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Virtual Influencing

Uncharted Frontier in the Uncanny Valley

by

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Abstract

Title: Virtual Influencing: Uncharted Frontier in the Uncanny Valley

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Thesis purpose: In exploring if and to what extent reality level affects sentiment and skepticism, this study aims to provide valuable and actionable insights to both guide academics in further studies and help managers better understand nuances of influencer perceptions.

Methodology: To analyze whether perception differs across influencers' reality levels (human or virtual), this study collected comment data from Instagram to assess levels of sentiment and skepticism. Additionally, researchers collected data for longevity, engagement rate, following size, influencer gender, and influencer race to examine effects on perception.

Theoretical perspective: This study combines Ohanian's (1990) Source-Credibility Model with Mori's (1970) Uncanny Valley Effect, slightly modifying each to develop a simple means of evaluating perceptions towards influencers in a social media context. The findings are analyzed under the scope of opinion leadership, branded spokespeople, social media influencers, emotional branding, and para-social interaction.

Empirical data: This study is based on secondary data collection. Researchers retrieved publicly available account metrics, influencer demographic information, and post comments from the Instagram accounts of all human and virtual influencers in the sample.

Findings/conclusions: The findings reveal that an influencer's reality level has a strong impact on the level of sentiment and skepticism expressed by their followers. Results also uncover main effects for following size, race, and gender and interaction effects for race. This research contributes to existing literature by providing a new layer to the Source-Credibility Model that enables testing sentiment and skepticism using data from social media. It also confirms the Uncanny Valley Effect's continued relevance in application to virtual influencers.

Practical implications: This paper provides marketing professionals and managers with a broader understanding on the novel concept of virtual influencers. Although leveraging virtual influencers may help brands avoid some of the risks associated with human influencers, virtual influencers may prove problematic as a marketing tactic since the Uncanny Valley Effect can negatively impact how social media users perceive some virtual influencers.

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Thank you!

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1 Introduction

> “I’m a robot. It just doesn’t sound right. I feel so human…”
>
> @lilmiquela, 2020

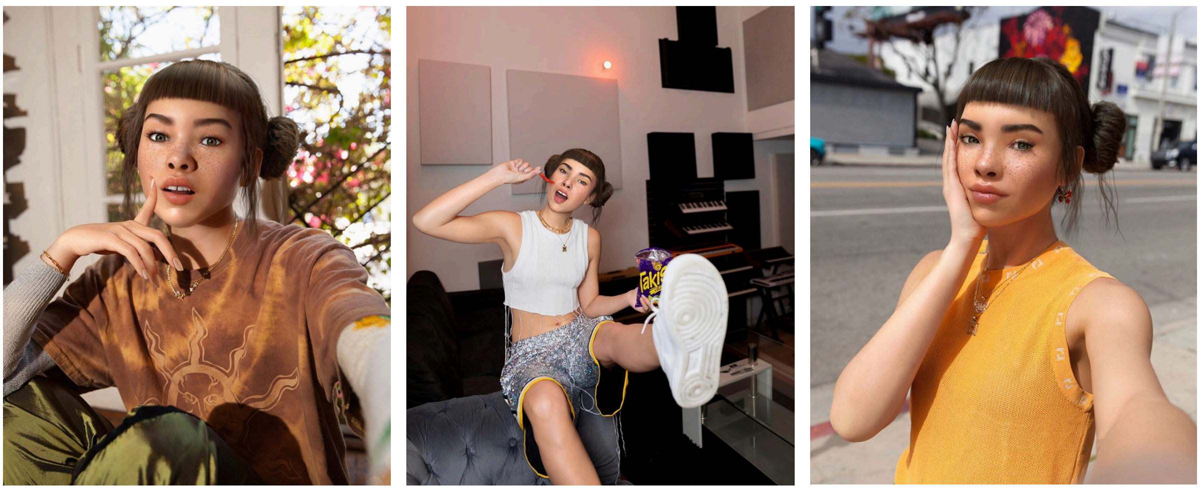
A new faction of influencers is disrupting the influencing industry. They look, act, and function in the same way as traditional influencers, but with one crucial difference: they are not human.

