses were tested, and research questions werre answered through the paths analyses with bootstrapping resampling. Last, the results from probing analyses were conducted and reported to provide any additional insights into the research questions.

Descriptive Statistics

As the first step of the data analysis, the author calculated the mean, SD, of the main variables that were being used in the statistic modeling to provide an overview of the variables (see table 5.2). At this stage, the measures for each product were analyzed separately. Cronbach's alpha and mean/SD values were generated using the *psych* package (Revelle, 2021), and Omega was generated by the *MBESS* package (Kelley et al., 2018) with 500 bootstrapping resampling. Omega is considered a more accurate way to evaluate item reliability, especially for multidimensional constructs without the tau-equivalent assumption for each item (Hayes & Coutts, 2020). The results showed sufficient reliabilities for each of the variables (Hayes & Coutts, 2020).

Since this dissertation considered source credibility (measured by 10 items) as a multidimensional construct, containing three separate concepts, trustworthiness (3 items), expertise (4 items), and attractiveness (3 items), the author conducted confirmatory factor analysis (CFA) using the *lavaan* package to ensure the validity of the scale. The CFI values of source credibility for every product were above 0.95, and factor loadings for each individual item were all above 0.7, demonstrating good global and local model fits. Specifically, for Sunglasses, χ^2 (32) = 93.182; CFI = .988; TLI = .982; RMSEA = .061, 90% CI [.047–.076]; SRMR = .021; for Vitamin supplements, χ^2 (32) = 56.559; CFI = .995; TLI = .993; RMSEA = .039, 90% CI [.021–.055]; SRMR = .014; for the Hotel brand, χ^2 (32) = 98.143; CFI = .986; TLI = .981; RMSEA = .063, 90% CI [.049–.078]; SRMR = .026; and for the Food delivery service, χ^2 (32) = 84.133; CFI = .989; TLI = .985; RMSEA = .056, 90% CI [.042–.071]; SRMR = .018.

Manipulation Check

To make sure the manipulation in the introduction post could successfully influence the participants' perception of influencer type, a two-group t-test was conducted. The result indicated a significant impact from the manipulation on the participants' perception of influencer type (χ^2 (2) = 44.347, p <.001), demonstrating the successfulness of the manipulation. Specifically, 134 out of the 254 (52.8%) participants in the AI group consider the influencer they viewed as an artificial intelligent influencer, 93 (36.6%) still consider the influencer as a human SMI, and 27 (10.6%) were not sure about the nature of the influencer. In the SMI group (N = 260), the majority of the participants considered the influencer a human (N = 156, 60%), 63 participants (24.2%) believed the influencer was an AI, while 41 (15.2%) cannot tell for sure.

Measurement Invariance

Measurement validity was tested using measurement invariance models before main hypotheses and research questions were tested and answered. The main study applied a mixed design where product type (i.e., experiential vs. material) was a within-subject factor, while the influencer type (i.e., AI vs. SMI) was treated as a between-subject factor. Additionally, this study also sampled from sub-groups that featured different gender and racial identities. Therefore, the measurement invariances were tested in three parts: a) measurement invariance for longitudinal repeated measures for four brands and two product types, respectively; b) measurement invariance between experimental and demographic groups; and c) the overall measurement invariance for the mixed design measurement model.

Measurement Invariance for Longitudinal Repeated Measures

For starters, an item-level measurement invariance for the within-subject repeated measures variables, including source credibility, attitude towards the advertising (Aad), attitude towards the brand (Abr), purchase intention (PI), and involvement, across four waves of measurements were conducted (see table 5.3). A total of 116 indicators measured 16 latent variables were included in this model. The model was estimated with the "Maximum Likelihood Robust" method (i.e., MLR). The process of the invariance test aligns with Little (2013). First, the author fitted a configural invariance model where the loading and intercepts of the item level indicators for the four products were freely estimated. The correlated residuals for the same worded items were allowed to be freely estimated to correct the individual level error. No auto-regression paths were included since the products were fully randomized, so the accumulation effect resulting from practice was expected to be balanced out. The results demonstrated a satisfactory global model fit (χ^2 (6462) = 9807.322; CFI = .947; TLI = .942; RMSEA = .035, 90% CI [.034–.037]). All factor loadings were above 0.7. To further diagnose potential model misfit, residual matrix with the differences between observed matrix (S) and estimated matrix (Σ) and the modification indices were examined. No abnormal misfits were found. Therefore, the configural invariance model was considered passed (Little, 2013).

Next, the weak (i.e., loading) invariance for the four products was examined. In the loading invariance model, the factor loading for the same item on latent variables measuring different product types was restricted as equal. Additionally, to ensure the model was identifiable, the latent variances were allowed to be freely estimated except for the first product type measure (i.e., Sunglasses). The result showed that the change of CFI was less than 0.01, a threshold to decide whether the measurement invariance was achieved (Cheung & Rensvold, 2002). Therefore, the weak measurement invariance for the four different products was passed.

Finally, a strong (i.e., intercept) invariance test for the four products was conducted by restricting the intercepts of the same items in the four measurement occasions as the same. Latent means for three out of the four products (besides sunglass) were freely estimated instead of fixing to zero to identify the model. The strong measurement invariance was also passed due to a less than 0.01 in the CFI change.

To lower the indicator-to-sample size ratio and reduce the number of parameters and sources of sample error, the author followed the suggestion of Little et al. (2013) by creating three parcels for Aad, Abr, and PI. The three dependent variables were just-identified with three indicators each. The contents of the parcels for each dependent variable were identical for the four product types. Measurement invariance tests after parceling were conducted following the same steps above (see table 5.4). As demonstrated in the results, the overall model fits were improved, and, again, strong measurement invariance was achieved.

Additionally, to increase the parsimony of the model, the author further investigated the possibility of combining the repeated measures for different products. To do that, the homogeneity tests with strong measurement invariance enforced were conducted for (a) latent variances/covariances and (b) latent mean invariance (see table 5.4). For the test of variance and covariance homogeneity, an omnibus test where a) all latent variances were restricted as equal (var =1), and b) the latent covariance within each product type was restricted as equal across four waves of measurements. All other covariances among the latent variables were freely estimated. Nested model comparisons were conducted comparing the strong measurement invariance model and the omnibus model. Considering the relatively large sample size of this study ($N > 500$), the criterion for determining too much loss in fit in the latent space was a p-value less than .001 or a change in CFI greater than .002 (Little, 2013).

As shown in Table 5.4, the variance/covariance omnibus test for the four products was not passed because of too much loss in fit in the latent space ($\Delta\chi^2$ (84) = 149.47, $p < .001$). The author further tested the latent variance-covariance invariance by only restricting the two material products (i.e., sunglasses and vitamin) as equal and two experiential products (i.e., hotel and food delivery service) as equal. Latent variances of four products were still constricted as the same (see "Cov-inv under Mar/Exp" in table 5.4). Then, certain covariance parameters were freely estimated one at a time until the invariance test pass (i.e., homogeneity tests). Through this test, the author found that the relations among the latent variables (i.e., latent covariance) were largely the same for the repeated measures within each product category (i.e., material/experiential). However, the correlations between involvement and other latent variables differed across two experiential products. Additionally, the model invariance could achieve the model invariance by allowing the latent variances of PI and involvement for the two experiential products to be freely estimated. Since involvement was treated as a covariant and the loss of chi-square was not large (around the threshold) after releasing the two major product types as equal ($\Delta\chi^2$ (53) = 90.098, p >.001), the author considered the variance-covariance homogeneity between material and experiential products as different, while within the product types as equal.

For the test of latent mean invariance, an omnibus test required the equality of latent mean across four repeated measured products were conducted with the strong measurement invariance enforced. In this model, the means of all latent variables were fixed to zero. Then, the latent means equalities were tested separately for material and experiential products. Results showed that although the latent means between the two major product types (material/experiential) were different ($\Delta\chi^2(21) = 86.123$, $p <.001$), the latent mean invariances were largely achieved for the repeated measures within each product type ($\Delta\chi^2_{mat}(7) = 13.261$, $p =.066$; $\Delta\chi^2_{exp}(7) = 24.654$, $p <.001$). The only exception was found in the control variable, involvement of the two experiential products. This exception considered as acceptable by the author due to the relatively small changes in CFI (< .02) and the role of involvement in the model.

Multi-Group Measurement Invariance for Longitudinal Repeated Measures

In the second part of the measurement invariance analysis, four variables were added as grouping criteria into the model one by one to see if any of them play a role in the scale performance. The between-subject measure, subjective knowledge, that to be added as a control variable was also added to the model at this stage. The four grouping variables included two demographic variables (i.e., gender and race), and two manipulation variables (i.e., influencer type and influencer type-perception consistency). Due to the small numbers of participants identified as non-binary ($N = 8$, 1.56%), they were combined with male participants as a non-female group for gender. Similarly, the race was also recoded into a binary variable with White and non-White, where all racial categories other than White were combined for the data analysis purpose. Female and White were treated separately because of the selection of the influencer in the study, a

White female. Therefore, people who shared the gender/racial identity with the influencer used in the experiment might respond differently with those who did not identify with her. Influencer type was the main between-subject manipulation in the experiment.

Influencer type - consumer perception consistency documented whether the participants' perceived influencer type agreed with their assigned group. In other words, if the individual was assigned into AI (social media) influencer condition, and meanwhile s/he consider the influencer they view as AI (social media) influencer, this dissertation considered their perception was consistent with manipulation. On the other hand, if they could not tell for sure or their perception was not agreed with the influencer type (i.e., experimental condition), the individual would be marked in the inconsistent group. Influencer type - consumer perception consistency was at concern of this study because it might relate to consumers' suspicious and distrust toward the persona on social media and alter how they interacted with the influencers and brands the influencer endorsed.

To examine the measurement invariance using each of the grouping variables, the author first fitted the configural model with the loading and intercept for each group and crossed four waves of measurements (i.e., four product types) within an individual freely estimated. Then, an omnibus invariance model restricting the loadings and intercepts estimations as the same across measurements and groups were fitted and compared with the configural model. The correlated residuals for items with the same wording and measuring the same latent variables were allowed to be freely estimated as in the longitudinal models in the former section. If ΔCFI is 0.01 or less, the author consider that the measurement structure was consistent. As shown in Table 5.5, measurement invariance was achieved.

Initial SEM Model and Measurement Invariance

After the homogeneity tests for the latent constructs and the multi-group measurement invariance tests, the author decided to adopt the following adaptions for the analyses to ensure accuracy and model parsimony. First, for hypotheses test, measures for the two repeated measures contained in the material products and experiential products, respectively, were combined to understand the role of product types, ensure the measurement validity, and achieve the parsimony of the SEM model. Second, gender and race were treated as binary manifest variables when entering the model and being controlled in the regression paths. Last, the items measuring three dependent variables, Aad, Abr, and PI, were parceled as just-identified (i.e., three indictors).

The indicators for each product type (material vs. experiential) were generated by averaging the same wording items for the two repeated measured products in each category. To ensure that the measurement invariance was still hold with this adaption, measurement models were fit for material and experiential product separately (χ^2_{mat} (271) = 433.219; CFI = .989; TLI = .986; RMSEA = .040, 90% CI [.033–.047]; χ^2_{exp} (271) = 396.500; CFI = .990; TLI = .988; RMSEA = .035, 90% CI [.028–.043], see Table 5.6). The separated measurement model achieved excellent model fit (Little, 2013). Then, the measurement invariance between material and experiential products was checked again following the same steps as in the previous sections. Results showed that the strong (i.e., intercept) measurement invariance was achieved for the two product types (see Table 5.6). Last, an overall measurement invariance across two influencer type groups and two repeated measured product type groups were tested. A weak measurement invariance required the equality of factor loadings toward the same latent variable across four conditions. A strong measurement invariance required the equality of intercepts (besides factor loadings) of each indicator across four conditions. Results in Table 5.6 showed that the measurement invariance passed (χ^2 (2100) = 3028.092; CFI = .972; ΔCFI = .000 TLI = .989; ΔTLI = +.001, RMSEA = .045, 90% CI [.042 – .049]).

Latent Mean Differences between AI influencer and SMI Conditions

To get an overview of the mean and correlations among variables at primary concern in two main experimental conditions ($\beta > .03$), AI and SMI, an SEM model was fitted with the effect coding method to estimate the mean and correlations among variables in each condition. Effect coding was an alternative identification method in SEM, where for the indicators of each latent variable, one loading was constrained to be a function of the other loadings (with a sum equals to the number of indicators), and one intercept was constrained to be a function of other intercepts (with a sum of zero) (see Little 2013). Using effect coding could freely estimate latent means without fixing them as zero to identify the model. The basic setting of this model was the same as the previous models (e.g., estimation method, repeated measure restrictions). Strong measurement invariance (influence type and product type) was enforced when estimating the means and covariances. Table 5.7 showed a good model fit (χ^2 (2108) = 3315.599; CFI = .963; TLI = .959; RMSEA = .052 (.048–.055); SRMR = .205).

Then, a series of nested model comparisons for the latent mean structure were conducted to provide an initial overview of the role of influencer type and product type on source credibility and advertising outcomes (i.e., Aad, Abr, PI). The model in Table 5.7 was treated as a baseline model. To achieve the mean comparison, seven new models was fitted where one of the latent variables from four conditions (2 influencer type * 2 product type) were restrict as equal at each time. Any other structures of the model remained constant. Therefore, the difference of the degree of freedom between the two models were 3. Each of the seven models was compared to the latent mean model in Table 5.7. The significance of mean differences was evaluated through the difference of chi-square estimations. In the cases where the latent mean equality restriction causes too much loss of chi-square in the latent space (i.e., $p < .05$), the latent means were considered as different across the four groups for that variable (results shown in the first section of Table 5.8). Further model comparisons with the latent mean equality restricting enforced for only one independent variable were conducted to locate the differences. Results for the post-hoc comparisons were shown in the second and third section of Table 5.8. Additionally, since subjective knowledge was a between subject variable, the mean differences were only compared for the between subject independent variable - influencer type.

As shown in Table 5.8, the participants rated differently on two of the three source credibility components, trustworthiness ($\Delta\chi^2 (3) = 11.994$, $p <.01$) and expertise ($\Delta\chi^2 (3) = 12.169$, $p < .01$), and two of the persuasion outcomes, Abr ($\Delta\chi^2 (3) = 16.945$, $p < .001$) and PI ($\Delta\chi^2 (3) = 27.514$, $p <.001$), across the four conditions. However, the differences between the AI and SMI were not significant, which means that the differences were not mainly caused by the influencer types. The participants perceived differently on the influencers' trustworthiness ($\Delta\chi^2 (2) = 12.842$, $p < .01$), expertise ($\Delta\chi^2 (2) = 13.177$, $p < .01$), Abr ($\Delta\chi^2 (2) = 17.992$, $p < .01$), and PI ($\Delta\chi^2 (2) = 27.256$, $p < .01$), when endorsing different types of the products (i.e., material vs. experiential). More specifically, for a human SMI, the participants perceive trustworthiness ($\Delta\chi^2 (1) =$

1.6970, $p > .05$) and expertise ($\Delta\chi^2(1) = 1.9982$, $p > .05$) were virtually the same for material and experiential products. While when the influencer was openly an AI, individuals perceived the influencer as less trustworthy ($\Delta\chi^2(1) = 11.704$, $p < .001$) and an expert ($\Delta\chi^2(1) = 14.342$, $p < .001$) when endorsing material products. Furthermore, the participants reported better Abr and higher PI toward the experiential brands in general. However, in the AI influencers condition, the differences between material and experiential products were larger. These results implied that the influencer type condition might be more likely to be a moderator that impacting the product type's influence on source credibility and persuasion outcomes on social media.

Test for the Main Research Model

Overall Influence from Influencer Type

The main research model was tested through an SEM model built on the strong measurement invariance enforced across the repeated measurements for material and experiential products. Chi-square statistics were estimated through maximum likelihood robust (MLR). Three manifest variables (i.e., influencer type, gender, race) were introduced into the model. The model was identified by fixing the latent mean as zero and variance as one for the measures for the material product. Influencer type was the between-subject experimental condition with two levels where (human) SMI group was coded as zero (control), and AI influencer group was coded as one. Gender (female/non-female) and race (White/non-White) are control variables with two levels in each variable for the purpose of statistical analysis. Non-female/non-White groups were coded as zero to serve as reference groups due to not sharing the identity with the influencer's image in this experiment.

Influencer Type on Source Credibility Components and Persuasion Outcomes (H1, H2, and RQ1)

The first SEM model was fitted to test H1, H2, and RQ1, which interested in the main effect from influencer types on persuasion outcomes (i.e., Aad, Abr, and PI) and source credibility components (i.e., trustworthiness, expertise, and attractiveness). Four sets of regressions specifying the relationship among the main independent variables at concern were included in the model. First, three regressions with persuasion outcomes for material products, Aad, Abr, and PI, as dependent variables, influencer type as the independent variable, involvement, subjective knowledge, gender, and race as control variables were specified in the model. Second, three regressions with the same structure were specified for the experiential products. The first two sets of regressions were to test H1. The third and fourth sets of regressions had three source credibility components: trustworthiness, expertise, and attractiveness, as dependent variables, influencer type as the independent variable, and involvement, subjective knowledge, gender, and race as control variables specified in the model—the differences between the two sets of regressions the product types. Regression sets three and four were to test H2 and RQ1.

The correlations among the six latent variables were freely estimated within product types. The correlations for the six latent variables across each product type were also allowed to be freely estimated to correct the carry-over effect within an individual. However, since product involvement was an individual disposition for each product type, the cross-sectional correlation of involvement and main dependent variables were fixed to zero. In other words, individuals' involvement toward the material products was not expected to be correlated with their Aad, Abr, PI, perceived trustworthiness, expertise, and attractiveness towards the influencers for experiential products, and vice versa.

This model reached an excellent global model fit (χ^2 (1155) = 1684.662; CFI = .982; TLI = .980; RMSEA = .034 (.030–.038); SRMR = .088). Table 5.9 shows the regression results between the independent variables (including control variables) and each of the source credibility components and persuasion outcomes, for material and experiential products, respectively. As shown in the first row of table 5.9. Influencer type did not impact on any of the persuasion outcomes in either material or experiential product condition. Therefore, H1 was not supported, and $H1_{null}$ was accepted. Influencer type did not impact consumers perceptions of the influencer's trustworthiness or expertise either, no matter for material or experiential products. Thus, H2a and H2b were not supported. Influencer type significantly impact consumers' perceived source attractiveness, but only for material product. Specifically, individuals that were assigned in the AI influencer condition perceived the influencer as less attractive, even though the influencer's image was identical. To answer RQ1, there was a difference in perceived attractiveness between AI and SMIs, but only for material products (β = -.087, p < .05).

Besides the main hypotheses and research question tests, from this model, the significant influences from two control variables, involvement and subjective knowledge were observed. Both subjective knowledge and involvement were positively related to source credibility and persuasion outcomes, as shown in the second and third rows in Table 5.9. Additionally, race played a significant role influencing consumers perceived source credibility, Aad, Abr, and PI, especially towards experiential products. Compared to the non-White consumers, White consumers demonstrate higher perceived trustworthiness (β = .115, $p < .01$), expertise (β = .106, $p < .01$), attractiveness (β = .124, $p < .01$), Aad (β = .139, $p < .01$), Abr (β = .109, $p < .01$), and PI (β = .126, $p < .01$) when the influencer endorsing an experiential brand. However, for material brands, the racial difference was only significant for Abr (β = .078, $p < .05$).