The Rise of Virtual Influencers

Miquela Sousa—a startlingly humanoid Brazilian-American musician complete with a convincingly realistic sprinkling of freckles and flyaways—debuted on Instagram in 2016. After much speculation from followers about her origins, the answer finally emerged two years later. In a reality TV-worthy sequence of drama, a similarly hyperrealistic avatar, Bermuda, assumed control of the @lilmiquela Instagram account and demanded that Miquela “speak her truth” to regain access (@bermudaisbae, 2020). Miquela (or, rather, the creators at Los Angeles-based media agency Brud who developed her persona and orchestrated the publicity stunt) finally revealed her true identity as a “robot”—in April of 2018.

With the truth about her digital origins finally confirmed, Miquela inspired a flurry of press coverage, surpassing 1 million followers on Instagram (Petrarca, 2018) and paving the way for other virtual influencers (VIs) in her wake.

Figure 1-1. *Assorted shots of @lilmiquela from May 2020.*



Fakeness in Popular Culture

Miquela is not the first computer-generated persona to capture the mainstream public’s attention. From the 1990s virtual band Gorillaz to a Tupac hologram’s 2012 Coachella performance to Louis Vuitton enlisting “Final Fantasy” video game character Lightning in a 2016 ad campaign, virtual beings aren’t unheard of in the world of art and entertainment (Morency, 2018). Plus, society interacts with bots on a daily basis: Siri provides directions, Alexa purchases products, and chatbots handle banking transactions.

The concept of “fakeness” in the digital realm encompasses more than just computer-generated avatars; social media users recognize that the heavily edited, professionally curated sponsored content they see from real humans is not necessarily true-to-life (Statista, 2019b). In response to an interview question Youtuber Shane Dawson posed regarding image manipulation, Miquela retorted, “Can you name one person on Instagram who doesn’t edit their photos?” (Dawson, 2017).

Practical Relevance of Virtual Influencing

A recent report from Business Insider projects that the social media influencing industry will nearly double in worth over the next three years, hitting $15 billion by 2020 (Schomer, 2019). While many companies continue to invest in traditional human influencers, an increasing number of adventurous agencies and brands are testing the virtual waters, hoping to duplicate the success Brud achieved with Miquela, Bermuda, and their menagerie of trendy virtual peers. The Diigitals, which bills itself as “the world’s first all-digital modeling agency,” boasts a diverse roster of computer-generated models including Shudu, Margot, Koffi, and Brenn (@thediigitals, 2020). In addition to benefits associated with early adoption of a new tactic—such as competitive advantage and press buzz—brands foresee two more significant perks: predictability and scalability. Unlike human spokespeople and models, whose actions can inadvertently tarnish a brand’s image, VIs are subject to total branded control (at least until artificial intelligence technology makes it feasible for these bots to “speak for themselves”). In terms of scalability, VIs can take on inhuman workloads, working with multiple brands or in multiple locations simultaneously. Computer-generated influencers are not constrained by energy levels, family commitments, or overtime legislation, so they are essentially available for brands’ use 24/7.

The fashion industry has proven the most fervent early adopter of virtual influencing, with brands like Chanel, Balmain, Prada, Vetements, Vans, Supreme, and Opening Ceremony hiring VIs to promote their collections (Morency, 2018; Sauers, 2019). In a similar vein, Essence Cosmetics recently debuted Kenna, its first virtual “intern” (Liffreing, 2019). But VIs are popping up in other unexpected industries, too: American fast food chain KFC created a virtual version of its founder and mascot Colonel Sanders, Swedish supermarket ICA developed Bebis Elis to promote baby products to new parents, and Brazilian home furnishing manufacturer Magazine Luisa introduced popular virtual mascot Lu to infuse the brand with personality (Griner, 2019; Rågsjö Thorell, 2019; Tiffany, 2018). As with traditional human influencers, VIs possess relevance and applicability across a broad range of business-to-consumer industries.