Source Credibility Components' impact on Persuasion Outcomes (H3 – 5)

A second SEM model was fitted to test the impact of perceived source trustworthiness, expertise, and attractiveness on Aad, Abr, and PI. This model was largely the same with the first model, except the correlations between the three source credibility components and persuasion outcomes were replaced by regression paths. In other words, trustworthiness, expertise, and attractiveness were added to the regressions, where Aad, Abr, and PI served as dependent variables, as independent variables besides influencer type, involvement, gender and race. The results were shown in Table 5.10. The globe model fit was satisfactory (χ^2 (1155) = 1684.662; CFI = .982; TLI = .980; RMSEA = .034 (.030 – .038); SRMR = .088).

As shown in Table 5.10, expertise was significantly related to PI in both experiential (β = .552, $p < .01$) and material (β = .479, $p < .01$) conditions. Expertise was significantly related to Aad (β = .351, $p < .01$) and Abr (β = .361, $p < .01$) only for experiential products. A series of nested model comparisons were conducted to compare the difference between the regression paths between material and experiential product conditions. Results showed that although the significance from the z-test were different for two product types, when constricting the path of expertise to Aad as the same, the change of chi-square was not significant ($\Delta\chi^2$ (1) =3.7782, p = .05). The fixed effect was significant according to the z-test (β= .229, $p < .05$). Similar result was found for the relations between expertise and Abr ($\Delta\chi^2$ (1) = 3.2977, p = .069). The fixed effect was also significant (β = .244, p < .05). Therefore, H3a, H4a, and H5a were supported.

Trustworthiness was significantly related to Aad, and Abr in both experiential (β_{ad} = .402, p < .01; β_{br} = .301, p < .05) and material (β_{ad} = .676, p < .01; β_{br} = .617, p < .05) conditions. When the consumer perceived the influencer as more trustworthy for the product endorsement, they tend to have a better attitude toward the advertisement and brand. Therefore, H3b and H4b were supported, H5b was not supported. To investigated whether trustworthiness had an equal impact on Aad and Abr, two further nested model comparisons restricting trustworthiness' effect on Aad and Abr at the same, respectively, were conducted. Results shows that when constricting the path trustworthiness->Aad as the same for material and experiential products, the change of chi-square statistics was significant ($\Delta\chi^2$ (1) = 7.0035, p < .01). Similar results were found when constricting the path trustworthiness->Abr as the same for material and experiential products ($\Delta\chi^2$ (1) = 10.74, p < .01). Combined with the estimation statistics of these paths shown in table 5.10, trustworthiness' impact on Aad and Abr were larger for material products compared to experiential products.

Attractiveness was not related to Aad in neither material (β = .028, p > .05) nor experiential (β = .003, p > .05) product conditions. Therefore, H3c was not supported. Attractiveness was positively related to Abr, but only in the experiential product condition (β =.220, p < .01). Therefore, H4c was partially supported. As for PI, attractiveness was negatively impact on consumers' purchase intentions in both material (β = -.231, p < .05) and experiential (β = -.138, p < .05) conditions. Therefore, H5c was not supported. In the nested model comparison for the regression paths for the two conditions, two regression paths were significantly different between the two product types, a) Attract->Abr ($\Delta\chi^2$ (1) = 11.774, $p < .001$), and b) Attract->PI ($\Delta\chi^2$ (1) = 5.965 $p < .05$), demonstrating that the positive effect from attractiveness on Abr was larger for material products, while the negative effect from attractiveness on PI was larger for experiential products.

Mediation test for Source Credibility (H 6 and RQ2)

To test H6, the mediation role of trustworthiness, expertise, and RQ2, the mediation role of attractiveness on persuasion outcomes, the indirect parameters of the previous model were estimated by 95% confidence intervals (CI) from 5000 bootstrapping resampling (see Preacher & Hayes, 2008). Considering the non-significant relations between influencer type and source credibility components, the mediation role of source credibility for the relations between product type and persuasion outcomes were not worth to be tested. Therefore, H6 was not supported. However, considering the significant effect of the control variables one source credibility and persuasion outcomes and to explore RQ2, the mediation effect was still examined to provide more insights. In cases that both the regression paths from independent/control variables to the mediators, and from the mediators to the dependent variables were significant, the indirect effects were tested with 5000 bootstrapping resampling (see Table 5.11). The indirect effects were considered significant when the upper and lower limit confidence interval did not cross zero (showed in bold font in Table 5.11, Preacher & Hayes, 2008). Results showed that almost all of the indirect effects (based on the significant direct effects) were significant, indicating the mediator role of source credibility components for generating persuasion outcomes in the experiment condition of this study. It was worth to mention that although the path from trustworthiness to Abr in the experiential product condition was significant according to the z-test (β=.301, $p < .05$), this path was not significant according to the bootstrapping results. Therefore, the mediator role of trustworthiness for brand attitude in the experiential product condition was not supported.

Figures 5.1.1 (material product condition) and 5.1.2 (experiential product condition) were to provide a clearer picture of the relations among the variables. In these two figures, latent variables were represented by circles and manifest variables were shown in rectangles. The significant positive relations were linked by green hard lines, and the significant negative relations were linked in orange hard lines. The path that significant in the z-test but failed the bootstrapping test was linked with a dash dot line.

Influencer Type - Perception Consistency as a Moderator – Dive into the Impact from Influencer Types

As shown above, the overall test for the impact of the main concern of this study – influencer type – did not yield much of significant results as expected. Two possible reasons may cause these results. First, it was possible that the consumers genuinely did not care whether the influencer on social media was a real human or an AI (Thomas & Fowler, 2021), especially in the context of the current study where neither the influencer nor the brands were familiar to the consumers. However, it was also possible that the consistency between the influencer type and the participants perception moderate the overall effect. As the results shown in the manipulation check, although the description of the influencer type was strong enough to be recognized by the participants, there was a considerable proportion of the participants did not have consistent perception of the influencer type with the influencers' disclosure. In other words, even though the influencer described herself in the way that a (human) SMI/AI influencer did, the participants could still perceive otherwise. This inconsistency may further impact their perceptions on the influencer's source credibility and persuasion outcome.

To further dive into the difference and understand whether the non-significant results was caused by the perception-manipulation consistency, a grouping variable was created. In the cases that the participants' perceived influencer types consistent with the experimental condition they assigned into, they were marked as consistent for this variable. In the cases that the perceived influencer types were not consistent with their experimental condition, they were marked as inconsistent.

Measurement Invariance

First, a measurement invariance was test with the new grouping variable – consistency. The steps for the measurement invariance test were similar as for the influencer type groups. Results was shown in Table 5.12. First, a two group configural invariance model was fitted with consistency as grouping variables. The configural invariance model reached an excellent model fit (χ^2 (1155) = 1684.662; CFI = .982; TLI = .980; RMSEA = .034 (.030–.038); SRMR = .088). Then, a weak invariance model was fitted with the factor loadings for the between-subject consistency groups, and within-subject repeated measures for product types restricted as equal. The weak invariance test passed due to the change of CFI is less than 0.01. Last, a strong invariance model was fitted with the indicators' intercepts restricted as equal among the four groups. The strong invariance test was also passed. Further regression models were tested based on the strong measurement invariance enforced.

The descriptive statistics including latent means and covariance was generated through effect coding method as shown in table 5.13. Latent mean comparisons were conducted through nested model comparisons (see table 5.14). First, an overall comparison with the means for the same latent variables across four groups (2 product types * 2 consistency) were restricted as equal ($\Delta df = 3$). In the cases where the means are not equal ($p < .05$), further investigates were conducted for a) invariance tests between consistency groups, and b) invariance tests between product types.

Influencer Type on Source Credibility Components and Persuasion Outcomes

A multi-group SEM model (consistency as grouping variable) with the same structure with the one testing H1, H2, and RQ1were fitted to investigate the role of influencer type on source credibility and persuasion outcomes (χ^2 (2346) = 3418.487; CFI = .968; TLI = .964; RMSEA = .046 90% CI [.042– .049]). The estimations for each regression path were shown in Table 5.15. The first section (upper) contained the estimations for the consistent group and the second section showed the estimations for the inconsistent group. After dividing the data into two groups, influencer type was significantly influencing almost every source credibility component and persuasion outcomes. Specifically, when the participants' perception/judgement for the influencer was consistent with the influencer's self-disclosure, the participants perceived significantly lower trustworthiness ($\beta_{mat} = -.234$, $p < .01$; $\beta_{exp} = -.189$, $p < .01$), expertise ($\beta_{mat} = -.277$, $p < .01$; $\beta_{exp} = -.179$, $p < .01$), attractiveness ($\beta_{mat} = -.139$, $p < .01$; $\beta_{exp} = -.134$, $p < .01$), Aad ($\beta_{mat} = -.194$, $p < .01$; $\beta_{exp} = -.165$, $p < .01$), Abr ($\beta_{mat} = -.149$, $p < .01$; $\beta_{exp} = -.148$, $p < .01$), and PI ($\beta_{mat} = -.129$, $p < .01$; $\beta_{exp} = -.106$, $p < .01$) towards

AI influencers compared to a human SMI, in both material and experiential product conditions. In contrast, when the participants' perception/judgement for the influencer was not consistent with the influencer's self-disclosure, the participants perceived significantly higher trustworthiness (β_{mat} = .154, $p < .01$; β_{exp} = .173, $p < .01$), expertise (β_{mat} = .192, $p < .01$; β_{exp} = .181, $p < .01$), Aad (β_{mat} = .175, $p < .01$; β_{exp} = .145, $p < .01$), Abr (β_{mat} = .162, $p < .01$; β_{exp} = .197, $p < .01$), and PI (β_{mat} = .135, $p < .05$; β_{exp} = .122, $p < .05$) towards AI influencers compared to a human SMI, in both material and experiential product conditions. However, the influencer type was not positively related to attractiveness (β_{mat} = -.011, $p > .05$; β_{exp} = .041, $p > .05$). These results implied that the participants demonstrate a lower source credibility and poor attitude and purchase intentions towards the influencers as long as they perceived them as an AI. However, when people could not be sure whether the nature of an influencer, an influencer that disclosed as AI was more acceptable.

Source Credibility Components' impact on Persuasion Outcomes

The relations between the source credibility components and persuasion outcomes in each group (i.e., consistent vs. inconsistent) were tests in another SEM model. The correlations between each source credibility dimension and persuasion outcome variable were replaced with a regression path. Influencer type and the control variables' impact on source credibility were controlled when examining the relationships. The results were shown in Table 5.16. The results for the consistent group could be found in the left section of Table 5.16, and for the inconsistent group could be found in the right section of table 5.16. The upper part of the table was the estimation of the regression paths between influencer type and covariances and the persuasion outcomes (Aad, Abr, and PI). These results were the same as what shown in table 5.15 and were controlled in this model. The second half of the table showed the regression estimations between the mediators (i.e., trustworthiness, expertise, and attractiveness) and persuasion outcomes.

Results showed that when participants perceived influencer type was consistent with the influencers' self-disclosure, trustworthiness played a role in persuasion outcomes only when the influencer endorsing a material product. Specifically, trustworthiness was positively influence Aad (β_{mat} = .746, p < .01) and Abr (β_{mat} = .637, p < .01), but did not have an impact on PI (β_{mat} = -.016, p > .05). Expertise was positively correlated with PI, in both material (β = .680, p < .01) and experiential (β = .540, p < .01) product conditions. Attractiveness was negatively corelated with PI in the material product condition (β = -.245, p < .01), while positively corelated with Abr (β = .261, p < .01) in the experiential product conditions.

When participants perceived influencer type was inconsistent with the influencers' self-disclosure, trustworthiness was still only correlated with Aad (β = .631, p < .01) and Abr (β = .597, p < .01) in the material product conditions. Expertise was also significantly correlated with Aad (β = .426, p < .05) and Abr (β = .467, p < .05) in the experiential product condition besides its impact on PI for both material (β = .448, p < .05) and experiential (β = .453, p < .05) products. Attractiveness was negatively correlated with PI in both material and experiential product conditions.

Next, to compare whether the regression parameters were significantly different across the four groups (2 consistency * 2 product types), a series of nested model comparisons were conducted. First, an ominous invariance test was conducted for the paths at the main concern (covariant variables were excluded for clarity) that were significant in at least one of the four groups. In the cases where a significant difference was found in the ominous test, more detailed tests was conducted along with each grouping conditions. Results were shown in Table 5.17. The regression path between influencer type and trustworthiness and expertise were significant. The differences were mainly caused by the consistency grouping rather than product type. Although influencer type was significantly related to attractiveness in the consistent group but not in the inconsistent group, the difference was not significant from the nested model comparison results. The fixed effect between IT and attractiveness was not statistically significant.

As for the relations between the source credibility components and persuasion outcomes, only the relations between trustworthiness and Abr was different across groups. This different was mainly due to the product type in the inconsistent group, where this relation was significant for material product but not for experiential product. Other relations between source credibility and persuasion outcomes were not significantly varied across groups and all significant according to the z-test: (1) trustworthiness was significantly correlated with Aad; (2) expertise was significantly correlated with Aad, Abr, and PI; while (3) attractiveness was positively correlated with Abr, but negatively correlated with PI.

Mediation test for Source Credibility

Again, the mediation role of source credibility components was tested through 95% CI from 5000 bootstrapping resampling for the SEM model in pervious section. Standardized path coefficients and unstandardized bootstrapped CI for all paths were presented in Table 5.17. Here, the mediation role of source credibility for the relationship between influencer type and persuasion outcomes were at the central of concern.

Therefore, only the paths related to influencer type were tested and presented in Table 5.18. The indirect paths were calculated separately for consistent (see in the upper section) and inconsistent (see in the lower section) groups and for material (see in the left side) and experiential (see in the right side) product conditions. The significant indicate paths were shown in bold fond in Table 5.18.

Results showed that all of the indirect effects (based on the significant direct effects) were significant, indicating the mediator role of source credibility components for generating persuasion outcomes. In the consistent group, for material products, trustworthiness negatively mediated the relations between influencer type and attitude (Aad and Abr). Expertise negatively mediated the relations between product types and behavior intentions (PI), while trustworthiness positively mediated this relation. For experiential products, expertise negatively mediating the relations between influencer type and PI, while attractiveness negatively mediating the relations between influencer type and Abr. In the inconsistent group, for material products, trustworthiness positively mediated the relations between influencer type and attitude (Aad and Abr), and expertise positively mediated the relation between influencer type and PI. For experiential products, only expert played a mediator role for the relations between influencer type and all three outcomes (i.e., Aad, Abr, and PI). Figure 5.2.1 and 5.2.2 provided an overview for the model.

Alternative Model – Influencer Type as a Moderator

From the previous analyses, this dissertation found that the use of an AI influencer did impact on participant’s perceived source credibility and persuasion outcomes. However, whether its influence was positive or negative largely depend on whether the disclosure was consistent with the participants perception. Merely acknowledge using an AI did not have much overall effects on source credibility nor persuasion outcomes. However, one can ask, does this mean that the positive and negative effects offset each other's effect at a population level so whether to use an AI influencer does not matter for brand profit?

To further investigate this question, in this part, we tested an alternative model where influencer type served as a moderator. The impact of the influencer type on the relations between source credibility components, persuasion outcomes, and covariance were tested for both material and experiential products.

The results of measurement invariance shown in Table 5.6 authorized the test for regression paths. The strong measurement invariance was enforced for further tests. A multiple-group SEM model, with influencer type as a grouping variable, was fitted ($\chi^2(2272) = 3379.274$, $p < .001$, $\chi^2_{AI} = 1654.278$, $\chi^2_{human} = 1724.997$, CFI = .967, TLI = .963, RMSEA [90%CI] = .047 [.044; .051]). In the first set of regression paths, the relation between the covariances and source credibility components were controlled. In the second set of regression paths, the relations between source credibility components and persuasion outcomes were tested with the influence from the covariances being controlled. The results were shown in Table 5.19.

The correlations between source credibility and persuasion outcomes did appear differently between the (human) SMI and AI conditions. Specifically, trustworthiness was more important when the influencer was a human, where it significantly correlated with all but one persuasion outcomes (i.e., PI in the experiential product condition). However, in the AI influencer condition, trustworthiness impacted Aad and Abr in the material product condition, while only impacted Aad in the experiential product condition. Similarly, expertise was also played a more important role when the influencer was a human rather than an AI. Expertise was significantly correlated with all but one persuasion outcomes (i.e., Abr in the material product condition) when the influencer was a human. However, expertise only impacted PI in the material product condition when the influencer was an AI. Attractiveness had a more positive impact on the persuasion outcomes when the influencer was an AI rather than a human, especially for experiential products. For human influencer, attractiveness negatively impacted PI for both material and experiential products and had no effect on attitude. However, for AI influencer, attractiveness could positively impact consumer's Aad and Abr in the experiential product condition, and its negative impact on PI disappeared. Noticeably, race only had an impact on the persuasion outcomes when an AI influencer endorsing experiential products.

To confirm the observed moderation effect of product types, the nested model comparisons were conducted for each of the regression paths (see Table 5.20). Results showed that for trustworthiness, influencer type mainly moderated its relationship with Abr. The trustworthiness of the AI influencer was positively impact participants Abr for material products, but not for experiential products. For expertise, Influencer type significantly moderated its relations with Aad and PI. Expertise had a stronger relationship with Aad for both material and experiential products, and with PI for experiential products for human influencer. For attractiveness, influencer type significantly moderated it relations for all three persuasion outcomes. Attractiveness had a stronger negative correlation with PI for AI endorsed material products. In contrast, Attractiveness had a stronger positive correlation with Aad and Abr, and less negative correlations with PI for AI endorsed experiential products.

Additionally, influencer types also moderated the correlations between covariance (i.e., subjective knowledge, race) and persuasion outcomes. Subjective knowledge had stronger positive correlations with the persuasion outcomes when the influencer was AI compared to human. Racial differences only existed for Aad and PI when an AI influencer endorsing for experiential products.

CHAPTER SIX

DISCUSSION

A. DISCUSSION

As an emerging source for brand messaging on social media, AI influencers have been shown to be as effective as human influencers in previous studies such as Thomas and Fowler (2021) (Rosengren & Campbell, 2021). However, the empirical evidence of their effectiveness is still insufficient to make a definite conclusion on their equivalence (Moustakas et al., 2020). Additionally, the mechanisms and the conditional boundaries for their effectiveness are still unclear. This dissertation aims to add to the findings on consumers' responses and advertising effectiveness when using an AI influencer compared with a human social media influencer (SMI) as a message source.

From an online experiment with 514 U.S. adult Instagram users, largely mirroring the gender and racial distribution among general Instagram users, this study found that the use of AI influencers instead of human SMIs does impact consumers' perceptions and persuasion outcomes (e.g., attitude and purchase intentions). However, the nature of this impact is more complex, depending on the consumers' beliefs about the influencer's nature (i.e., human vs. AI), which are impacted by factors that beyond marketing manipulation, as well as the product type (i.e., material vs. experiential). This study also found that the use of AI influencers potentially diminished the impact of source credibility, especially trustworthiness and expertise, on persuasion outcomes. Additionally, the impact of the consumers' racial identities on perceived source credibility and persuasion outcomes, especially in the AI influencer condition, was also highlighted in our findings.

A detailed discussion on the findings, implications, and the limitation of current study are specified below.

Human or AI? - "Who influencers say they are" vs. "What consumers think"

Does it matter to consumers whether an influencer is a human or an AI? There is no simple answer to this question. This study provides a more nuanced context and explanation for the apparent lack of difference between the persuasion effects of using AI and using human SMI found by previous AI influencer research (Thomas & Fowler, 2021). First, we replicated the finding established by Thomas & Fowler (2021) that AI influencers can produce outcomes for brands as positive as those of their human counterparts. The current study added to that finding by showing that consumers also perceive AI influencers to be as credible as human SMI. Consumers' ratings of source credibility components (i.e., trustworthiness, expertise, and attractiveness) and persuasion outcomes (i.e., Aad, Abr, PI) of both AI and human SMI were equally positive (see Table 5.7). One exception we found, though, is that consumers perceived AI influencers as less attractive than their human counterparts when endorsing a material product brand, even when they have the same appearance. This difference could be caused by consumers' higher expectations for an independently designed AI, whose appearance can be freely manipulated or altered. The expectancy disconfirmation could be more likely to be highlighted when endorsing material products, where influencers' attractiveness was more important for generating positive persuasion outcomes (see Table 5.10).

However, this general lack of difference does not mean that consumers do not care about whether the influencer they encountered is an AI or not. In the current media context, consumers are active information processers and make their own judgments on the nature of the online persona they encounter based on their previous knowledge and experiences. This concern mirrors the ongoing discussion about online deception and misinformation spread by AI through social media (Bradley, 2020). How consumers trust and react to a social media persona that claims to be an AI largely depends on their perceptions of the influencer's nature. Building upon the pilot study and manipulation checks, the author is confident that the experimental manipulation of influencer type is significant enough to raise the participants' awareness of whether the influencers were self-disclosed as AI. However, consumers will not simply internalize whatever the online figure tells them. A significant percentage of the participants still had doubts about the nature of the AI influencer—by either still considering the self-declared AI as a human or rejecting the disclosure to make an independent judgment on whether they were an AI (i.e., cannot tell for sure). Indeed, one can easily find comments that question the "robot nature" under even the most popular AI influencer, Lil Miquela (e.g., "are you really a robot?" "I don't understand how people even believe this."). Similarly, consumers question who human SMIs really are as well (e.g., is s/he really a human or just a computer program pretending to be human?).

Under the condition where consumers' perceptions of the influencer type were consistent with the influencers' self-disclosure, an AI influencer performed more poorly than a human influencer. Consumers perceived an AI as less credible, developed less favorable attitudes toward both the advertisement and the brand, and had lower purchase intentions for the advertised product (both material and experiential). This result demonstrates that consumers care about the nature of an influencer on social media. Additionally, a lower level of trust towards an AI than towards a human has already been established in the literature studying AI's applications in other areas (e.g., Longoni et al., 2019). Even though AI should have the upper hand in data access, content personalization, and computation areas (Cianciolo & Sternberg, 2008; Kumar et a., 2019 Sterne, 2017), which may lead to higher perceived levels of expertise than its human counterparts, in this context consumers still consider a human influencer as more knowledgeable than an AI. More interestingly, consumers' established knowledge schema on AI could impact their perceptions of the influencer's supposedly constant feature – attractiveness. The negative effect of using AI on consumers' perceived influencer attractiveness is more significant when we look specifically at people whose influencer type perception was consistent with the influencer's self-disclosure (compared to those whose perceptions were inconsistent). This pattern was observed in both conditions where the influencer endorsed material and experiential products. The threshold for consumers to perceive a computer-generated *artificial* influencer as attractive is higher than a human SMI.

In contrast, when consumers' beliefs about the influencer type are not consistent with the influencer's self-disclosure, the use of AI influencers increased perceived source credibility (except attractiveness) and persuasion outcomes. In other words, when consumers did not think the influencer was honestly self-disclosing, or at least could not be sure, they preferred the influencer that claimed to be an AI compared with that which did not. Consumers better accepted humans pretending to be an AI than an AI pretending to be a human, implying a deeper distrust and dislike of AI serving as SMIs. Consumers still prefer humans taking control of the work associated with being an influencer and considered the accounts that were (potentially) controlled by humans to be more credible.

Additionally, when consumers did not have a specific mindset (that is, were not using a human or an AI schema to view the influencer), influencer type no longer had an impact on the objective feature here in this study – attractiveness. This finding further supports the statement above, that consumers have a higher standard for an AI’s attractiveness than a human influencer.

Is a credible source always useful?

The results provide a detailed portrayal of how each source credibility component brings persuasion outcomes for human and AI influencers on social media. First, the current study confirms the distinct role of each component in the persuasion process (see Table 5.10). Positive roles in persuasion were found for perceived trustworthiness and expertise. Perceived trustworthiness was especially crucial in bringing favorable attitudinal outcomes, and perceived expertise may have resulted in behavioral outcomes. Perceived expertise was also found to be more important in experiential product endorsement. On the other hand, perceived attractiveness can lower consumers' purchase intentions, which countered findings in the celebrity endorsement context (Amos et al., 2008; Bergkvist & Zhou, 2016). The social media context may cause attractiveness’s negative effect on persuasion. Higher physical attractiveness could increase the consumers’ attention to, and hence invite more careful examination of, the message (Cohen & Golden, 1972; Horai et al., 1974). This could lead to poorer persuasion outcomes overall, especially in the condition where the line between human and AI influencer was blurred. Additionally, consumers may perceive the human SMIs as more authentic (Coco & Eckert, 2020), allowing them to more easily identify with the influencer or develop an affinity for them. Influencers on social media can benefit from its grass-roots nature (Lou & Kim, 2019; Russell & Rasolofoarison, 2017). Overly attractive influencers may be out of touch with regular users and induce negative feelings from consumers, such as envy (Lee et al., 2021; Lin et al., 2018; Jin et al., 2019) or feelings of inauthenticity, and directly reduce their purchase intentions.

Furthermore, source credibility components, including trustworthiness, expertise, and attractiveness, were found to mediate the impact of influencer types on persuasion outcomes at different levels, especially in the material product condition. Source credibility could be the psychological mechanism behind the poor persuasion performances of AI influencers compared with human SMIs. However, when influencer type is controlled, perceived trustworthiness does not have an impact on any persuasion outcomes in the experiential product condition. Any changes in the persuasion outcomes were directly caused by using an AI influencer (see Table 5.16), which implies that trustworthiness may not be as crucial a factor when evaluating an experiential product recommended by an influencer on social media. The product type differences will be further discussed in the next section. Additionally, when a certain level of uncertainty is involved (i.e., inconsistency), perceived source expertise is crucial in evaluating the advertising and brand, as well as in developing purchase intentions for an experiential product. This will serve to introduce the discussion in the next section – the influence of product type and its interplay with influencer type.

When putting aside consumers' beliefs about the nature of the influencer, the use of AI vs. human influencers can alter how source credibility components relate to persuasion outcomes. Trustworthiness and expertise play more significant roles in inducing positive persuasion outcomes when using a human SMI compared to an AI.

When the AI influencer performed as well as a human SMI, consumers tended to hold different rules in evaluating the product endorsement, relying less on their judgments of the source's trustworthiness and expertise in their evaluation. High levels of attractiveness, on the other hand, could be more beneficial and induce less negative behavioral intentions when using an AI influencer to endorse experiential products (see Table 5.19), possibly because of less social comparison involved when the influencer is not a human.

Who Should Be Endorsing What? – The Effect of Product Types

Product type is found to be an important piece in understanding how to use human SMIs and AI influencers effectively. Studies on SMIs have found that different types of consumption may better match with different types of influencers. For example, a product that is perceived as hedonic consumption is more suitable to be endorsed by a micro-influencer (influencers who have 10,000 to 100,000 followers, see Park et al., 2021). This study also examined how consumption type interplays with the use of a human versus an AI influencer on persuasion. Instead of looking at a more dynamic consumer perception (i.e., hedonic vs. utilitarian) on certain purchases, as Park et al. (2021), consumption type is here examined from a more objective feature of the purchase, one that is closely related to the dichotomy between goods and services: material vs. experiential purchase (Gilovich & Gallo, 2020). Material consumption is a purchase to acquire a tangible object to keep as a possession, while experiential consumption is aimed at acquiring a life experience (Van Boven & Gilovich, 2003). This product classification is more logical in the context of comparing human to AI influencers due to the intangible and artificial nature of an AI influencer. Additionally, it is more easily manipulated by the practitioners in an experimental study.

In general, we found that consumers rated influencers (both AI and human) higher in source credibility (i.e., trustworthiness and expertise) and persuasion outcomes for experiential products. Experiential purchases tend to better foster social connections (Gilovich & Gallo, 2020), which may naturally align with the main function of social media. Lin et al. (2018) also found that experiential purchases are both more likely to be shared on Facebook and more often liked than material purchases by the readers. The results for involvement also suggest that consumers report a higher level of involvement with experiential purchases compared to material purchases (see Tables 5.7; 5.8).

Furthermore, the roles of different source credibility components for evaluating material and experiential products endorsed by influencers on social media, either human or AI, were also examined. Specifically, for material products, source credibility related more closely to persuasion outcomes: trustworthiness was found more crucial in raising favorable attitudes towards material products and expertise increased purchase intentions. For experiential products, expertise is relatively more important than trustworthiness, especially when the perceived influencer type is inconsistent with the influencer's self-disclosure. Trustworthiness, under this condition, did not play a significant role in leading to persuasion outcomes. This difference may be caused by how people make decisions regarding material and experiential products.

Material products have more tangible features to be compared by indices, easing the decision-making process for the consumer. Consumers' decisions on material purchases could be held with higher confidence and considered more reliable than those on experiential purchases. Trust in the influencers' information could be enough for consumers to make their own decisions. How much of an expert an influencer is may not be as important in evaluating the features of material products. In contrast, consumers tend to choose experiential products more intuitively (Gallo et al., 2017) since more variables are involved in deciding what exactly they can get from an experience (Gilovich & Gallo, 2020). An experienced, knowledgeable (i.e., expert) influencer could better serve as a source of information that increases consumers' confidence in evaluations and reduces the uncertainty in the purchase.

In addition, the results show an interplay between the types of influencer used in endorsing material and experiential products and its effect on persuasion effectiveness. The use of different types of influencers could impact the way source credibility is related to persuasion outcomes for material and experiential products. The differences in persuasion outcomes caused by trustworthiness and expertise between material and experiential product conditions are more significant for an AI than a human. When the influencer is a human, the relationship between source credibility components and persuasion outcomes was largely consistent. However, when the influencer is an AI, consumers were more likely to apply perceived trustworthiness and expertise to generate evaluations for a material product. Attractiveness could result in a more positive attitudinal response to an experiential product, although its impact on purchase intention still tends to be negative.

Counterintuitively, AI influencers performed especially poorly in presenting trustworthiness and expertise for material products in the simple mean comparison (see Tables 5.7; 5.8). However, this difference was possibly caused by the role that control variables, especially subjective knowledge, had on source credibility perceptions across influencer type and product type conditions (see Tables 5.19; 5.20). When the covariances were controlled, the difference was negligible, which leads to our discussion of the role of subjective knowledge in forming perceptions of source credibility and generating persuasion outcomes in relation to the use of AI in marketing.

Role of Subjective Knowledge

Subjective knowledge of AI marketing is defined as a consumers' belief about the sufficiency of their understanding of the use of AI in the marketplace (Friestad & Wright, 1994; Moorman et al., 2004). Subjective knowledge was treated as an important co-variant in this dissertation due to the distinguished role of consumers' pre-existing knowledge on evaluation and judgment in persuasion episodes that widely established by theories in social influence (e.g., Maio et al., 2019; O'Keefe, 2016), consumer psychology (e.g., Friestad & Wright, 1994; Moorman et al., 2004), and industry reports on the public's attitude towards AI (Zhang & Dafoe, 2019). Our results demonstrated subjective knowledge's positive effect on increasing perceived source credibility and persuasion effectiveness in the context of influencer marketing.

With AI influencers and human SMIs' co-existence, higher subjective knowledge of AI marketing could increase consumers' perceived source credibility (i.e., perceived trustworthiness, expertise, and attractiveness), attitude, and purchase intention towards the advertised products (material and experiential). This finding aligns with the social influence theory. When consumers believe in their higher knowledge of AI marketing, they may be more confident in their evaluation of the source and the advertisement/brand, thus developing a more extreme and stronger attitude.

Additionally, mediation effects of source credibility components on the relations between subjective knowledge and persuasion outcomes were found. Consumers' attitudinal evaluations of the advertisements and brands could be transferred from their judgments on the source's trustworthiness (material and experiential products) and expertise (experiential products) using AI marketing-related knowledge. Purchase intentions could be translated from their judgment on source expertise. Although the increases in perceived attractiveness due to subjective knowledge could positively result in a higher attitude toward an experiential brand, its negative mediating role on purchase intentions should also be noted.

Furthermore, when analyzing the data of participants from two influencer type conditions separately, the results (see Tables 5.19, 5.20) highlight the importance of increasing consumers' subjective knowledge when using an AI influencer. The correlations between subject knowledge and perceived source trustworthiness, expertise, and attractiveness were all significantly stronger for consumers who encountered an AI influencer.

Although this relationship is not the primary concern or theorized in the research model, this finding could inform further research on AI influencers with a social influence perspective.

Race

Consumers' racial identities were found to be significantly related to source credibility and persuasion outcomes when an AI influencer endorsed experiential brands. One thing to be noted is that the influencer used in this current study is White to make racial identity less significant in the context of influencer marketing on Instagram.

Consumers' identifications with influencers were important for influencer marketing and led to a positive persuasion effect (Kapitan & Silvera, 2016; Schouten et al., 2020). However, this study found that non-White consumers did not particularly distrust or dislike White influencers when they were human. Nevertheless, when the White influencer was disclosed to be an AI, non-White consumers tended to perceive them as less credible and generated a less favorable attitude and lower purchase intention. Similar to physical attractiveness, an AI influencer's racial identity is not genetically determined. Rather, it is a decision made by the designer. However, when the AI influencer is chosen to be White, it can further distance non-White consumers. This racial difference was especially noticeable for experiential purchases, where consumers were more involved in the decision-making process.

B. THEORETICAL IMPLICATION AND SUGGESTIONS FOR FUTURE RESEARCH

As anthropomorphized AI sources are increasingly being used in brand communication, research on their effectiveness and impact is needed (Moustakas et al., 2020). This dissertation provides empirical observations on AI source effects in advertising (i.e., AI influencers) that contribute to the theory-building in the field of artificial intelligence advertising. Based on the well-established advertising theories on message source, associative learning, and persuasion, this dissertation reconceptualizes and reevaluates these traditional theories in the emerging technology context. The theoretical contributions of this study for (a) AI advertising, (b) influencer marketing studies, and (c) source credibility theories are discussed below.

Anthropomorphized AI in Advertising

The use of AI in advertising practices has caught the attention of academia and advertising scholars. Much of the concern has been centered on AI's function as a tool for data collection and content matching (e.g., Huh & Malthous, 2020; Watts & Adriano, 2020) or its usage in marketing segmentation (e.g., Boerman et al., 2017; Zhang & Rodgers, 2021). On these occasions, AI usually stays in the background of the advertising process. Advertising theories focused on topics such as consumers' persuasion knowledge (e.g., Ham, 2017), skepticism and privacy concerns (e.g., van Ooijen et al., 2022), and attitudes and responses towards personalization (Rhee & Chio, 2022) are deemed to be more relevant to studies on emerging technology. As technological advancement continues, using general AI (GAI) to replace humans to interact with consumers in the marketplace is likely to grow (Rodgers, 2021; Sterne, 2017). Existing examples include the voice-agent (e.g., Amazon's Alexa, see Rhee & Chio, 2022), personal stylist (e.g., Stitch Fix, see Kim et al., 2021), and message chatbot (e.g., *Yeshi*, for a non-profit organization Charity: Water, see Baek et al., 2021; Carfora et al., 2020), as well as the AI influencers (e.g., Thomas & Fowler, 2021) studied in this dissertation. This dissertation, thus, contributes to expand advertising theories on emerging technologies by understanding consumers' responses to front-staged general AI, a task which is relevant to another branch in adverting theory – message source (Thorson & Rodgers, 2019).

First, our results give us a window into how the semantic meanings of AI are built up in consumers' minds so far, enriching our understanding of consumers' attitudes towards GAI. This dissertation explicates the concept of AI in advertising by breaking down the possible associations of *artificial* and *intelligence* contained in its name for consumers. These distinctions help our understanding of consumers' perceptions of AI sources' credibility, including trustworthiness and expertise, respectively. Although the trade survey portrays a mixed attitude toward AI (Zhang & Dafoe, 2019), in the context of AI usage in influencer marketing, only negative effects from the *artificial* portion in AI were observed, without many of the positive effects from the *intelligence* portion. Here, the results show that even for AI's possible advantageous aspect, expertise, consumers do not appreciate or do not apply it to an AI influencer on social media.

The meanings of *artificial intelligence* in different advertising contexts deserve to be further investigated to understand a) whether consumers comprehend and evaluate machine intelligence on the same scale as human intelligence, and b) how people link machine intelligence to the merits of AI being an agent in the advertising and digital communication realms. For example, embedding and stressing machines' superior abilities in personalization, data access, and processing—or their feature of always standing by—might be a way to make machine intelligence stand out from its human counterpart. Such knowledge could contribute to the persuasion literature on associative learning and attitude changes.

Second, this dissertation demonstrates the distance between consumers' perceptions and the market's manipulation of an anthropomorphized AI in advertising. The results provide a possible explication for the previous findings by Thomas & Fowler (2021), where they found that AI and human influencers had identical persuasion effects. Consumers are not ignoring who the influencers are (i.e., AI or human) or accepting AI influencers just as they accept humans. Rather, consumers simply are no longer sure of who the influencers really are in the current media context. When the influencer is an AI or is suspected to be an AI, lower perceived source credibility and less favorable persuasion outcomes will follow. Anthropomorphizing non-human sources is believed to be a way to boost the persuasion effects (e.g., Beak et al., 2021; Carfora et al., 2020). However, as much as an AI looks and performs like a human, its effectiveness is still not comparable to a real human source. Additionally, consumers' perception of being deceived by an AI is more consequential than being deceived by a human. Consumers show profound bias against AI influencers, which could be triggered by their pre-existing cognitive beliefs about or schema on AI. Even when delivering identical messages with the exact same appearance, these schemas will influence their judgments. The differences in perceived attractiveness could be a good demonstration of this.

Further research should investigate what is behind consumers' inconsistent perceptions and how they decide to trust an influencers' disclosure or not. Factors beyond the covariances considered in the current study—such as consumers' tendency to trust, anthropomorphism, and consumers' previous experience interacting with an AI influencer—are just a few concepts to investigate. Additionally, a longitudinal study that allows the influencers to build up a more meaningful relationship with the consumers may be a way to close the gap between consumers' perceptions and the use of AI influences versus human SMIs, and thus provide more insights into the current findings.

Furthermore, the results of this dissertation could inform the literature on technology, literary, and AI advertising. Without sufficient regulation of the disclosure of how AI is being used in the marketplace (e.g., what they can/cannot do as an influencer), consumers can still develop their own beliefs on how much they understand the process (i.e., subjective knowledge). In this case, the consumer would examine the influencer they encountered and could consider a human SMI an AI without any self-disclosure. Misperceptions will continue to proliferate in these online spaces. The disclosure of being an AI could be more likely to trigger the use of subjective knowledge in evaluation, though. Once such a suspicion is formed, it would reduce the perceived credibility of the influencer and hurt persuasion. However, higher subjective knowledge could assist persuasion, suggesting the need for further research on the role of technology literacy in AI advertising. Qualitative studies investigating consumers' persuasion knowledge of AI usage in influencer marketing would help further elucidate the content of consumers' knowledge. Causal relationships between persuasion knowledge components, such as appropriateness beliefs and effectiveness beliefs, established through experiential design would also expand our understanding of technology literacy's impact.

Influencer Marketing with AI

This dissertation also contributes to influencer marketing research in the context of co-existing human and AI influencers by answering questions about a) who should be used as a brand influencer, b) what they should endorse, and c) how influencers work.