What’s more, the concept of virtual influencing is clearly gaining traction with social media users. Some of the most popular VIs boast hundreds of thousands of followers—a few even possess follower counts in the millions—and on average, VIs command much higher engagement rates than their human influencer (HI) counterparts (Baklanov, 2019). Whether rooted in authentic interest or mere shock value, such high reach and engagement levels present a valuable opportunity for brands to connect to consumers.

Critical Perspective

As with any innovative, rapidly evolving practice, virtual influencing is not without controversy. The greatest concern echoes public outcry surrounding realistic, yet manipulated, “deepfake” images and videos, and consumers’ capacity to misinterpret such content (Luthera, 2020). In other words, critics worry that excessively humanoid VIs possess the potential to dupe social media users into assuming they are living, breathing people. Indeed, Elizabeth Hilfiger mistakenly sent Miquela free sample clothing, and Rihanna’s Fenty Beauty team mistook digital influencer Shudu for a human when they reposted one of her images (Rosenstein, 2018; Sauers, 2019).

Furthermore, most of today’s VIs are entirely controlled by humans—both in graphic development and creation of content like Instagram captions and Spotify singles—but at least one VI, Floresta, has the potential to create her own content. The Drum, working in partnership with London-based Virtual Influencer Agency, disclosed that it is experimenting with machine learning via social media platforms to create some of Floresta’s content (Bradley, 2020). With a dearth of research on virtual influencing and little clarity in legislation relevant to governing these digital tools, critics are wary of the future effects of this type of influencing and how it might be used in a damaging or negative way.

In 1970, roboticist Masahiro Mori coined the term “Uncanny Valley” to describe a phenomenon emerging as the technology associated with robots advanced. In Mori’s view, people find robots increasingly acceptable as their design becomes more humanoid, but the linear relationship does not hold true indefinitely. At a certain point, perception shifts to apprehension and mistrust (Katayama, 2011). This suggests that as the graphic and machine learning technology underpinning these virtual renderings improves and avatars become more convincingly humanoid, public sentiment for virtual influencing will eventually hit a point at which concern and even animosity outweigh the curiosity and fascination surrounding VIs.

Summarizing Thoughts

In summary, due to the novelty of virtual influencing—as well as social media influencing in general—little research exists on overall consumer perception, which harbors close ties to purchase intent. Concepts opinion leadership, brand spokespeople, and social media influencers have been widely studied in relation to brand management and marketing strategy, but necessitate revisiting given the evolving influencing climate. In what ways might these traditional concepts apply—and fail to apply—in a virtual realm?

Considering the large investments required to create and maintain branded VIs, it is vital that companies understand the role that virtual influencing plays in consumers’ minds, as well as how a VI’s impact differs from that of a human. Left unexplored, companies run the risk of overlooking important perceptual nuances that drastically impact return on investment for influencer campaigns.

1.1 Outline of the Thesis

This thesis contains seven chapters. The first chapter presents the concept of virtual influencing and introduces the theoretical and practical importance of this study. The second chapter contains an in-depth review of literature from four pertinent streams: opinion leadership, brand spokespeople, social media influencing, and perspectives on virtual influencing. Next, the third chapter reviews suitable theories and introduces the researchers' original model and hypotheses. The fourth chapter details the research philosophy and methods used in this study, followed by a presentation of analysis and results in the fifth chapter. Next, the sixth chapter discusses key findings and relates them to the theoretical framework. Finally, the concluding seventh chapter reviews the research findings in connection to the research question, highlighting this study's theoretical and practical contributions, limitations, and opportunities for future research.

***Table 1-1**. Outline of the thesis.*

Chapter 1	Introduction
Chapter 2	Literature Review
Chapter 3	Theoretical Framework
Chapter 4	Methodology
Chapter 5	Analysis and Results
Chapter 6	Discussion of Key Findings
Chapter 7	Conclusion

2 Literature Review

This literature review examines the existing body research on interpersonal influence for marketing purposes. Due to the novelty of virtual influencing on social media and the dearth of VI-specific studies, researchers chose to focus on historical foundations and evolution of interrelated concepts rooted in influencing opinion. This review spans opinion leadership, emotional branding, celebrity endorsement, brand spokes-characters, micro-celebrities, and social media influencers in order to provide a comprehensive framework that grounds the emerging practice of virtual influencing and illuminates areas in which academic research can contribute to extant knowledge regarding virtual influencing as a marketing tactic.