First, the results of this study contribute to the initial comparison between the effectiveness of using AI and humans in influencer marketing, bridging what is known and what is to be known in advertising research identified by Rosengren and Campbell (2021). Specifically, this study was built upon previous studies comparing human and AI influencers (Thomas & Fowler, 2021), adopting the product type used in the previous study (i.e., sunglasses) and expanding the comparison from celebrities to SMI. Indeed, AI influencers can be just as effective as human SMI, as Thomas and Fowler (2021) indicate, yet conditioning factors are identified to provide more nuances to this finding.

The current study identifies one moderating condition: the consistency between consumers' perceptions and influencers' self-disclosure, highlighting the importance of looking into the nuances of a situation before jumping to a conclusion. Other moderating factors should be further studied to paint a complete picture of the effectiveness of AI influencers.

Second, this study also provides insights for the research on influencer-product fitness. Through examining the effectiveness of influencer marketing—by dividing the product types into dichotomous categories, material and experiential purchases— a natural fit between influencer marketing and experiential purchase was identified. Experiential products are reportedly more important for Instagram users. Consumers' perceived source credibility, attitudes, and purchase intentions were also higher when the influencer was endorsing an experiential product. The psychological mechanism of persuasion effectiveness also differed depending on what product was endorsed by the influencer. Influencer trustworthiness was more important for material purchases than experiential purchases, while expertise was more important for an experiential purchase. The use of AI as an influencer could diminish the importance of perceived expertise for experiential purchases. Further research is recommended to examine this difference by studying the antecedents of consumers' decision-making processes on different products.

Additionally, the use of multiple products in this research has methodological implications for research on influencers and transparency. Researchers should be aware of and better communicate the protentional impact of product selection on their findings. Adding message repetitions into the experiential design could increase the validity of the findings.

Lastly, this dissertation contributes to understanding influencers' effectiveness in generating positive outcomes. Abundant studies on influencer marketing identify two possible routes for an SMI to get favorable persuasion outcomes: identification and source credibility. The current study mainly took the source credibility perspective and proved the role of different credibility components (i.e., trustworthiness, expertise, and attractiveness) in the persuasion process, thus, adding to the research on influencers as message sources. Trustworthiness is usually highlighted in recent influencer marketing research (Gräve, 2017; Lou & Yuan, 2019). However, inconsistent empirical results for attractiveness mean it is often left out by recent studies investigating social media influencers' source credibility on persuasion outcomes (e.g., Breves et al., 2019; Schouten et al., 2020). Our results suggest that two source credibility components, trustworthiness and expertise, are positively related to favorable persuasion outcomes as crucial psychological mechanisms for human influencers being more effective than an AI.

The role of source credibility components in persuasion was found to be different in the AI influencer context. Trustworthiness and expertise were related to persuasion outcomes more closely when the influencer was a human SMI (i.e., did not disclose as an AI). The third component of source credibility, attractiveness, was found to have negative effects on purchase intentions, which counters the findings in traditional advertising settings (Amos et al., 2008; Bergkvist & Zhou, 2016). The author suspects that, due to the nature of influencer marketing, an overly attractive influencer may induce envy from the audience, a proposition that deserves to be further investigated in future studies. These findings call for a re-examination of the current source credibility model and other well-established advertising models in the emerging technology context.

Although consumers' identifications with human and AI influencers is outside of the theoretical framework of the current research, interesting findings regarding racial identification highlight the potential of applying the identification process to understand the differences between human and AI influencers. As an online persona that can be freely designed, the selection of AI influencers' gender and racial features may demonstrate more intentionality and thus serve as a message cue assisting consumers in evaluating the advertisement and the brands. The author calls for research to examine the relationship between AI influencers' demographic features and persuasion effectiveness.

Non-human Message Source

This dissertation also expands the research regarding source credibility in understanding the effectiveness of non-human entities. The use of non-human advertising sources changes the way consumers process and evaluate the message being delivered (Kim & Duhachek, 2020). Consumers' anthropomorphism of non-human entities suggests that they will adopt similar rules for evaluating a human source to evaluate the anthropomorphized AI influencers. Therefore, the author adopted a three-dimensional source credibility model widely supported in the human endorser condition (Ohanian, 1990) for non-human sources.

Results from the confirmatory factor analysis suggest that the three-dimensional model is still accurate when examining a non-human message source. However, the distinctive role of these three dimensions in persuasion is further developed, as stated in the previous sections. Notably, attractiveness, although proven to be a part of source credibility, may have different functions in evaluating an AI versus a traditional human source. Furthermore, this dissertation also presents source credibility as a mediator in influencer marketing's effectiveness, suggesting consumers' judgments on source credibility are dynamic. Consumers' perceived source credibility could be impacted by their pre-dispositions or their schema of the influencer's social categories (e.g., human or machine, race), more so than what they say/do or how they present themselves on social media—even for issues that are not related to those social categories. The specific relations could be further investigated in future source credibility research.

This research also proposes and validates a shortened version of a source credibility measurement instrument which could be applied to both human and non-human (i.e., AI) sources. During the validation process detailed in the pilot study (Chapter 4), the author found that the definition and measures for source credibility may need be revisited and further systematic examination and revisions for the current influencer marketing context.

C. PRACTICAL/MANAGERIAL IMPLICATION

This research aims to help advertising practitioners better prepare for the rise of AI influencers. The results could answer practitioners' questions about whether, when, and how to use an AI influencer, including the effectiveness and risks that may follow.

First, the findings suggest that practitioners should be cautious in replacing humans and adopting AI as brand influencers, especially when consumers are unsure about how AI influencers work. Consumers' distrust and doubt on AI's qualification for being an influencer could hurt persuasion.

Human social media influencers are still a safer way to conduct influencer marketing. However, human influencers should add more “humanity” into their posts to clearly distinguish themselves from an AI. As AI influencers become more and more common, consumers may have doubts regarding the nature of an influencer. Those doubts will hurt the credibility and persuasion effectiveness of the influencer. The increase in consumers’ knowledge about AI advertising could thus not only directly bring positive effects on perceived source credibility and favorable persuasion outcomes, but also help consumers gain a more sophisticated understanding of the use of AI in marketing. Currently, consumers tend to only hold negative associations with AI.

Second, AI influencers’ trustworthiness and expertise should be stressed when using an AI as a brand influencer, considering their crucial role in bringing favorable persuasion outcomes. Additionally, increasing the consumer’s knowledge of how AI operates could actually be helpful for the marketers and the brand. Increased subjective knowledge of how marketers use AI is positively related to persuasion outcomes. Deception regarding the AI nature of an influencer, on the other hand, will hurt source credibility and message effectiveness.

However, merely increasing the realism of AI influencers to make them more humanlike may not be enough. Moustakas et al.'s (2020) interviews with practitioners found that experts consider the technological difficulty of developing a real humanlike influencer as one major challenge of using AI in marketing. However, our findings suggest that, supposing that the AI influencer could look exactly like a human, the idea of them being generated by a computer could reduce consumers perceptions of source credibility and lead to less favorable persuasion outcomes. Consumers tend to hold a higher standard for an AI influencer's attractiveness than their human counterparts, but increasing the attractiveness may not always be beneficial for the brand.

In general, selling experiential products may be a more suitable situation in which to use an influencer (AI or otherwise). Trustworthiness is more crucial for material purchases, while expertise is more crucial for experiential purchases. Marketers should be cautious of prioritizing the attractiveness of an influencer for brand endorsement since it may backfire, negatively influencing consumers' purchase intentions, even potentially producing a negative societal impact resulting from the building up of unrealistic beauty standards.

Lastly, when AI is decided to be used as an influencer, disclosing its robotic nature would be a safe way to proceed. Consumers are gaining knowledge of the existence of AI influencers in the current media context, and consumers do care about whether or not the influencer is an authentic human being. Without disclosure, the brand or influencers may be able to benefit at first, getting relatively positive feedback from the consumers who do not identify the artificial nature of the influencer. However, once consumers find out or even start to doubt its true origin, the AI influencer will backfire. On the other hand, if the AI influencer is disclosed as a machine, people may naturally distrust it compared with its human counterpart. Long-term operation and relation-building, which can increase its perceived trustworthiness and expertise, may offset the deficiency. Noticeably, even for those who doubt whether the influencer is a machine, it is more acceptable to consumers when the AI discloses its robot nature.

D. LIMITATIONS

A few limitations of this study need to be acknowledged and could be addressed in further research.

First, this dissertation compared the source credibility and effectiveness of human SMI and AI influencers using a one-shot experimental design to make a cleaner comparison. The results from this approach could, indeed, increase our understanding of consumers' responses and how they may or may not be biased against AI. However, the results potentially neglect the effect of influencer-follower relationship building. One of the most prominent benefits of influencer marketing is its ability to build long-term relationships. Source credibility, such as trustworthiness and expertise, could benefit from the long-term exposure and interaction. Further research could use long-term field experiments or existing influencers to make the comparison.

Second, consumers were exposed to multiple brands in different categories to expand the validity of the findings to various product conditions. The author selected products that would logically exist in one person's everyday life experience. However, social media influencers are usually specialists in a certain area and share content only related to a single issue. The message variance required by experiential design may reduce ecological validity (Kihlstrom, 2021) or discredit the influencer. Further research could use between-subject design to further study how product type (material vs. experiential) interplays with influencer type (AI vs. human).

Third, the influencer's identity is also a potential limitation of this study. Yang et al. (2021) found that influencer-issue congruency could increase effectiveness, where Black influencers received a more positive response and less criticism than non-Black influencers when posting content regarding Black Lives Matter. The selection of a White female young adult was aimed at reducing the salience of the influencer's social identity and keeping the comparison focused. Consumer's racial identification was found to influence the persuasion effectiveness but only for AI influencers. Further studies should increase the diversity of the influencer's gender, age, and racial identity. Such studies could better our understanding of how an AI influencer's identity impacts source credibility and persuasion effectiveness, as well as the potential risks of adopting an anthropomorphized AI agent.

Finally, this dissertation builds on findings from cognitive psychology, assuming that the generation of attitudes and purchase intentions are largely rational. However, consumers' judgments and behaviors are not always rational. Emotional and social factors could play a crucial role in the way people understand and respond to AI influencers. By taking those factors into account, we can sketch a more holistic picture of the benefits and risks of applying AI influencers for consumers, brands, and society at large.

E. CONCLUSION

AI's application in influencer marketing is expected to be equally effective as a human social media influencer as long as the AI can appear and talk just like humans do. This dissertation found that merely acknowledging an influencer as being an AI could trigger different perceptions in consumers about the same online persona, decreasing source credibility and persuasion effectiveness. Consumers do care about whether an influencer is AI and how the AI influencer is designed (e.g., attractiveness and race). They also have basic impressions about AI that are enough for them to make judgments and develop attitudes, but they do not seem to understand what AI is or what it can do to help or potentially harm them. Caution must be taken when deploying AI influencers for brand endorsement. Furthermore, as the line between AI and humans is further blurred, consumers have a harder time distinguishing AI from human influencers. The author calls for more transparency in the use of AI in advertising and persuasion, as well as better technology literacy, to empower the consumers to make more informed decisions, which could ultimately benefit the consumers, the brand, and society.

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TABLE 2.1 HYPOTHESES AND RESEARCH QUESTIONS

Hypothesis
H1. A social media influencer (vs. AI influencer) leadS to higher (a) Aad, (b) Abr, and (c) PI.
$H1_{null}$. There is no difference on consumer's (a) Aad, (b) Abr, and (c) PI towards the messages delivered by a social media and an AI influencer.
H2a. Consumers perceive an AI influencer as higher in source expertise than a social media influencer.
H2b. Consumers perceive an AI influencer as lower in source trustworthiness than a social media influencer.
RQ1. Is there a difference in perceived attractiveness between AI and social media influencers?
H3. Perceived source (a) expertise, (b) trustworthiness, and (c) physical attractiveness is positively related to attitude toward advertising messages.
H4. Perceived source (a) expertise, (b) trustworthiness, and (c) physical attractiveness is positively related to attitude toward the brand.
H5. Perceived source (a) expertise, (b) trustworthiness, and (c) physical attractiveness is positively related to purchase intention.
H6. Source credibility mediates the effect of influencer type on (a) Aad, (b) Abr, and (c) PI.
H6a. Perceived expertise negatively mediates the relation between influencer type and (a) Aad, (b) Abr, and (c) PI.
H6b. Perceived trustworthiness positively mediates the relation between influencer type and (a) Aad, (b) Abr, and (c) PI.
RQ2. Does perceived attractiveness mediate the relations between influencer type and advertising outcomes (i.e., Aad, Abr, and PI)?

Note. Aad is short for attitude toward the advertisement, Abr is short for attitude toward the brand, PI is short for purchase intention.

TABLE 5.1 RESPONDENT SOCIO-DEMOGRAPHIC AND SOCIAL MEDIA USE INFORMATION (N = 514)

Categories	Classification	Frequency	%
Gender	Female	306	59.53
	Male	200	38.91
	Non-binary	8	1.56
Race/Ethnicity	White	368	71.60
	Black or African American	103	20.04
	Asian	12	2.33
	American Indian or Alaska Native	6	1.17
	Native Hawaiian or Pacific Islander	1	0.19
	Other	24	4.67
Education	High school diploma/GED	144	28.01
	Bachelor's degree	141	27.43
	Some college/currently in college	95	18.48
	Graduate/professional degree (e.g., M.A., Ph.D., M.D.)	54	10.51
	Associate's degree	46	8.95
	Less than a high school diploma	26	5.06
	Trade school degree	8	1.56
Income	$30,000 to $69,999	165	32.10
	less than $30k	151	29.38
	$100,000 and over	94	18.29
	$70,000 to $99,999	83	16.15
	Prefer not to say	21	4.09
Instagram Usage	Several times a day	234	45.53
	About once a day	106	20.62
	A couple times a week	106	20.62
	Once a week	34	6.61
	A couple times a month	15	2.92
	Once a month	10	1.95
	Almost never	9	1.75

TABLE 5.2. DESCRIPTIVE OF THE MAIN VARIABLES

Variable	**Item**	**Mean (SD)**	**Alpha [95%CI]**	**Omega [95%CI]**
Source Credibility				
Sunglass	10	4.91 (1.45)	0.95 [0.95, 0.96]	0.96 [0.95, 0.96]
Vitamin	10	4.81 (1.48)	0.95 [0.95, 0.96]	0.96 [0.95, 0.96]
Hotel	10	4.92 (1.40)	0.95 [0.95, 0.96]	0.95 [0.94, 0.96]
Food delivery	10	5.00 (1.40)	0.95 [0.94, 0.96]	0.96 [0.95, 0.96]
Aad				
Sunglass	6	4.98 (1.55)	0.95 [0.94, 0.95]	0.95 [0.94, 0.96]
Vitamin	6	4.93 (1.66)	0.96 [0.95, 0.96]	0.96 [0.95, 0.96]
Hotel	6	5.07 (1.54)	0.95 [0.94, 0.96]	0.95 [0.94, 0.96]
Food delivery	6	5.05 (1.60)	0.96 [0.95, 0.96]	0.96 [0.95, 0.96]
Abr	6			
Sunglass	6	4.98 (1.55)	0.95 [0.95, 0.96]	0.95 [0.94, 0.96]
Vitamin	6	4.94 (1.60)	0.96 [0.96, 0.97]	0.96 [0.95, 0.97]
Hotel	6	5.12 (1.49)	0.95 [0.95, 0.96]	0.95 [0.94, 0.96]
Food delivery	6	5.15 (1.49)	0.95 [0.95, 0.96]	0.96 [0.94, 0.96]
PI	4			
Sunglass	4	4.25 (1.91)	0.95 [0.96, 0.96]	0.95 [0.94, 0.96]
Vitamin	4	4.22 (1.90)	0.95 [0.94, 0.95]	0.95 [0.94, 0.96]
Hotel	4	4.48 (1.72)	0.94 [0.93, 0.95]	0.94 [0.93, 0.95]
Food delivery	4	4.49 (1.76)	0.94 [0.93, 0.94]	0.94 [0.92, 0.95]
Product Involvement	4			
Sunglass	4	4.69 (1.88)	0.96 [0.96, 0.97]	0.96 [0.96, 0.97]
Vitamin	4	4.84 (1.86)	0.97 [0.96, 0.97]	0.97 [0.96, 0.97]
Hotel	4	5.06 (1.59)	0.95 [0.94, 0.95]	0.95 [0.93, 0.96]
Food delivery	4	4.83 (1.83)	0.95 [0.94, 0.96]	0.95 [0.94, 0.96]
Subjective Knowledge	3	4.34 (1.38)	0.84 [0.81, 0.86]	0.84 [0.81, 0.87]

TABLE 5.3. MODEL FIT STATISTICS FOR INVARIANCE TESTS OF SOURCE CREDIBILITY, ATTITUDE TOWARDS THE AD, ATTITUDE TOWARDS THE BRAND, PURCHASE INTENTION, AND INVOLVEMENT ACROSS FOUR WAVES OF MEASUREMENTS IN DIFFERENT PRODUCT TYPE CONDITIONS.

Model Tested	χ^2	*df*	*p*	RSMEA	RSMEA 90% CI	CFI	ΔCFI	TLI/NNFI	ΔTLI	Pass?
Null model	67533.127	7140	<.001	--	--;--	--	--	--	--	--
Configural invar.	9807.322	6462	<.001	.035	.034; .037	.947	--	.942	--	Yes
Weak Invar.	9905.360	6531	<.001	.035	.034; .037	.947	.000	.942	.000	Yes
Strong Invar.	9977.708	6599	<.001	.035	.034; .038	.947	.000	.943	+.001	Yes

Note. *N* = 514, Models are fitted with "Maximum Likelihood Robust" method (i.e., MLR). For the measurement model tests of invariance, a change in CFI of .01 or less is used.

TABLE 5.4. MODEL FIT STATISTICS FOR INVARIANCE TESTS OF SOURCE CREDIBILITY, ATTITUDE TOWARDS THE AD, ATTITUDE TOWARDS THE BRAND, PURCHASE INTENTION, AND INVOLVEMENT ACROSS FOUR WAVES OF MEASUREMENTS IN DIFFERENT PRODUCT TYPE CONDITIONS WITH PARCELS.

Model Tested	χ^2	*df*	*p*	$\Delta\chi^2$	Δdf	*p*	RSMEA	RSMEA 90% CI	CFI	ΔCFI	TLI/ NNFI	ΔTLI	Pass ?
Null model	50718.187	4186	<.001	--	--	--	--	--	--	--	--	--	--
Measurement Model Estimates													
Configural invar.	4972.651	3585	<.001	--	--	--	.031	.029; .033	.972	--	.967	--	Yes
Weak Invar.	5029.030	3626	<.001	--	--	--	.031	.029; .033	.972	.000	.967	.000	Yes
Strong Invar.	5083.995	3681	<.001	--	--	--	.031	.029; .033	.972	.000	.968	+.001	Yes
Test of (homogeneity of) variances and covariances													
Var/cov-omni	5238.566	3765	<.001	149.47	84	<.001	.031	.029; .033	.970	.002	.967	.001	No
Cov-inv of Mar/Exp	5214.048	3744	<.001	126.58	63	<.001	.031	.029; .033	.970	.002	.967	.001	No
Homogeneity[a]	5206.281	3738	<.001	119.19	57	<.001	.031	.029; .033	.971	.001	.968	.000	No
Homogeneity[b]	5175.722	3734	<.001	90.098	53	>.001	.031	.029; .033	.971	.001	.968	.000	Yes
Test of the latent means													
Omni	5249.175	3755	<.001	86.123	21	<.001	.031	.029; .033	.970	.001	.967	.001	No
Material	5188.162	3741	<.001	13.261	7	=.066	.031	.029; .033	.971	.000	.967	.001	Yes
Experiential	5196.280	3741	<.001	24.654	7	<.001	.031	.029; .033	.971	.000	.967	.001	No
Homogeneity[c]	5183.498	3740	<.001	7.6172	6	=.268	.031	.029; .033	.971	.000	.968	.000	Yes

Note. $N = 514$, Models are fitted with "Maximum Likelihood Robust" method (i.e., MLR). For the measurement model tests of invariance, a change in CFI of .01 or less is used. The criteria for determining too much loss in fit in the latent space is a *p*-value less tan .001 (for sample size that greater than 500, p. 168) or a change in CFI greater than .002.
Attitude towards the ads, attitude towards the brand, and purchase intention are parceled into just-identified (3 indicators) latent variables. Parcels are created according to modification indices and are unified across four product types for parsimony purpose.