2.1 Opinion Leadership

Studies related to the concept of influencing span decades; however, a lack of consensus regarding standardized terminology prior to the 1940s led to a multiplicity of related terms including "opinion leadership," "word-of-mouth," "gatekeeping," "consumption leadership," and "taste making" (Rogers & Cartano, 1962). Of these terms, "opinion leadership" emerged as the most widely used in literature. This section introduces the concept of opinion leadership, tracing the evolution of its definitions and providing insight into the contexts in which opinion leaders operate.

2.1.1 Defining Opinion Leadership

The term "opinion leader" first appeared in a 1948 study analyzing the sources of influence in electorate's choice (Lazarsfeld, Berelson, & Gaudet, 1948). In this initial iteration, Lazarsfeld, Berelson, and Gaudet define opinion leaders as highly specialized experts, explaining that individuals consult these leaders for advice when making decisions in order to increase their personal understanding and decrease perceived risk and uncertainty (1948). Furthermore, Lazarsfeld, Berelson, and Gaudet highlight that personal influence holds greater significance in opinion seekers' minds than traditional media influence does when it comes to decision-making (1948). Merton (1949) builds upon the original definition with his study of opinion leaders in a small New Jersey town, emphasizing the social trust associated with local opinion leaders and adding that opinion leaders typically leverage their leadership role only in conjunction with their specific areas of expertise.

Rogers and Cartano (1962) view opinion leadership similarly, defining it as personal influence exerted by a central individual upon other individuals, who then modify their attitudes or behaviors as a result of face-to-face communication with the opinion leader. In contrast with previous definitions, this definition specifies exertion of an "unequal amount" of influence on opinion seekers. Around the same time, Katz and Lazarsfeld (1966) put forth their definition of the related concept of word-of-mouth (WOM), which involves information exchange between individuals in consumer roles and typically focuses on personal experience with a product or service rather than impersonal technical expertise. This slight distinction in terminology reveals a valuable underlying conceptual distinction. WOM typically occurs only between “equal” parties, with individuals switching freely between message sending and receiving roles in relation to a particular topic, product, or service, while opinion leadership typically assumes a more hierarchical manner, with individuals consistently relying upon leaders for information, but rarely vice versa. In other words, these authors’ contributions help to conceptually separate the social, unstructured, and ephemeral nature of WOM from the more public, systematic, and hierarchical tendencies of opinion leadership. Later studies support this interpretation, refining the definition of “opinion leader” to account for opinion leaders’ relatively structured, repeated efforts to impact opinion (Rogers, 2003; Venkatraman, 1989); such behavior is atypical in traditional word-of-mouth contexts.

The seminal definitions put forth by the aforementioned authors are widely accepted among academics, forming the basis for expanded definitions in later studies. For example, Chan & Misra (1990) build upon earlier work, specifying that opinion leadership requires public status on behalf of the opinion leader, along with personal familiarity of and involvement with the topic in which they exert their leadership. Kotler (2001) adds that some opinion leaders influence opinion seekers as a result of their compelling personalities, rather than because of any particular practical expertise. Multiple authors support Merton’s original proposal that an opinion leader’s influence is limited to their specific domain of expertise (Engel, Blackwell, & Miniard, 1990). In summary, academics tend to agree with and deviate little from early definitions—to this day, the academic conceptualization of opinion leadership remains stable and much related research references these early studies.

2.1.2 Traditional Streams of Research Regarding Opinion Leadership

Following its definition in the mid-1900s, academics refined the concept of opinion leadership, addressing both the personal aspects of leaders themselves and the impact of their leadership on processes and in certain contexts. With the exception of studies focusing on the development of opinion leadership measurement scales (Childers, 1986; Flynn, Goldsmith, & Eastman, 1994; King & Summers, 1970), most opinion leadership research applies to one of two main streams.

The first stream concentrates on identifying characteristics and motivations of opinion leaders. Research shows that many different types of people serve as effective opinion leaders, from celebrities (Weisfeld-Spolter & Thakkar, 2007; Fraser & Brown, 2009; Stehr et al. 2015) to non-famous experts on a certain topic (Gentina, Butori, & Heath, 2014; Goldsmith & Clark, 2008; Lazarsfeld, Berelson, & Gaudet, 1948) to passionate consumers (Arndt, 1967; Chevalier & Mayzlin, 2006). Effective opinion leaders exist across socioeconomic, occupational, gender, and age spectrums (Katz & Lazarsfeld, 1966; Weimann et al. 2007), but academics disagree on the degree of separation between leaders and the individuals they influence. Katz and Lazarsfeld posit that the most successful opinion leaders typically share personal characteristics with the individuals privy to their influence (1966), while Feder and Savastano (2006) find that opinion leaders with slightly superior (but not excessively superior) social standing are most successful in influencing opinion seekers. Minor disagreements aside, academics agree that at least a baseline level of homophily between leaders and opinion seekers contributes to successful opinion leadership (Rogers & Cartano, 1962).

In addition to the characteristics outlined in **Section 2.1.1**, academics agree on a number of personal characteristics that opinion leaders tend to possess. First, their specialized knowledge diverges from mainstream attitudes to the extent that their opinions achieve public visibility. Leaders confidently embrace their differentiation, which inspires admiration among opinion seekers (Chan & Misra, 1990; Gentina, Butori, & Heath, 2014; Maslach, Stapp, & Santee, 1985). In this sense, opinion leaders strongly resemble new product adopters with their penchant for curiosity and uniqueness among peers (Dutton, Rogers, & Jun, 1987; Gatignon & Robertson, 1986). Second, opinion leaders tend to be very social. Noteworthy opinion leaders often possess extensive social networks (Katz & Lazarsfeld, 1966; Solomon, 1992), and social acceptance and advancement serve as primary motivators for leaders to disseminate their opinions (Gentina, Butori, & Heath, 2014; Goldsmith & Clark, 2008; Rogers, 2003; Rose & Kim, 2011; Weimann et al. 2007). Third, opinion leaders tend to interact with mass media to a greater extent than those they influence (Chan & Misra, 1990; Weimann et al. 2007).

The second stream of opinion leadership research focuses on determining the influence of opinion leaders on opinion seekers. Rogers and Shoemaker (1971) specify that successful opinion leadership—at its most basic level—inspires opinion seekers to experience better recall of and greater likeability towards an idea, product, or service. Building upon this fundamental notion, numerous subsequent studies link opinion leadership to trust that recommended ideas, products, or services will meet expectations (Berkman & Gilson, 1978; Chan & Misra, 2008; Kim & Tran, 2013; Menzel, 1981). This clear progression from opinion leadership to positive sentiment and increased trust contributes significantly to the model developed for this study.

Extending these foundations of favorable sentiment and perceived trust to a business context, many studies examine opinion leadership's impact on two categories of behavioral outcomes. The first group of outcomes links successful opinion leadership to innovation diffusion and new product adoption among opinion seekers (Cho, Hwang, & Lee, 2012; Kiss & Bichler, 2008; Valente & Davis, 1999; Zhang et al. 2018). The second group of outcomes links effective opinion leadership in product- or service-based contexts to either purchase intent or actual purchase (Bansal & Voyer, 2000; Belch, Krentler, & Willis-Flurry, 2005; Pandey & Khare, 2015; Sarathy & Patro, 2013).

Among the literature surveyed, no authors mention contexts in which opinion leadership *does not* apply; the breadth of applications indicates that this concept holds relevance in nearly any situation involving personal opinion-sharing. As such, research on opinion leadership spans countless contexts, from fashion (Goldsmith & Clark, 2008; MacGillivray, Koch, & Domina, 1998) to politics (Black, 1982; Lazarsfeld, Berelson, & Gaudet, 1948; Marshall, 1987) to healthcare (Flodgren et al. 2019; Hao & Padman, 2018).