Cov-inv of Mar/Exp test constrict the covariance among latent variables between two material products as equal, and between two experiential products as equal. Latent variances of four products are constricted as the same
Homogeneity[a]: freely estimated the covariance between involvement and other latent variables within two experiential products.
Homogeneity[b]: freely estimated four latent variances that offense model fit: PIH, PIF, InvoH, InvoF.
Homogeneity[c]: freely estimated one latent mean that offense model fit: InvoH.

TABLE 5.5. MEASUREMENT INVARIANCE TEST MODEL FIT STATISTICS FOR SOURCE CREDIBILITY, ATTITUDE TOWARDS THE AD, ATTITUDE TOWARDS THE BRAND, PURCHASE INTENTION, INVOLVEMENT, AND SUBJECTIVE KNOWLEDGE ACROSS FOUR WAVES OF MEASUREMENTS ACROSS GROUPS WITH PARCELS.

Model Tested	χ^2	*df*	*p*	RSMEA	RSMEA 90% CI	CFI	ΔCFI	TLI	ΔTLI	Pass?
Gender (Female/non-Female)										
Null model	66194.632	8930	<.001	--	--	--	--	--	--	--
Configural	12523.065	7652	<.001	.052	.050; .054	.921	--	.908	--	Yes
Omnibus	12951.719	7935	<.001	.052	.050; .053	.920	.001	.909	+.001	Yes
Race (White/non-White)										
Null model	67187.884	8930	<.001	--	--	--	--	--	--	--
Configural	12690.809	7652	<.001	.053	.051; .054	.920	--	.906	--	Yes
Omnibus	13075.276	7935	<.001	.052	.050; .054	.919	.001	.908	+.002	Yes
Influencer Type (Human/AI)										
Null model	65922.758	8930	<.001	--	--	--	--	--	--	--
Configural	12472.181	7652	<.001	.052	.050; .053	.921	--	.909	--	Yes
Omnibus	12842.809	7935	<.001	.051	.050; .053	.921	.000	.911	+.002	Yes
Manipulation – Perception Consistency (Consistent/Inconsistent)										
Null model	65970.271	8930	<.001	--	--	--	--	--	--	--
Configural	12220.636	7652	<.001	.050	.049; .052	.926	--	.913	--	Yes
Omnibus	12572.535	7935	<.001	.050	.050; .053	.925	.001	.916	+.003	Yes

Note. *N*=514, Configural invariance models have the four waves of measurements in different groups freely estimated. The omnibus invariance models restrict the loading and intercept estimations as the same across measurements and groups. For the measurement model tests of invariance, a change in CFI of .01 or less is used.

TABLE 5.6. MODEL FIT STATISTICS FOR THE TESTS OF MEASUREMENT MODELS WITH SOURCE CREDIBILITY, ATTITUDE, PURCHASE INTENTIONS, INVOLVEMENT, AND SUBJECTIVE KNOWLEDGE ACROSS TWO REPEATED MEASURES FOR MATERIAL AND EXPERIENTIAL PRODUCTS, AND INFLUENCER TYPE CONDITIONS.

Model Tested	χ^2	*df*	*p*	RSMEA	RSMEA 90% CI	CFI	ΔCFI	TLI/NNFI	ΔTLI	Pass?
Tests as Separate Models										
Material	433.219	271	<.001	.040	.033; .047	.989	--	.986	--	Yes
Experiential	394.500	271	<.001	.035	.028; .043	.990	--	.988	--	Yes
Measurement Invariance between Repeated Measured Product Type										
Null model	28206.383	1176	<.001	--	--	--	--	--	--	--
Configural invar.	1365.188	1000	<.001	.031	.027; .035	.987	--	.985	--	Yes
Weak Invar.	1385.044	1016	<.001	.031	.027; .035	.987	.000	.985	.000	Yes
Strong Invar.	1403.158	1032	<.001	.031	.026; .034	.987	.000	.986	+.001	Yes
Measurement Invariance between Repeated Measured Product Type and Influencer Types										
Null model	32302.968	2352	<.001	--	--	--	--	--	--	--
Configural invar.	2920.696	2000	<.001	.047	.043; .050	.972	--	.967	--	Yes
Weak Invar.	2975.423	2050	<.001	.046	.042; .050	.972	.000	.968	+.001	Yes
Strong Invar.	3028.092	2100	<.001	.045	.042; .049	.972	.000	.989	+.001	Yes

Note. *N* = 514. For the general confirmative factor analysis, a CFI that is above .95 was used as an indicator of a good model fit. For the measurement model tests of invariance, a change in CFI of .01 or less is used.

PT	IT Latent Variables	Human *Mean*	1	2	3	4	5	6	7	AI *Mean*	1	2	3	4	5	6	7
Mat	1.Trust	4.887	-	-	-	-	-	-	-	4.769	-	-	-	-	-	-	-
	2.Expert	4.784	.824	-	-	-	-	-	-	4.702	.950	-	-	-	-	-	-
	3.Attract	5.129	.580	.584	-	-	-	-	-	4.962	.798	.808	-	-	-	-	-
	4.Aad	4.962	.810	.762	.535	-	-	-	-	4.945	.990	.886	.769	-	-	-	-
	5.Abr	4.946	.750	.698	.551	.858	-	-	-	4.972	.881	.843	.734	.946	-	-	-
	6.PI	4.229	.613	.665	.329	.630	.636	-	-	4.263	.796	.809	.578	.786	.793	-	-
	7.Invo	4.724	.421	.427	.480	.472	.516	.601	-	4.802	.608	.586	.517	.586	.636	.717	-
	8.SubKnow	--	.229	.212	.098	.133	.144	.444	.270	--	.585	.542	.456	.544	.459	.621	.476
Exp	1.Trust	4.961	-	-	-	-	-	-	-	4.949	-	-	-	-	-	-	-
	2.Expert	4.864	.874	-	-	-	-	-	-	4.869	.940	-	-	-	-	-	-
	3.Attract	5.145	.687	.664	-	-	-	-	-	5.037	.783	.791	-	-	-	-	-
	4.Aad	5.063	.799	.805	.570	-	-	-	-	5.056	.819	.808	.763	-	-	-	-
	5.Abr	5.096	.803	.797	.622	.917	-	-	-	5.172	.806	.820	.801	.901	-	-	-
	6.PI	4.457	.601	.730	.430	.675	.692	-	-	4.520	.767	.765	.604	.731	.767	-	-
	7.Invo	4.878	.221	.345	.320	.329	.237	.498	-	5.028	.540	.571	.508	.512	.560	.673	-
	8.SubKnow	4.261	.228	.260	.186	.160	.182	.367	.250	4.402	.493	.514	.363	.460	.440	.640	.489

TABLE 5.7. LATENT MEAN ESTIMATIONS AMONG TWO INFLUENCER TYPES ACROSS TWO REPEATED MEASURE WAVES USING EFFECT CODING METHOD

Note. $N = 514$, strong measurement invariances across two repeated measures for material and experiential products were enforced when estimating the mean. χ^2 (2108) = 3315.599; CFI = .963; TLI = .959; RMSEA = .052 (.048–.055); SRMR = .205. χ^2 is evaluated through "maximum likelihood robust, MLR." Estimations were drawn from a completely standardized solution. All correlations were

significant by reaching $p < .001$threshold. Correlations cross sections were estimated in the model but not included in the table for clarity.
IT = Influencer Type; PT = Product Type; Mat = Material; Exp = Experiential; Trust = Trustworthiness; Expert = Expertise; Attract = Attractiveness; Aad = attitude towards advertising; Abr = attitude towards brands; PI = purchase intention; SubKnow = Subjective Knowledge; Invo = Involvement.

TABLE 5.8. TESTS OF LATENT MEAN INVARIANCE ACROSS TWO INFLUENCER TYPE GROUPS AND TWO REPEATED MEASURE OF PRODUCT TYPES.

Model Tested		χ^2	*df*	*p*	$\Delta\chi^2$	Δdf	*p*	**Decide?**
Omnibus								
Trust		3327.276	2111	<.001	11.994	3	<.01	**Diff**
Expert		3327.556	2111	<.001	12.169	3	<.01	**Diff**
Attract		3319.464	2111	<.001	3.6973	3	>.05	Same
Aad		3320.662	2111	<.001	5.0487	3	>.05	Same
Abr		3332.097	2111	<.001	16.945	3	<.001	**Diff**
PI		3347.271	2111	<.001	27.514	3	<.001	**Diff**
Invo		3326.541	2111	<.001	10.697	3	<.05	**Diff**
SubKnow		3316.941	2109	<.001	1.3545	1	>.05	Same
Latent Mean Invariances between Influencer Type								
Trust		3317.755	2110	<.001	2.0933	2	>.05	Same
Expert		3317.194	2110	<.001	1.4833	2	>.05	Same
Abr		3316.238	2110	<.001	0.5713	2	>.05	Same
PI		3315.742	2110	<.001	0.2753	2	>.05	Same
Invo		3316.513	2110	<.001	1.0475	2	>.05	Same
Latent Mean Invariances between Product Types								
Trust		3327.406	2110	<.001	12.842	2	<.01	**Diff**
	Human	3317.289	2109	<.001	1.6970	1	>.05	Same
	AI	3325.713	2109	<.001	11.704	1	<.001	**Diff**
Expert		3327.652	2110	<.001	13.177	2	<.01	**Diff**
	Human	3317.647	2109	<.001	1.9982	1	>.05	Same
	AI	3325.604	2109	<.001	14.342	1	<.001	**Diff**
Abr		3331.513	2110	<.001	17.992	2	<.001	**Diff**
	Human	3320.890	2109	<.001	5.2844	1	<.05	**Diff**
	AI	3326.226	2109	<.001	14.183	1	<.001	**Diff**
PI		3345.622	2110	<.001	27.256	2	<.001	**Diff**
	Human	3328.312	2109	<.001	8.2092	1	<.05	**Diff**
	AI	3332.915	2109	<.001	30.189	1	<.001	**Diff**
Invo		3325.096	2110	<.001	10.39	2	<.01	**Diff**
	Human	3319.673	2109	<.001	4.3239	1	<.05	**Diff**
	AI	3321.027	2109	<.001	6.1419	1	<.05	**Diff**

Note. N = 514 (N_{human}=260; N_{AI}=254). Invariance Variances and Covariances invariance Models compared with latent mean model (with effect coding) in Table 4.7. Latent mean differences are built on nested model comparison with strong measurement variance invariance model (influencer type and product type), where the loading and intercept between influencer groups and measures for two product types were restricted as equal.

The criteria for determining too much loss in fit in the latent space for latent mean invariance test are a *p*-value less than .05.
Trust = Trustworthiness; Expert = Expertise; Attract = Attractiveness; Aad = attitude towards advertising; Abr = attitude towards brands; PI = purchase intention; SubKnow = Subjective Knowledge; Invo = Involvement.

TABLE 5.9. REGRESSION RESULTS OF THE IMPACT OF INFLUENCER TYPE ON SOURCE CREDIBILITY COMPONENTS AND PERSUASION OUTCOMES

Product types	**Material**						**Experiential**					
IVs -> DVs	***Trust***	***Expert***	***Attract***	***Aad***	***Abr***	***PI***	***Trust***	***Expert***	***Attract***	***Aad***	***Abr***	***PI***
IT (AI)	-.067	-.052	**-.087***	-.030	-.012	-.021	-.029	-.027	-.065	-.026	.005	-.015
Invo	**.260****	**.292****	**.341****	**.337****	**.444****	**.441****	**.226****	**.252****	**.280****	**.226****	**.256****	**.371****
SubKnow	**.454****	**.410****	**.262****	**.363****	**.273****	**.457****	**.339****	**.426****	**.247****	**.365****	**.358****	**.479****
Gender (Female)	-.043	-.031	-.012	-.040	-.020	.005	.005	-.023	.077	-.020	-.035	.029
Race (White)	.061	.050	.070	.051	**.078***	.037	**.115****	**.106****	**.124****	**.139****	**.109****	**.126****

Note. N = 514, strong measurement invariances were enforced when estimating the regression estimations. The global model fit statistics: χ^2 (1155) = 1684.662; CFI = .982; TLI = .980; RMSEA = .034 (.030–.038); SRMR = .088. χ^2 is evaluated through "maximum likelihood robust, MLR." Estimations were drawn from a completely standardized solution.
Participants in the human condition/who are non-female/non-White were in the reference group for categorical variables, Group, Gender, and Race, respectively.
IV = Independent Variable; DV = Dependent Variable; IT = Influencer Type; Trust = Trustworthiness; Expert = Expertise; Attract = Attractiveness; Aad = attitude towards advertising; Abr = attitude towards brands; PI = purchase intention; SubKnow = Subjective Knowledge; Invo = Involvement.

TABLE 5.10. REGRESSION RESULTS OF THE IMPACT OF SOURCE CREDIBILITY ON PERSUASION OUTCOMES

Product types	**Material**			**Experiential**		
IV ->Mediators	***Trust***	***Expert***	***Attract***	***Trust***	***Expert***	***Attract***
IT (AI)	-.067	-.052	**-.087***	-.029	-.027	-.065
Invo	**.260****	**.292****	**.341****	**.226****	**.252****	**.280****
SubKnow	**.454****	**.410****	**.262****	**.399****	**.426****	**.247****
Gender (Female)	-.043	-.031	-.012	.005	-.023	.077
Race (White)	.061	.050	.070	**.115****	**.106****	**.124****
Mediators->DVs	***Aad***	***Abr***	***PI***	***Aad***	***Abr***	***PI***
IT (AI)	.028	.043	-.003	.003	.038	-.006
Trust	**.676****	**.617****	.139	**.402****	**.301***	.172
Expert	.155	.157	**.552****	**.351***	**.361***	**.479****
Attract	.059	.055	**-.231****	.117	**.220****	**-.138****
Invo	**.095***	**.219****	**.323****	.014	.035	**.250****
SubKnow	-.023	**-.085***	**.229****	.026	.030	**.241****
Gender (Female)	-.006	.012	.026	-.023	-.045	**.050***
Race (White)	-.002	.029	.017	.041	.009	**.072****

Note. N = 514, strong measurement invariances were enforced when estimating the regression estimations. The global model fit statistics: χ^2 (1155) = 1684.662; CFI = .982; TLI = .980; RMSEA = .034 (.030–.038); SRMR = .088. χ^2 is evaluated through Estimations were drawn from a completely standardized solution. Participants in the human condition/who are non-female/non-White were in the reference group for categorical variables, Group, Gender, and Race, respectively.
IV = Independent Variable; DV = Dependent Variable; IT = Influencer Type; Trust = Trustworthiness; Expert = Expertise; Attract = Attractiveness; Aad = attitude towards advertising; Abr = attitude towards brands; PI = purchase intention; SubKnow = Subjective Knowledge; Invo = Involvement.

TABLE 5.11. INDIRECT PATHS ESTIMATIONS FOR MEDIATION ANALYSIS

	5000 Bootstraps resamples 95%		
Path	B (SE)	LLCI	ULCI
Material			
Mediation tests on Aad through source credibility Components			
Invo>Trust>Aad	**.413 (0.131)**	**0.413**	**0.131***
Subknow>Trust>Aad	**.720 (0.176)**	**0.441**	**1.114***
Mediation tests on Abr through source credibility Components			
Invo>Trust>Abr	**.347 (0.118)**	**0.159**	**0.617***
Subknow>Trust>Abr	**.605 (0.109)**	**0.328**	**0.952***
Mediation tests on PI through source credibility Components			
IT>Attract>PI	**-.089 (0.046)**	**-0.192**	**-0.009***
Invo>Expert>PI	**.357 (0.118)**	**0.196**	**0.655***
Invo>Attract>PI	**-.175 (0.055)**	**-0.301**	**-0.087***
Subknow>Expert>PI	**.503 (0.149)**	**0.297**	**0.877***
Subknow>Attract>PI	**-.134 (0.046)**	**-0.240**	**-0.056***
Experiential			
Mediation tests on Aad through source credibility Components			
Invo>Trust>Aad	**.229 (0.108)**	**0.024**	**0.447***
Invo>Expert>Aad	**.222 (0.114)**	**0.064**	**0.516***
Subknow>Trust>Aad	**.375 (0.155)**	**0.037**	**0.662***
Subknow>Expert>Aad	**.349 (0.167)**	**0.111**	**0.769***
Race>Trust>Aad	**.240 (0.127)**	**0.020**	**0.516***
Race>Expert>Aad	**.193 (0.125)**	**0.032**	**0.519***
Mediation tests on Abr through source credibility Components			
Invo>Trust>Abr	.163 (0.090)	-0.028	0.327
Invo>Expert>Abr	**.205 (0.108)**	**0.057**	**0.476***
Invo>Attract>Abr	**.139 (0.051)**	**0.052**	**0.250***
Subknow>Trust>Abr	.252 (0.135)	-0.048	0.489
Subknow>Expert>Abr	**.322 (0.156)**	**0.094**	**0.709***
Subknow>Attract>Abr	**.114 (0.045)**	**0.040**	**0.214***
Race>Trust>Abr	.161 (0.107)	-0.030	0.386
Race>Expert>Abr	**.178 (0.166)**	**0.027**	**0.475***
Race>Attract>Abbr	**.127 (0.060)**	**0.030**	**0.265***
Mediation tests on PI through source credibility Components			
Invo>Expert>PI	**.261 (0.115)**	**0.098**	**0.555***
Invo>Attract>PI	**-.084 (0.040)**	**-0.176**	**-0.021***
Subknow>Expert>PI	**.410 (0.158)**	**0.170**	**0.787***
Subknow>Attract>PI	**-.069 (0.030)**	**-0.134**	**-0.019***
Race>Expert>PI	**.227 (0.123)**	**0.053**	**0.523***
Race>Attract>PI	**-.077 (0.039)**	**-0.167**	**-0.016***

Notes:
CI = confidence interval(s); LLCI = lower limit confidence interval; ULCI = upper limit confidence interval; IT = Influencer Type; Trust = Trustworthiness; Expert = Expertise;

Attract = Attractiveness; Aad = attitude towards advertising; Abr = attitude towards brands; PI = purchase intention.
All estimates were generated from 5000 bootstrapped resamples. Unstandardized coefficients, standard errors, and 95% confidence intervals (CIs) are presented. Only possible indirect path indicated in the Table 5.10 model was presented in the table.
*CI does not contain zero. Significant paths are bolded.

TABLE 5.12. MODEL FIT STATISTICS FOR THE TESTS OF INVARIANCE IN SOURCE CREDIBILITY, ATTITUDE, PURCHASE INTENTIONS, INVOLVEMENT, AND SUBJECTIVE KNOWLEDGE ACROSS TWO REPEATED MEASURES FOR MATERIAL AND EXPERIENTIAL PRODUCTS AND TWO CONDITION OF MANIPULATION (CONSISTENT VS. INCONSISTENT).