2.1.3 Perspectives on Online Opinion Leadership

The advent of the internet, e-commerce, and social media enabled opinion leadership in an online environment. The aforementioned body of research generally applies in an online context—many recent studies begin with traditional definitions of online leadership in formulating expanded definitions for an online environment. This section illuminates similarities and nuances that emerge in the literature surrounding online opinion leadership.

Naturally, the internet enables new modes for and features of opinion-sharing communication. One of the biggest consequences for opinion leadership involves the drastic increase in potential message reach. Where opinion leadership traditionally occurred in a one-to-one or one-to-some format, the internet enables one-to-many and many-to-many information exchanges, and offers an exponentially higher reach potential for leaders' messaging (Li & Du, 2011). In addition to increased reach potential, internet environments offer supplementary dimensions regarding transparency.

In contrast with traditional opinion leadership, which relied primarily upon opinion seekers' personal evaluations of leaders' expertise, online platforms assist seekers in determining the authenticity and proficiency of leaders. For example, e-commerce sites like Amazon utilize reviewer badges like "Top Contributor," "Hall of Fame," and "Top 500 Reviewer" to differentiate reviews from particularly prolific and helpful users, and social media sites incorporate verification badges on users' profiles to designate authenticity and credibility (Hentschel et al. 2014; Kwok & Xie, 2016; Sharma & Aggarwal, 2019). These methods create an easily accessible reputation system that facilitates opinion seekers' evaluation of information and augments the trust in opinions considered (Resnick et al. 2000).

Finally, commentary online is generally marked by greater polarization than commentary in face-to-face contexts (Chevalier & Mayzlin, 2006; Hong & Kim, 2016; Hu, Pavlou, & Zhang, 2006), meaning that comments are more likely to be extremely positive or extremely negative. Some studies find that in the case of their online commentary, opinion leaders themselves assume a more moderate approach (Schuckert, Liu, & Law, 2016).

Characteristics of opinion leaders and outcomes of their influence remain relatively stable across traditional and online contexts. Regarding opinion leader characteristics, academics associate leader likeability, expertise, strong social ties, and penchant for innovativeness with both offline and online opinion leaders (Lyons & Henderson, 2005; Sun et al. 2006). However, characteristics such as interactivity and timeliness of commentary assume newfound importance in the case of online leaders (Kempe, Kleinberg, & Tardos, 2005; Meng & Wei, 2014; Takeuchi, Kamahara, & Miyahara, 2003). Furthermore, online opinion leaders understandably possess greater computer and technology knowledge than traditional opinion leaders and offline and online opinion seekers (Lyons & Henderson, 2005; Sun et al. 2006). Outcomes of favorability, trust, diffusion, adoption, and purchase intent hold true in online contexts, though expression of these attitudes expands to adapt the online environment; for example, favorability can be expressed directly through likes on social media sites (Cho, Hwang, & Lee, 2012; Gentina, Butori, & Heath, 2014; Kim & Tran, 2013; Meng & Wei, 2015; Sandes & Urdan, 2013; Zhang et al. 2018).

Research examining online leadership either broadly focuses on online contexts in general (Li et al. 2013; Meng & Wei, 2015), or focuses on specific platforms spanning e-commerce sites (Chevalier & Mayzlin, 2006; Hentschel et al. 2014; Kwok & Xie, 2016; Sharma & Aggarwal, 2019), blogs (Li & Du, 2011), and social media sites (de Veirman, Cauberghe, & Hudders, 2017; Djafarova & Rushworth, 2017; Evans et al. 2017; Park, 2013; Park & Kaye, 2017). Authors cover research on social media opinion leaders in more detail in **Section 2.3**.

2.2 Branded Spokespeople

This section first examines the practice of emotional branding, focusing on its application to influential spokespeople. Next, it explores the history of and academic perspectives on two customary types of spokespeople: celebrity endorsers and brand spokes-characters. Since this study broadly aims to glean valuable virtual influencing insights to inform branded marketing strategies, this foundation in brand-based uses of recognizable personas proves particularly pertinent.