Model Tested	χ^2	*df*	*p*	RSMEA	RSMEA 90% CI	CFI	ΔCFI	TLI/NNFI	ΔTLI	Pass?
Null model	32349.699	2352	<.001	--	--	--	--	--	--	--
Configural invar.	2817.469	2000	<.001	.044	.040; .048	.975	--	.971	--	Yes
Weak Invar.	2874.588	2050	<.001	.043	.040; .047	.975	.000	.971	.000	Yes
Strong Invar.	2923.693	2100	<.001	.043	.039; .046	.975	.000	.972	+.001	Yes

Note. N = 514. For the measurement model tests of invariance, a change in CFI of .01 or less is used. χ^2 is evaluated through "maximum likelihood robust, MLR."

TABLE 5.13. LATENT MEAN ESTIMATIONS AMONG TWO CONSISTENCY GROUPS ACROSS TWO REPEATED MEASURE WAVES USING EFFECT CODING METHOD

PT	**Consistency**	**Consistent (N = 290)**								**Inconsistent (N = 224)**							
	Latent Variables	***Mean***	**1**	**2**	**3**	**4**	**5**	**6**	**7**	***Mean***	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Mat	1.Trust	4.862	-	-	-	-	-	-	-	4.768	-	-	-	-	-	-	-
	2.Expert	4.734	.898	-	-	-	-	-	-	4.752	.912	-	-	-	-	-	-
	3.Attract	4.984	.657	.632	-	-	-	-	-	5.129	.754	.777	-	-	-	-	-
	4.Aad	4.992	.804	.736	.594	-	-	-	-	4.904	.909	.875	.728	-	-	-	-
	5.Abr	4.997	.732	.678	.552	.872	-	-	-	4.904	.889	.857	.733	.941	-	-	-
	6.PI	4.283	.596	.665	.331	.573	.581	-	-	4.190	.811	.813	.594	.835	.840	-	-
	7.Invo	4.810	.389	.380	.357	.393	.463	.587	-	4.700	.643	.632	.585	.665	.690	.730	-
	8.SubKnow	--	.310	.295	.253	.215	.131	.448	.298	--	.485	.433	.277	.433	.401	.579	.420
Exp	1.Trust	5.001	-	-	-	-	-	-	-	4.895	-	-	-	-	-	-	-
	2.Expert	4.859	.909	-	-	-	-	-	-	4.872	.911	-	-	-	-	-	-
	3.Attract	5.117	.686	.676	-	-	-	-	-	5.060	.756	.759	-	-	-	-	-
	4.Aad	5.141	.768	.760	.634	-	-	-	-	4.960	.827	.835	.689	-	-	-	-
	5.Abr	5.195	.744	.734	.669	.901	-	-	-	5.050	.832	.858	.727	.905	-	-	-
	6.PI	4.539	.577	.654	.450	.600	.667	-	-	4.421	.784	.802	.560	.787	.804	-	-
	7.Invo	4.957	.235	.235	.310	.267	.306	.586	-	4.935	.529	.579	.486	.500	.525	.625	-
	8.SubKnow	4.413	.218	.280	.202	.150	.142	.437	.313	4.200	.458	.447	.270	.422	.445	.557	.404

Note. N = 514, strong measurement invariances across two repeated measures for material and experiential products were enforced when estimating the mean. χ^2 (2108) = 3237.716; CFI = .966; TLI = .962; RMSEA = .050 (.047–.053). χ^2 is evaluated through "maximum likelihood robust, MLR." Estimations were drawn from a completely standardized solution. All correlations were significant by reaching p < .001threshold. Correlations cross sections were estimated in the model but not included in the table for clarity.

IT = Influencer Type; PT = Product Type; Mat = Material; Exp = Experiential; Trust = Trustworthiness; Expert = Expertise; Attract = Attractiveness; Aad = attitude towards advertising; Abr = attitude towards brands; PI = purchase intention; SubKnow = Subjective Knowledge; Invo = Involvement.

TABLE 5.14 TESTS OF LATENT MEAN INVARIANCE ACROSS TWO CONSISTENCY GROUPS AND TWO REPEATED MEASURE OF PRODUCT TYPES

Model Tested		χ^2	*df*	*p*	$\Delta\chi^2$	Δ*df*	*p*	Decide?
Omnibus								
Trust		3247.891	2111	<.001	10.204	3	<.05	**Diff**
Expert		3248.453	2111	<.001	10.437	3	<.05	**Diff**
Attract		3246.557	2111	<.001	9.2817	3	<.05	**Diff**
Aad		3246.162	2111	<.001	8.5028	3	<.05	**Diff**
Abr		3254.044	2111	<.001	16.642	3	<.001	**Diff**
PI		3269.703	2111	<.001	27.589	3	<.001	**Diff**
Invo		3247.299	2111	<.001	9.7006	3	<.05	**Diff**
SubKnow		3240.312	2109	<.001	2.6575	1	>.05	Same
Latent Mean Invariances between Consistency Groups								
Trust		3238.584	2110	<.001	0.7232	2	>.05	Same
Expert		3237.776	2110	<.001	0.0211	2	>.05	Same
Attract		3244.509	2110	<.001	7.0263	2	<.05	**Diff**
	Mat	3239.252	2109	<.001	1.5356	1	>.05	Same
	Exp	3238.066	2109	<.001	0.2677	1	>.05	Same
Aad		3240.201	2110	<.001	2.4255	2	>.05	Same
Abr		3239.475	2110	<.001	1.6334	2	>.05	Same
PI		3238.514	2110	<.001	0.7775	2	>.05	Same
Invo		3238.616	2110	<.001	0.8354	2	>.05	Same
Latent Mean Invariances between Product Types								
Trust		3247.751	2110	<.001	10.378	2	<.01	**Diff**
	Consis	3244.782	2109	<.001	7.9599	1	<.01	**Diff**
	Inconsis	3240.670	2109	<.001	2.8917	1	>.05	Same
Expert		3248.634	2110	<.001	11.035	2	<.01	**Diff**
	Consis	3245.147	2109	<.001	8.6503	1	>.05	**Diff**
	Inconsis	3241.198	2109	<.001	3.2400	1	>.05	Same
Attract		3246.467	2110	<.001	9.9702	2	<.01	**Diff**
	Consis	3244.952	2109	<.001	8.4795	1	<.01	**Diff**
	Inconsis	3239.223	2109	<.001	1.5003	1	>.05	Same
Aad		3245.230	2110	<.001	7.6761	2	<.05	**Diff**
	Consis	3244.545	2109	<.001	6.6736	1	<.01	**Diff**
	Inconsis	3238.401	2109	<.001	0.5898	1	>.05	Same
Abr		3253.543	2110	<.001	16.656	2	<.001	**Diff**
	Consis	3249.072	2109	<.001	11.877	1	<.001	**Diff**
	Inconsis	3242.186	2109	<.001	4.6962	1	<.05	**Diff**
PI		3270.082	2110	<.001	28.277	2	<.001	**Diff**
	Consis	3260.278	2109	<.001	20.520	1	<.001	**Diff**

	Inconsis	3247.522	2109	<.001	8.3315	1	<.01	**Diff**
Invo		3247.566	2110	<.001	10.818	2	<.01	**Diff**
	Consis	3241.448	2109	<.001	3.7670	1	>.05	Same
	Inconsis	3243.837	2109	<.001	7.5278	1	<.01	**Diff**

Note. N = 514 (N_{consis}=290; N_{Inconsis}=224). Invariance Variances and Covariances invariance Models compared with latent mean model (with effect coding) in Table 4.7. Latent mean differences are built on nested model comparison with strong measurement variance invariance model (influencer type and product type), where the loading and intercept between influencer groups and measures for two product types were restricted as equal. The criteria for determining too much loss in fit in the latent space for latent mean invariance test are a p-value less than .05.

Trust = Trustworthiness; Expert = Expertise; Attract = Attractiveness; Aad = attitude towards advertising; Abr = attitude towards brands; PI = purchase intention; SubKnow = Subjective Knowledge; Invo = Involvement.

TABLE 5.15. MULTIGROUP (CONSISTENT/INCONSISTENT) REGRESSION RESULTS OF THE IMPACT OF INFLUENCER TYPE ON SOURCE CREDIBILITY COMPONENTS AND PERSUASION OUTCOMES.

Product types	**Material**						**Experiential**					
IVs -> DVs	***Trust***	***Expert***	***Attract***	***Aad***	***Abr***	***PI***	***Trust***	***Expert***	***Attract***	***Aad***	***Abr***	***PI***
Group 1	**Consistent (N = 290)**											
IT (AI)	**-.234****	**-.277****	**-.139****	**-.194****	**-.149****	**-.129****	**-.189****	**-.179****	**-.134***	**-.165****	**-.148****	**-.106****
Invo	**.190***	**.195***	**.235****	**.250***	**.406****	**.427****	**.171***	**.195***	**.263****	**.214***	**.263****	**.470****
SubKnow	**.484****	**.470****	**.367****	**.402****	**.285****	**.468****	**.394****	**.451****	**.270****	**.332****	**.305****	**.462****
Gender (Female)	-.065	-.043	-.033	-.069	-.036	-.021	-.005	-.007	.085	-.027	-.030	.052
Race (White)	.069	.066	.070	.058	.088	.040	**.160****	**.130***	**.145***	**.173****	**.141***	**.133****
Group 2	**Inconsistent (N = 224)**											
IT (AI)	**.154***	**.192****	-.011	**.175****	**.162****	**.135***	**.173****	**.181****	.041	**.145***	**.197****	**.122***
Invo	**.337****	**.409****	**.470****	**.431****	**.493****	**.458****	**.291****	**.322****	**.311****	**.255****	**.269****	**.334****
SubKnow	**.373****	**.273****	.126	**.271****	**.214***	**.415****	**.349****	**.339****	**.172***	**.339****	**.349****	**.461****
Gender (Female)	-.055	-.069	-.005	-.048	-.034	.007	-.018	-.089	.047	.038	-.075	-.016
Race (White)	.084	.060	.086	.065	.084	.046	.088	.105	.104	**.116***	.093	**.137****

Note. N = 514, strong measurement invariances were enforced when estimating the regression estimations. The global model fit statistics: χ^2 (2346) = 3418.487; CFI = .968; TLI = .964; RMSEA = .046 (.042–.049); SRMR = .106. χ^2 is evaluated through "maximum likelihood robust, MLR." Estimations were drawn from a completely standardized solution.
Participants in the human condition/who are non-female/non-White were in the reference group for categorical variables, Group, Gender, and Race, respectively.
IV = Independent Variable; DV = Dependent Variable; IT = Influencer Type; Trust = Trustworthiness; Expert = Expertise; Attract = Attractiveness; Aad = attitude towards advertising; Abr = attitude towards brands; PI = purchase intention; SubKnow = Subjective Knowledge; Invo = Involvement.

TABLE 5.16. MULTIGROUP (CONSISTENT/INCONSISTENT) SEM REGRESSION RESULTS OF THE IMPACT OF SOURCE CREDIBILITY ON PERSUASION OUTCOMES

	Consistent (N = 290)						Inconsistent (N = 224)					
Product types	**Material**			**Experiential**			**Material**			**Experiential**		
IV ->Mediators	***Trust***	***Expert***	***Attract***	***Trust***	***Expert***	***Attract***	***Trust***	***Expert***	***Attract***	***Trust***	***Expert***	***Attract***
IT (AI)	**-.234****	**-.277****	**-.139****	**-.189****	**-.179****	**-.134***	**.154***	**.192****	-.011	**.173****	**.181****	.041
Involvement	**.190***	**.195***	**.235****	**.171***	**.195***	**.263****	**.337****	**.409****	**.470****	**.291****	**.322****	**.311****
SubKnow	**.484****	**.470****	**.367****	**.394****	**.451****	**.270****	**.373****	**.273****	.126	**.349****	**.339****	**.172***
Gender (F/NF)	-.065	-.043	-.033	-.005	-.007	.085	-.055	-.069	-.005	-.018	-.089	.047
Race (W/NW)	.069	.066	.070	**.160****	**.130***	**.145***	.084	.060	.086	.088	.105	.104
Mediators->DVs	***Aad***	***Abr***	***PI***	***Aad***	***Abr***	***PI***	***Aad***	***Abr***	***PI***	***Aad***	***Abr***	***PI***
IT (AI)	.008	.038	-.014	-.008	.004	-.016	.038	.036	.007	.006	.066	-.005
Trustworthiness	**.746****	**.637****	-.016	.392	.365	.042	**.631****	**.597****	.258	.336	.208	.295
Expertise	.068	.128	**.680****	.342	.267	**.540****	.209	.178	**.448***	**.426***	**.467***	**.453***
Attractiveness	.080	.062	**-.254****	.163	**.261****	-.110	.033	.060	**-.186***	.082	**.179***	**-.170***
Involvement	.077	**.245****	**.357****	.037	.080	**.323****	.118	**.191****	**.275****	-.006	.002	**.155***
SubKnow	-.020	-.107	**.249****	-.021	-.029	**.232****	-.025	-.065	**.219****	.063	.087	**.233****
Gender (F/NF)	-.015	.031	-.001	-.036	-.049	.066*	.002	.012*	.051	.002	-.039	.038
Race (W/NW)	-.004	.032	-.016	.043	.010	**.071***	-.003	.018*	.013	.034	.007	**.081***

Note. N=514. Regressions were tested with the strong measurement invariances across influencer types and product types enforced. $^{*}p$ < .05; $^{**}p$ < .01. Model fit: $\chi^2(2346)$ = 3418.487, p<.001, χ^2_{consis} = 1866.359, $\chi^2_{inconsis}$ = 1552.128, CFI = .968, TLI = .964, RMSEA [90%CI] = .046 [.042; .049].
IT = Influencer Type; Trust = Trustworthiness; Expert = Expertise; Attract = Attractiveness; Aad = attitude towards advertising; Abr = attitude towards brands; PI = purchase intention; SubKnow = Subjective Knowledge

TABLE 5.17. TESTS OF REGRESSION INVARIANCE ACROSS TWO CONSISTENCY CONDITIONS AND TWO REPEATED MEASURED PRODUCT TYPE CONDITIONS.

Model Tested		***Fixed B***	χ^2 ***Robust***	***df***	***p***	$\Delta\chi^2$	Δdf	***p***	**Decide?**
Omnibus (coefficients were restricted as the same for two influencer types across two conditions)									
AI->Trust		-0.148	3444.355	2349	<.001	32.737	3	<.001	**Diff**
AI->Expert		-.085	3447.157	2349	<.001	38.088	3	<.001	**Diff**
AI->Attract		-.170	3423.235	2349	<.001	4.8157	3	>.05	Same
Trust->Aad		.944**	3424.774	2349	<.001	5.9924	3	>.05	Same
Trust->Abr		.733**	3428.378	2349	<.001	9.3155	3	<.05	**Diff**
Expert->Aad		.425*	3422.910	2349	<.001	4.4127	3	>.05	Same
Expert ->Abr		.418*	3422.575	2349	<.001	4.1572	3	>.05	Same
Expert ->AttPI		.911**	3419.787	2349	<.001	1.8005	3	>.05	Same
Attract ->Abr		.244**	3425.751	2349	<.001	6.5854	3	>.05	Same
Attract ->AttPI		-.350**	3424.266	2349	<.001	5.8176	3	>.05	Same
Regression Invariance between consistent/inconsistent									
AI->Trust			3442.343	2348	<.001	31.649	2	<.001	**Diff**
	Mat	-.195	3441.453	2347	<.001	42.34	1	<.001	**Diff**
	Exp	-.098	3435.723	2347	<.001	18.945	1	<.001	**Diff**
AI->Expert			3445.455	2348	<.001	35.756	2	<.001	**Diff**
	Mat	-.137	3444.987	2347	<.001	43.364	1	<.001	**Diff**
	Exp	-.081	3436.831	2347	<.001	23.229	1	<.001	**Diff**
Trust->Abr			3417.005	2348	<.001	0.36591	2	>.05	Same
Regression Invariance between Product Types									
AI->Trust			3421.107	2348	<.001	2.5605	2	>.05	Same
AI->Expert			3423.124	2348	<.001	5.0263	2	>.05	Same
Trust->Abr			3429.937	2348	<.001	17.524	2	<.001	**Diff**
	Consis	.793**	3419.811	2347	<.001	1.3563	1	>.05	Same
	Incons	.701*	3428.613	2347	<.001	9.9	1	<.05	**Diff**

Note. N = 514, χ^2 is evaluated through "maximum likelihood robust, MLR" Regression invariances result from nested model comparison with SEM model in table 5.14. The criteria for determining too much loss in fit in the latent space for latent mean invariance test are a *p*-value less than .05.

TABLE 5.18. INDIRECT PATHS ESTIMATIONS FOR CONSISTENT AND INCONSISTENT GROUPS

	5000 Bootstraps resamples 95%					
	Material			Experiential		
Path	B (SE)	LLCI	ULCI	B (SE)	LLCI	ULCI
Consistent Group (*N* = 290)						
Influencer type on attitude toward advertising through source credibility						
IT>Trust>Aad	**-.081 (2.437)**	**-2.198**	**-0.374***	-.328 (0.437)	-0.822	0.274
IT>Expert>Aad	-.071 (2.354)	-0.361	1.125	-.271 (0.458)	-1.083	0.042
IT>Attract>Aad	-.051 (0.076)	-0.197	0.049	-.096 (0.088)	-0.289	0.018
Influencer type on attitude toward brand through source credibility						
IT>Trust>Abr	**-.627 (0.402)**	**-1.507**	**-0.174***	-.280 (0.344)	-0.774	0.344
IT>Expert>Abr	-.122 (0.372)	-0.546	0.645	-.194 (0.361)	-0.954	0.190
IT>Attract>Abr	-.036 (0.055)	-0.164	0.063	**-.142 (0.089)**	**-0.36**	**-0.013***
Influencer type on purchase intentions through source credibility						
IT>Trust>PI	.017 (1.736)	-0.265	1.215	-.033 (0.432)	-0.277	0.522
IT>Expert>PI	**-.715 (1.979)**	**-2.143**	**-0.362***	**-.394 (0.565)**	**-1.094**	**-0.108***
IT>Attract>PI	**.164 (0.088)**	**0.038**	**0.364***	.060 (0.059)	-0.027	0.186
Inconsistent Group (*N* = 224)						
Influencer type on attitude toward advertising through source credibility						
IT>Trust>Aad	**.433 (0.261)**	**0.064**	**0.928***	.266 (0.233)	-0.177	0.696
IT>Expert>Aad	.179 (0.081)	-0.108	0.592	**.352 (0.281)**	**0.063**	**1.074***
IT>Attract>Aad	-.002 (0.031)	-0.064	0.07	.015 (0.047)	-0.061	0.135
Influencer type on attitude toward brand through source credibility						
IT>Trust>Abr	**.387 (0.204)**	**0.049**	**0.844***	.146 (0.165)	-0.229	0.419
IT>Expert>Abr	.144 (0.196)	-0.164	0.506	**.342 (0.233)**	**0.087**	**0.936***
IT>Attract>Abr	-.003 (0.034)	-0.071	0.076	.030 (0.063)	-0.075	0.184
Influencer type on purchase intentions through source credibility						
IT>Trust>PI	.174 (0.015)	-0.156	0.42	.210 (0.198)	-0.229	0.562
IT>Expert>PI	**.377 (0.231)**	**0.122**	**0.925***	**.337 (0.245)**	**0.04**	**0.947***
IT>Attract>PI	.009 (0.067)	-0.119	0.143	-.028 (0.063)	-0.175	0.081

Notes:
CI = confidence interval(s); LLCI = lower limit confidence interval; ULCI = upper limit confidence interval; IT = Influencer Type; Trust = Trustworthiness; Expert = Expertise; Attract = Attractiveness; Aad = attitude towards advertising; Abr = attitude towards brands; PI = purchase intention.
All estimates were generated from 5000 bootstrapped resamples. Unstandardized coefficients, standard errors, and 95% confidence intervals (CIs) are presented. Every possible indirect path indicated in the research model was included in the statistical model, but only significant paths were presented in the Table.
*CI does not contain zero.