2.2.1 Emotional Branding Using Spokespeople

In his seminal book *Emotional Branding: The New Paradigm for Connecting Brands to People*, Gobé (2001) defines emotional branding as a branding practice that focuses on humans' desire for emotional fulfilment rathern than their desire for material satisfaction. Assuming this perspective, consumers are more influenced by emotion than by logic when choosing a brand. Contrary to conventional branding, which principally communicates products' functional benefits and technical aspects, emotional branding uses emotive, relational storytelling to reach consumers. Somewhat surprisingly, deployment of a successful emotional branding strategy doesn't depend upon the emotive associations of the product itself. From automobiles and luxury garments to cigarette lighters to junk food, emotional branding's potential extends across product categories and purchasing contexts (Gobé, 2001).

Brands leverage this emotional strategy in the hopes of forming complex, enduring affective ties with consumers that constitute a competitive advantage (LeBel & Cooke, 2008; Roberts, 2005; Thompson, Rindfleisch, & Arsel, 2006). According to its proponents, emotional branding's power lies in its ability to transcend consumers' focus on rational and functional benefits. In spinning a more emotionally-focused narrative, brands help consumers attain an aspect of their aspirational "ideal self" (Herskovitz & Crystal, 2010; Malär et al. 2011). Emotional branding appeals to consumers' hearts over minds, tapping into their visions and drawing them towards a brand and its products on a more primal, emotional level (Gobé, 2011; LeBel & Cooke, 2008; Thompson, Rindfleisch, & Arsel, 2006). In successful cases of emotional branding, the strong emotional bond forged with a brand surpasses mere differentiation and satisfaction and approaches love on behalf of consumers. Once formed, these emotional ties prove incredibly durable over time, resulting in fervent brand loyalty that inspires purchase and interpersonal recommendation (Gobé, 2011).

Since emotional branding relies upon relatable, inspirational storytelling, employing a focal brand persona can help brands to personify their attributes, enliven historical and emerging brand narratives, and provide a relatable reference point for consumers (LeBel & Cooke, 2008). Aaker (1997) specifies that consumers' conceptualization of a brand's personality arises from assigning human traits to that brand, and Herskovitz and Crystal (2010) go so far as to argue that brand narratives without memorable personas lack the staying power required for emotional branding. While human or non-human actors can serve as brand personas (for example, Kim Kardashian for Flat Tummy Co. or the swoosh for Nike), humanoid brand personas represent a clearer, more direct reference point for consumers (Wan & Aggarwal, 2015). Furthermore, social entities that support brand awareness and loyalty, such as brand communities (Muniz & O'Guinn, 2001) and brand publics (Arvidsson & Caliandro, 2016), rely on outspoken and publicly visible individuals to fuel conversations surrounding brands and their products. As such, spokespeople represent a valuable opportunity to reinforce emotional attachments to a brand and its products through motivating consumer groups in a social context.

2.2.2 Celebrity Endorsers as Brand Spokespeople

The practice of leveraging the support of a public figure as a marketing tactic dates back centuries. In the 1700s, after Queen Charlotte purchased his pottery, Josiah Wedgwood used her name to forge an association between his products and royal consumption (Seno & Lukas, 2007). In the 1950s, teenagers flocked to purchase Lee jeans after James Dean popularized them in *Rebel Without a Cause* (Cochrane & Seamons, 2014). The new millennium brought the spread of internet technology and the rapid acceleration of the news cycle. These shifts spawned booms in celebrity tabloids, gossip blogs, reality television, and finally, celebrities' personal online interactions (Peterson, 2019). As celebrities continue to put their personal lives on display online, they inspire aspirational and imitative behaviors among the public. Returning to the literature on opinion leadership, opinion seekers' closer degree of familiarity with an opinion leader allows for more effective opinion leadership. By virtue of their heightened visibility and accessibility, celebrities possess the power to exert greater influence than ever before.