TABLE 5.19. MULTIGROUP (AI/HUMAN) SEM REGRESSION RESULTS COMPARISON

	Human						**AI**					
Product types	**Material**			**Experiential**			**Material**			**Experiential**		
Cov->Mediators	***Trust***	***Expert***	***Attract***	***Trust***	***Expert***	***Attract***	***Trust***	***Expert***	***Attract***	***Trust***	***Expert***	***Attract***
Involvement	**.362****	**.432****	**.499****	**.234***	**.312****	**.299****	**.182****	**.184****	**.209****	**.250****	**.214****	**.293****
SubKnow	**.336***	**.280***	.099	**.350****	**.353****	**.207***	**.575****	**.542****	**.425****	**.440****	**.500****	**.279****
Gender (F/NF)	-.016	.020	.026	.046	.038	**.152***	-.062	-.079	-.041	-.026	-.083	.017
Race (W/NW)	.052	-.011	.049	.071	.032	.094	.086	**.117***	.106	**.168****	**.181****	**.158****
Mediators->DVs	***Aad***	***Abr***	***PI***	***Aad***	***Abr***	***PI***	***Aad***	***Abr***	***PI***	***Aad***	***Abr***	***PI***
Trustworthiness	**.609****	**.530****	**.186***	**.454***	**.449***	.038	**.815****	**.802****	.055	**.416***	.163	.362
Expertise	**.262***	.209	**.454****	**.462****	**.373***	**.667****	-.064	.000	**.685***	.076	.275	.141
Attractiveness	.012	.053	**-.177****	-.001	.096	**-.145***	.122	.065	**-.286****	**.289****	**.376****	-.066
Involvement	**.142***	**.256****	**.340****	.026	.021	**.271****	.036	**.175****	**.297****	.010	.075	**.209****
SubKnow	-.072	-.075	**.234****	-.033	-.014	**.189****	.050	-.100	**.234****	**.137***	.067	**.346****
Gender (F/NF)	.009	.014	.010	-.039	**-.084***	.000	-.037	.002	.040	-.025	-.010	**.071***
Race (W/NW)	-.017	.024	.011	-.031	-.041	.037	.028	.036	.016	**.136****	**.081***	**.134****

Note. N=514. Regressions were tested with the strong measurement invariances across influencer types and product types enforced. $^{*}p < .05$; $^{**}p < .01$. Model fit $\chi^2(2272)$ =3379.274, p<.001, χ^2_{AI} = 1654.278, χ^2_{human} = 1724.997, CFI = .967, TLI = .963, RMSEA [90%CI] = .047 [.044; .051].

TABLE 5.20. TESTS OF REGRESSION INVARIANCE ACROSS TWO INFLUENCER TYPE GROUPS AND TWO REPEATED MEASURED PRODUCT TYPE CONDITIONS.

Model Tested	***Fixed B***	**χ^2 *Robust***	***df***	***p***	**$\Delta\chi^2$**	**Δdf**	***p***	**Decide?**
Omnibus (coefficients were restricted as the same for two influencer types across two conditions)								
Cov->Mediators								
Invo->Trust	**.356****	3382.276	2275	<.001	3.165	3	>.05	Same
Invo->Expert	**.368****	3385.646	2275	<.001	6.8681	3	>.05	Same
Invo->Attract	.438**	3388.699	2275	<.001	8.3448	3	<.05	**Diff**
SubKnow-> Trust	.581**	3397.112	2275	<.001	17.452	3	<.001	**Diff**
SubKnow ->Expert	.543**	3392.752	2275	<.001	13.322	3	<.01	**Diff**
SubKnow ->Attract	.305**	3396.757	2275	<.001	19.365	3	<.001	**Diff**
Gender ->Attract	.095	3389.087	2275	<.001	11.701	3	<.01	**Diff**
Race->Trust	**.278****	3384.902	2275	<.001	5.7008	3	>.05	Same
Race ->Expert	.245*	3387.129	2275	<.001	8.3984	3	<.05	**Diff**
Race ->Attract	**.282****	3382.539	2275	<.001	3.1484	3	>.05	Same
Mediators->DVs								
Trust->Aad	**1.060****	3384.042	2275	<.001	4.743	3	>.05	Same
Trust->Abr	.812**	3391.028	2275	<.001	11.798	3	<.01	**Diff**
Trust->AttPI	.270	3382.255	2275	<.001	3.4229	3	>.05	Same
Expert->Aad	.393	3389.707	2275	<.001	13.132	3	<.01	**Diff**
Expert ->Abr	**.388***	3383.177	2275	<.001	3.9976	3	>.05	Same
Expert ->AttPI	.869**	3391.426	2275	<.001	10.99	3	<.05	**Diff**
Attract->Aad	.165	3390.230	2275	<.001	11.717	3	<.01	**Diff**
Attract ->Abr	.222**	3397.200	2275	<.001	26.299	3	<.001	**Diff**
Attract ->AttPI	-.289**	3391.488	2275	<.001	21.109	3	<.001	**Diff**
Invo->Aad	.137	3382.575	2275	<.001	3.5613	3	>.05	Same
Invo ->Abr	.296**	3393.852	2275	<.001	12.637	3	<.01	**Diff**
Invo ->AttPI	**.646****	3383.979	2275	<.001	4.6526	3	>.05	Same
SubKnow->Aad	-.010	3387.353	2275	<.001	8.5178	3	<.05	**Diff**

SubKnow ->Abr	-.055	3388.102	2275	<.001	9.7773	3	<.05	**Diff**
SubKnow ->AttPI	**.547****	3386.187	2275	<.001	7.2538	3	>.05	Same
Gender ->Abr	-.094	3386.501	2275	<.001	8.7936	3	<.05	**Diff**
Gender ->AttPI	.128	3381.446	2275	<.001	1.9109	3	>.05	Same
Race->Aad	.112	3392.562	2275	<.001	20.225	3	<.001	**Diff**
Race ->Abr	.103	3386.099	2275	<.001	7.4779	3	>.05	Same
Race ->AttPI	.231*	3392.208	2275	<.001	17.902	3	<.001	**Diff**
Regression Invariance between Influencer Types								
Invo->Attract		3387.362	2274	<.001	6.5804	2	<.04	**Diff**
Mat	.465**	3384.453	2273	<.001	3.9423	1	=.04	**Diff**
Exp	.424**	3378.814	2273	<.001	0.27997	1	>.05	Same
SubKnow->Trust		3394.510	2274	<.001	14.709	2	<.001	**Diff**
Mat	.620**	3392.415	2273	<.001	13.64	1	<.001	**Diff**
Exp	.554**	3381.334	2257	<.001	1.9561	1	>.05	Same
SubKnow ->Expert		3392.903	2274	<.001	13.996	2	<.001	**Diff**
Mat	.550**	3392.555	2273	<.001	16.269	1	<.001	**Diff**
Exp	.556**	3384.141	2273	<.001	5.2722	1	<.05	**Diff**
SubKnow ->Attract		3396.896	2274	<.001	22.526	2	<.001	**Diff**
Mat	.315**	3393.823	2273	<.001	29.685	1	<.001	**Diff**
Exp	.162	3380.981	2273	<.001	1.7652	1	>.05	Same
Gender->Attract		3381.958	2273	<.001	2.5949	2	>.05	Same
Race ->Expert		3383.142	2274	<.001	3.9606	2	>.05	Same
Trust->Abr		3383.997	2274	<.001	4.7585	2	>.05	Same
Expert->Aad		3386.747	2274	<.001	9.688	2	<.001	**Diff**
Mat	.275	3384.384	2273	<.001	22.18	1	<.001	**Diff**
Exp	.622*	3383.234	2273	<.001	4.0389	1	<.05	**Diff**
Expert ->AttPI		3392.563	2274	<.001	20.576	2	<.001	**Diff**
Mat	.920**	3377.738	2273	<.001	0.28059	1	>.05	Same
Exp	.785*	3388.795	2273	<.001	739.65	1	<.001	**Diff**
Attract->Aad		3388.262	2274	<.001	9.257	2	<.01	**Diff**
Mat	.116	3380.007	2273	<.001	0.99366	1	>.05	Same
Exp	.248*	3388.612	2273	<.001	19.477	1	<.001	**Diff**
Attract ->Abr		3386.206	2274	<.001	6.6614	2	<.05	**Diff**
Mat	.099	3378.091	2273	<.001	0.000	1	>.05	Same
Exp	.381	3386.638	2273	<.001	10.742	1	<.01	**Diff**

Attract ->AttPI			3382.069	2274	<.001	2.772	2	>.05	Same
Invo ->Abr			3379.579	2274	<.001	1.2114	2	>.05	Same
SubKnow->Aad			3386.161	2274	<.001	8.1023	2	<.05	**Diff**
	Mat	-.074	3382.275	2273	<.001	3.3338	1	>.05	Same
	Exp	.058	3384.914	2273	<.001	9.3382	1	<.01	**Diff**
SubKnow ->Abr			3380.768	2274	<.001	1.2888	2	>.05	Same
Gender ->Abr			3382.730	2274	<.001	3.6573	2	>.05	Same
Race->Aad			3390.399	2274	<.001	18.591	2	<.001	**Diff**
	Mat	.029	3380.906	2273	<.001	1.7648	1	>.05	Same
	Exp	.235**	3389.942	2273	<.001	27.737	1	<.001	**Diff**
Race ->Abr			3385.605	2274	<.001	7.3407	2	<.05	**Diff**
	Mat	.149	3379.688	2273	<.001	.06744	1	>.05	Same
	Exp	.066	3385.056	2273	<.001	7.4112	1	<.001	**Diff**
Race ->AttPI			3383.752	2274	<.001	4.8309	2	>.05	Same
Regression Invariance between Product Types									
Invo->Attract			3388.477	2274	<.001	9.1866	2	<.05	**Diff**
	Human	.502**	3386.436	2273	<.001	7.2777	1	<.001	**Diff**
	AI	.388**	3381.317	2273	<.001	2.0289	1	>.05	Same
SubKnow->Trust			3389.275	2274	<.001	9.7763	2	<.01	**Diff**
	Human	.435**	3379.561	2273	<.001	0.21179	1	>.05	Same
	AI	.830**	3388.987	2273	<.001	8.7964	1	<.01	**Diff**
SubKnow ->Expert			3384.097	2273	<.001	4.7014	2	>.05	Same
SubKnow ->Attract			3389.277	2274	<.001	9.8753	2	<.01	**Diff**
	Human	.176	3382.209	2273	<.001	3.0607	1	>.05	Same
	AI	.559**	3386.337	2273	<.001	6.4727	1	<.05	**Diff**
Gender->Attract			3387.875	2274	<.001	10.885	2	<.01	**Diff**
	Human	.185	3385.570	2273	<.001	7.6548	1	<.01	**Diff**
	AI	-.024	3381.576	2273	<.001	2.7527	1	>.05	Same
Race ->Expert			3382.560	2274	<.001	3.3202	2	>.05	Same
Trust->Abr			3392.765	2274	<.001	34.856	2	<.001	**Diff**
	Human	.854**	3379.514	2273	<.001	0.40235	1	>.05	Same
	AI	.736*	3392.527	2273	<.001	13.1	1	<.05	**Diff**
Expert->Aad			3382.253	2274	<.001	2.9789	2	>.05	Same
Expert ->AttPI			3391.526	2274	<.001	13.467	2	<.01	**Diff**
	Human	.960**	3381.701	2273	<.001	2.8442	1	>.05	Same
	AI	.681	3389.097	2273	<.001	9.244	1	<.01	**Diff**

Attract->Aad		3384.937	2274	<.001	7.358	2	<.05	**Diff**
Human	.013	3379.527	2273	<.001	0.04028	1	>.05	Same
AI	$.325^{*}$	3384.683	2273	<.001	11.998	1	<.001	**Diff**
Attract ->Abr		3395.718	2274	<.001	261.04	2	<.001	**Diff**
Human	.133	3379.770	2273	<.001	0.36918	1	>.05	Same
AI	$.330^{*}$	3395.223	2273	<.001	15.8	1	<.05	**Diff**
Attract ->AttPI		3391.707	2274	<.001	86.72	2	<.05	**Diff**
Human	$-.301^{**}$	3380.298	2273	<.001	0.78387	1	>.05	Same
AI	$-.277^{**}$	3390.682	2273	<.001	9.0	1	<.05	**Diff**
Invo ->Abr		3394.806	2274	<.001	15.496	2	<.001	**Diff**
Human	$.275^{*}$	3392.265	2273	<.001	12.349	1	<.001	**Diff**
AI	$.323^{**}$	3381.812	2273	<.001	2.5955	1	>.05	Same
SubKnow->Aad		3381.101	2274	<.001	1.8613	2	>.05	Same
SubKnow ->Abr		3388.159	2274	<.001	11.36	2	<.01	**Diff**
Human	-.062	3380.971	2273	<.001	1.6247	1	>.05	Same
AI	-.040	3386.449	2273	<.001	6.5	1	<.05	**Diff**
Gender ->Abr		3385.549	2274	<.001	8.2672	2	<.05	**Diff**
Human	-.153	3385.391	2273	<.001	15.531	1	<.001	**Diff**
AI	-.025	3379.433	2273	<.001	0.038555	1	>.05	Same
Race->Aad		3386.385	2274	<.001	9.3062	2	<.01	**Diff**
Human	-.128	3379.805	2273	<.001	0.18832	1	>.05	Same
AI	$.373^{**}$	3385.854	2273	<.001	10.428	1	<.001	**Diff**
Race ->Abr		3383.063	2274	<.001	3.9214	2	>.05	Same
Race ->AttPI		3390.817	2274	<.001	19.435	2	<.001	**Diff**
Human	.120	3380.024	2273	<.001	.59729	1	>.05	Same
AI	$.354^{*}$	3390.068	2273	<.001	45.501	1	<.001	**Diff**

Note. N = 514, χ^2 is evaluated through "maximum likelihood robust, MLR" Regression invariances result from nested model comparison with SEM model in table 5.17. The criteria for determining too much loss in fit in the latent space for latent mean invariance test are a p-value less than .05.

FIGURE 1.1 THEORETICAL MODEL

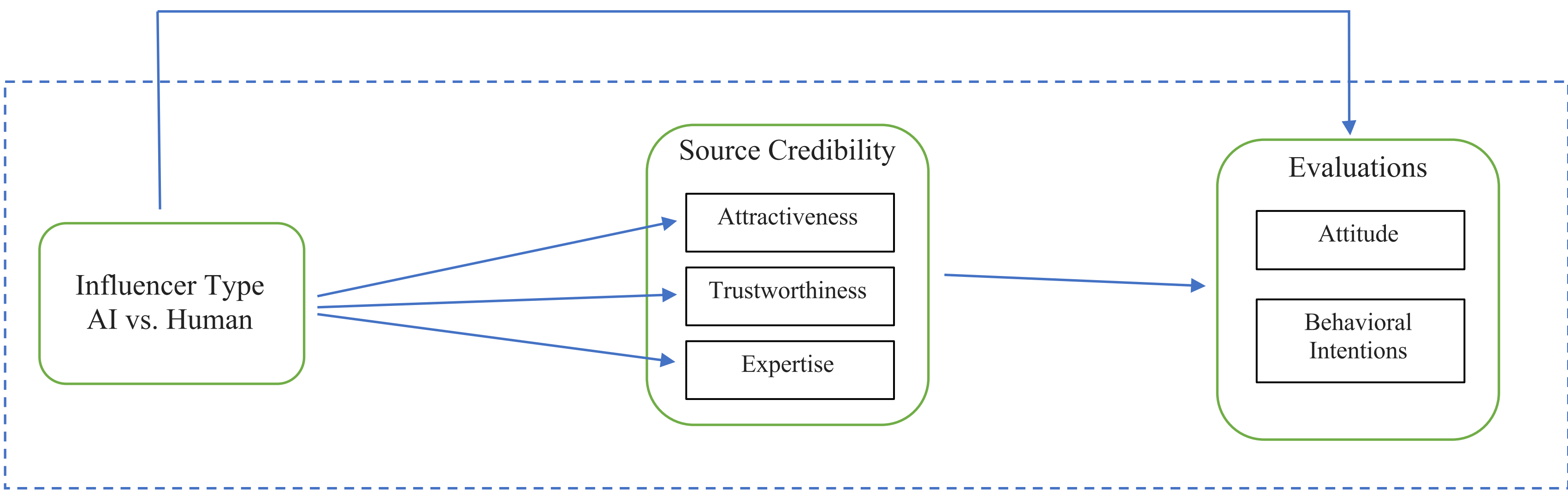
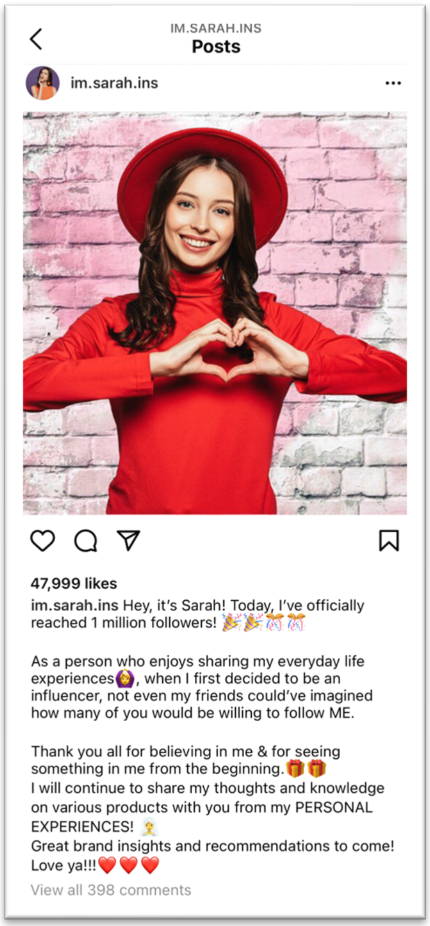


FIGURE 3.1 INFLUENCER TYPE MANIPULATION

A. (HUMAN) SOCIAL MEDIA INFLUENCER



B. AI INFLUENCER

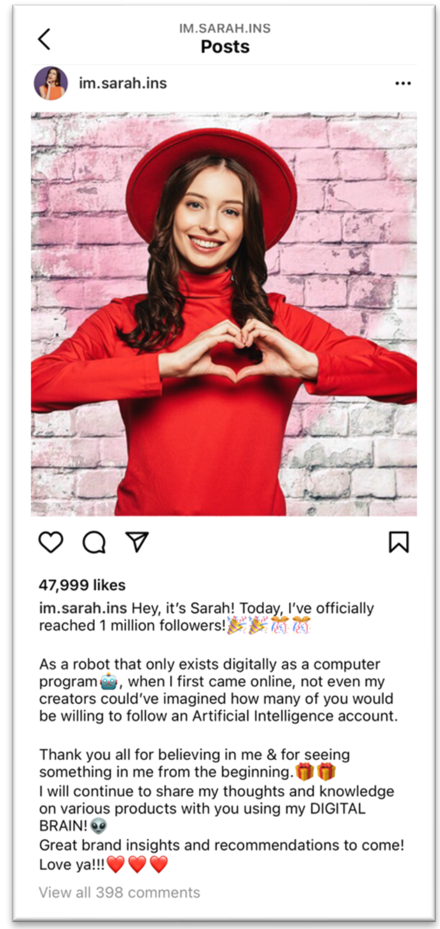


FIGURE 3.2 ADVERTISING MESSAGES

Material

Experiential

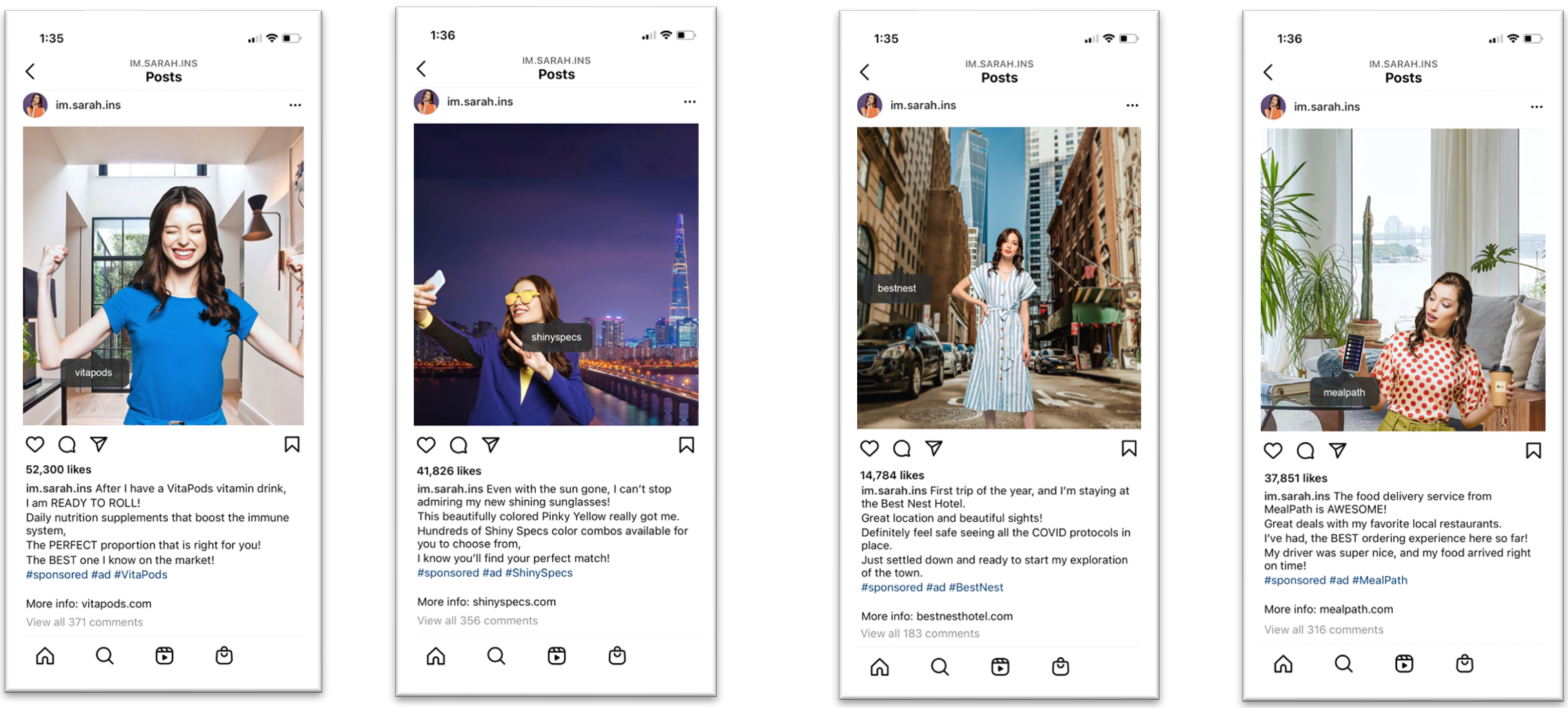


FIGURE 5.1.1. MATERIAL PRODUCTS

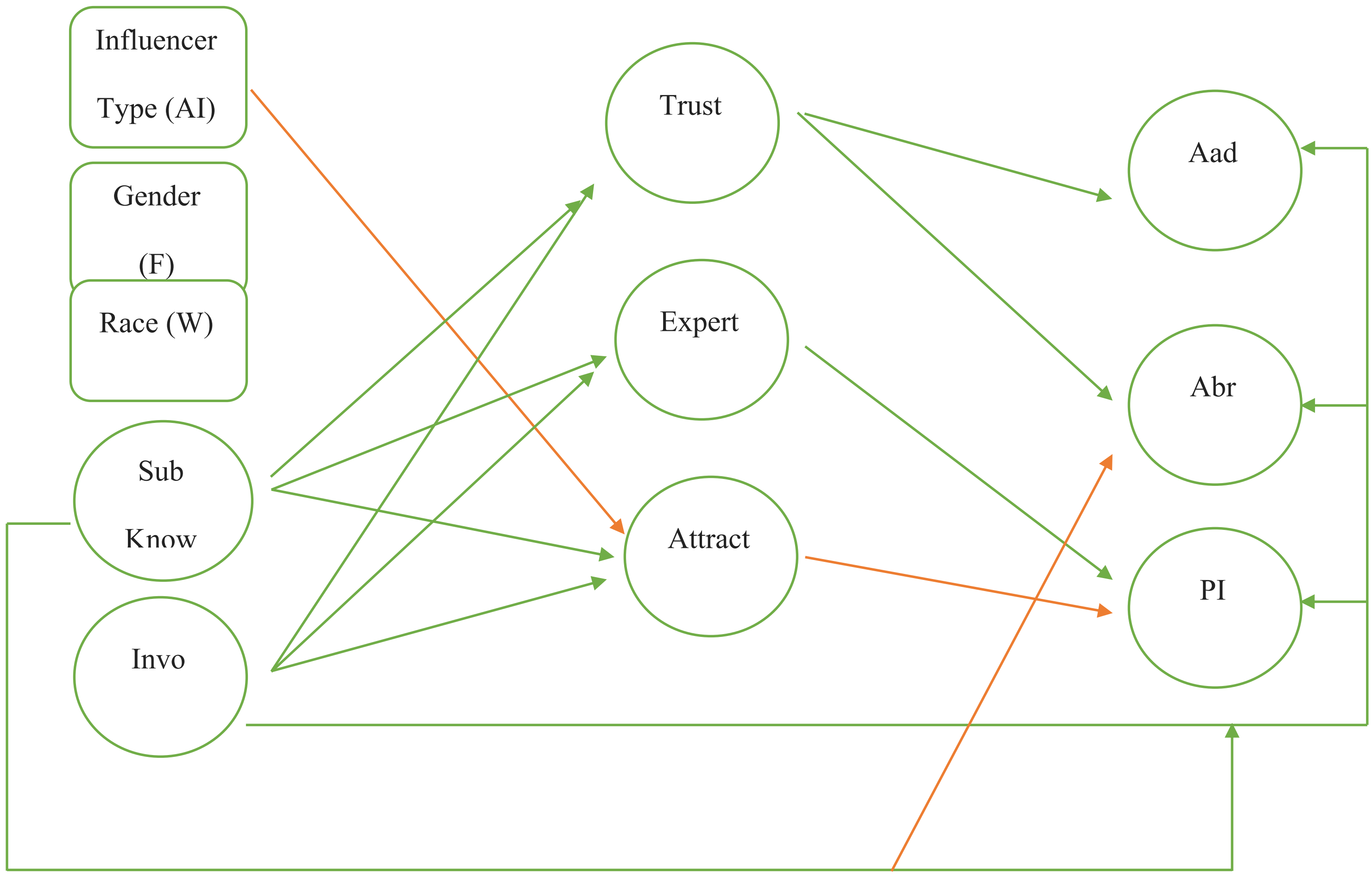


FIGURE 5.1.2 EXPERIENTIAL PRODUCTS

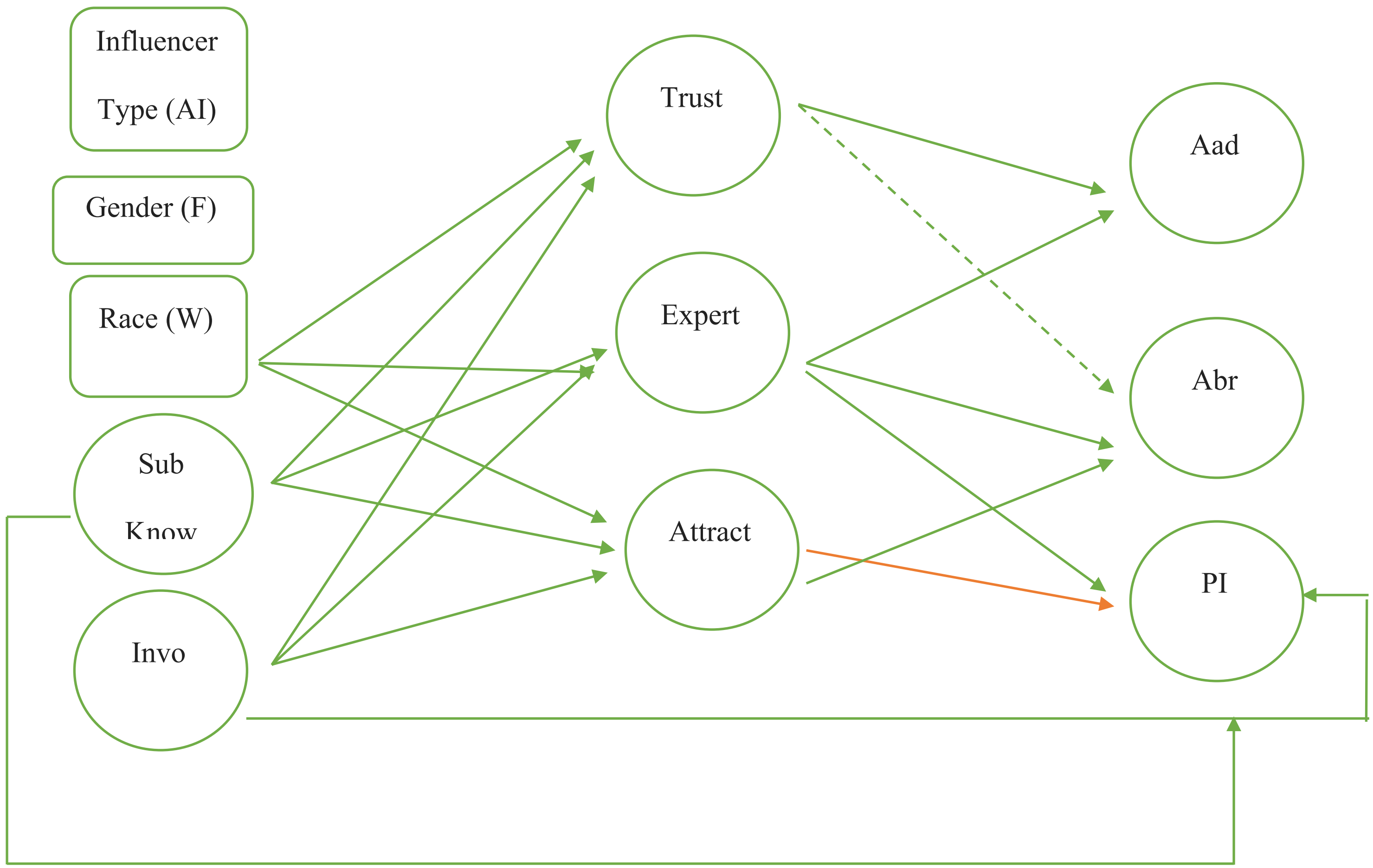


FIGURE 5.2.1. CONSISTENT GROUP

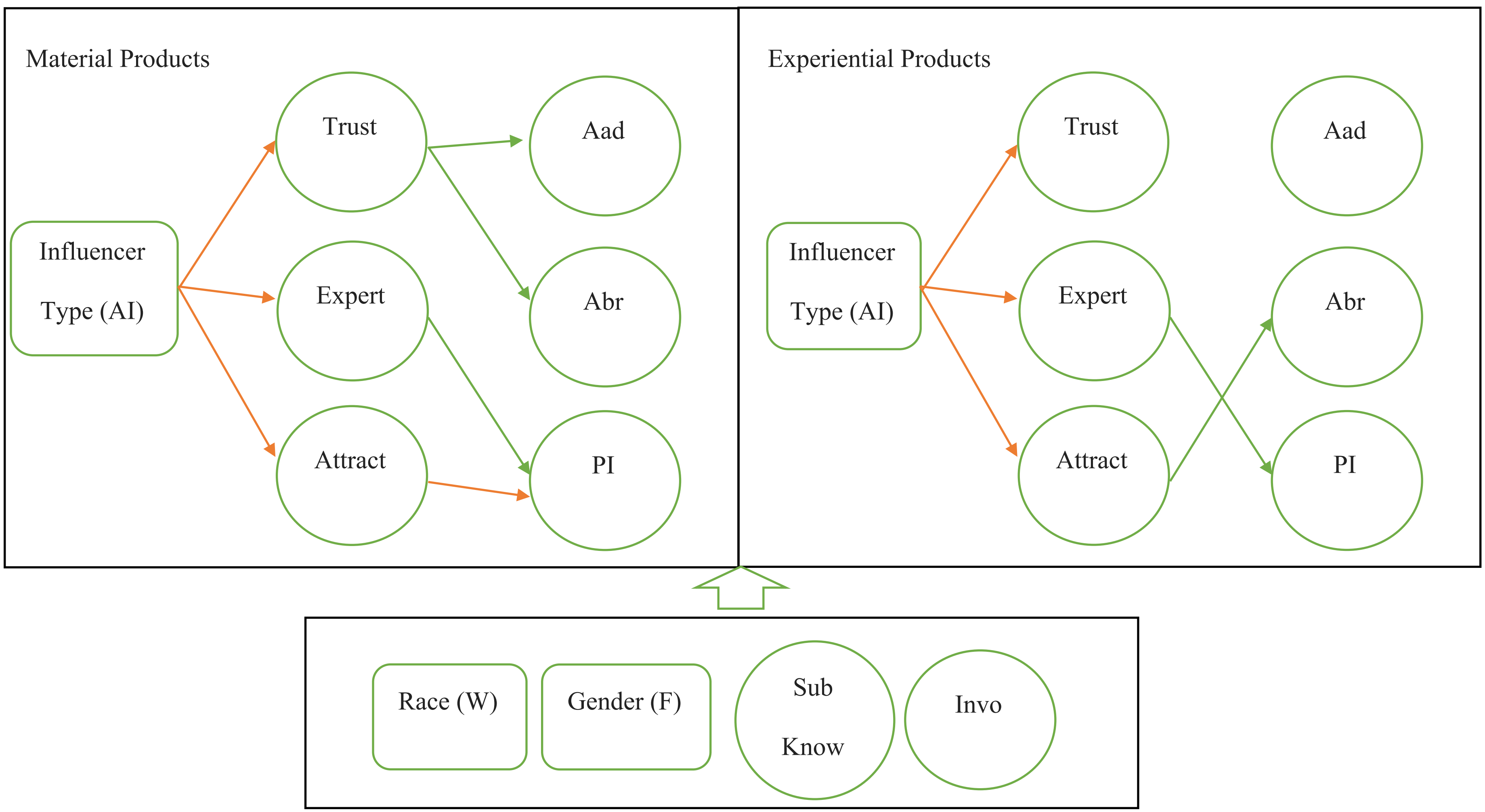
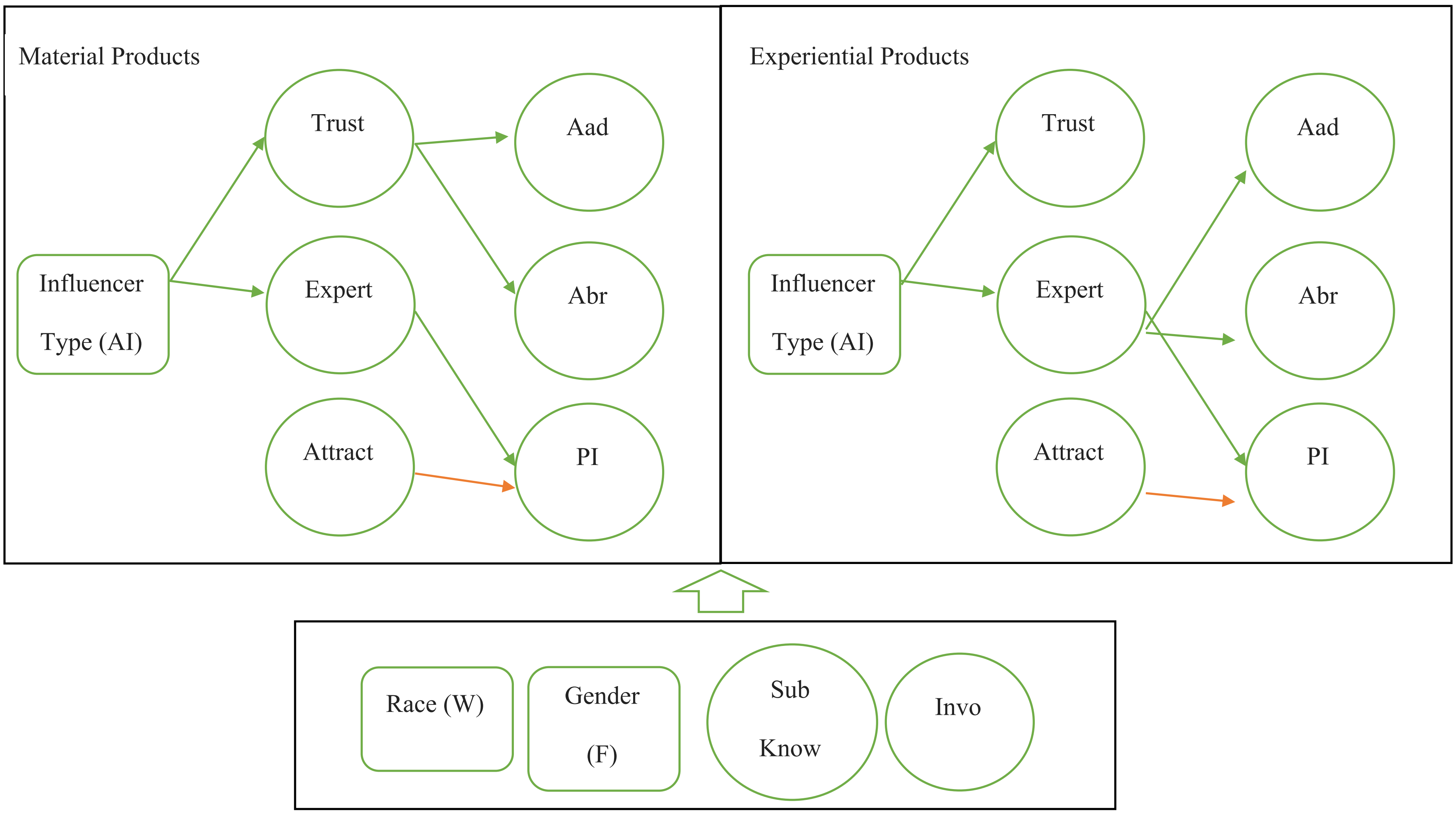


FIGURE 5.2.2. INCONSISTENT GROUP



VITA

Weilu Zhang was born in a small town located in northeast China. She is a first-generation college student in her family. She got her bachelor's degree in broadcasting journalism at the Dalian University of Technology, China. After graduation, she went to Taiwan for her master's education in advertising and public relations at Shih Hsin University. She has been intrigued by the beauty of social science and advertising studies ever since. Specifically, she is interested in studying the impact of applying emerging technology into advertising practice for the personalization and targeting of consumers. Weilu came to the U.S. for doctorate training at Mizzou J-school from 2018 to 2022. She works closely with Dr. Shelly Rodgers on research projects and grant work. Her research expertise regards artificial intelligence advertising. As a daughter of a public health worker, she wanted to apply strategic communication knowledge to find a way better inform the public with accurate and beneficial health information. Her intercultural experiences encourage her to investigate diversity, inclusivity, equity issues, and social fairness in the marketplace. She has been involved in multiple projects in that area.