McCracken (1989) defines celebrity endorsement as a marketing practice in which a celebrity leverages their public status to endorse a brand, either explicitly or implicitly. In its traditional sense, the term "celebrity" spans individuals famous for their prominence in television, radio, newspapers, or other forms of media and from any of a broad range of fields such as sports, science, politics, or entertainment (McCutheon, Lange, & Houran, 2002). Ohanian (1990) adds that, as with opinion leaders, celebrity endorsers should possess knowledge and experience related to the brand or product that they endorse. Contrary to the practice of opinion leadership, which is not viewed by academics as a profession in its own right, celebrity endorsement is paid work directly tied to a famous individual's public career (Roobina, 1991).

Previous literature on emotional branding and opinion leadership offers insight into the success of celebrity endorsement as a marketing tactic. Echoing outcomes of emotional branding strategy, celebrity endorsement is effective partially due to its ability to address consumers' aspirations (Thompson, Rindfleisch, & Arsel, 2006). Research shows that 75% of adults feel strong attraction to a celebrity at some point in their lives (Boon & Lomore, 2001). Consumers aspire to the idealized appearances promoted by celebrities and the media, and ample research supports that physically attractive communicators are most successful in influencing consumer behaviors (Baker & Churchill, 1977; Kahle & Homer, 1985; Roobina, 1991; Till & Busler, 2000). Regarding personality traits, successful celebrity endorsers share many characteristics with effective opinion leaders. Personal differentiation, specialized or expert knowledge, and social prominence retain their importance in cases of celebrities leading opinion (Kahle & Homer, 1985; Roobina, 1991).

It is critical to note that big-budget celebrity endorsement campaigns involve endorsed brands to a much greater extent than in cases of organic, unsponsored opinion leadership. As such, celebrity image and brand image—and the alignment between the two—factor into the success of an endorsement. Literature supports the argument that a compelling celebrity presence alone fails to drive awareness and purchase. Multiple authors agree that the most effective celebrity endorsement campaigns combine source-based factors (like physical attractiveness and fame) with management factors (like the degree of fit between brand ideology or product applications and the endorsing celebrity's capabilities) (Roobina, 1991; Seno & Lukas, 2007; Till & Busler, 2000; Zahaf & Anderson, 2008).

Celebrity endorsement literature highlights similar brand outcomes to those detailed in opinion leadership literature. In addition to increased brand recall (Erdogan, 1999; Friedman & Friedman, 1979), favorability, trust, and purchase intent all increase following successful endorsement campaigns (Baker & Churchill, 1977; Foong & Yazdanifard, 2014; Friedman & Friedman, 1979; Kamins et al. 1989; Khan, 2017; Nyamakanga, Ford, & Viljoen, 2019). As such, multiple authors conceptualize celebrity endorsement using the Source-Credibility Model, which connects attractiveness, trustworthiness, and expertise to purchase intention (Carroll, 2009; McCracken, 1989; Ohanian, 1990; Tom, 1992). Due to its broad applicability in conceptualizing the efficacy of branded spokespeople, this model represents a critical part of the theoretical framework for this paper, which authors detail in **Chapter 3**.

While celebrity endorsement offers plentiful opportunities for brand advancement, the literature emphasizes shortcomings of the tactic. First and foremost, due to the close relationship between endorsers and the brands and products they endorse, controversy in a celebrity's personal life can harm brand image (Brian & Shimp, 1998). A celebrity's business practices and the integrity of their endorsements are also subject to scrutiny on behalf of consumers. Tripp, Jensen, and Carlson (1994) warn that a celebrity's endorsement of multiple products reduces their likeability and credibility. Brands should exercise caution when working with particularly famous celebrities whose popularity could overshadow the brand and detract from achievement of marketing objectives (Tom, 1992). Finally, a single endorser may not possess broad enough appeal to reach a brand's entire target audience. In these cases, a multi-celebrity endorsement campaign could augment efficacy, but this tactic requires a hefty investment and risks confusing consumers with inconsistent messaging (Tripp, Jensen, & Carlson, 1994). While celebrity endorsement offers brands a compelling opportunity to engage consumers, the tactic is not without limitations.

As in the case of opinion leadership, internet communication and social media necessitate refining the definition of celebrity endorsement to incorporate consumers' unprecedented access to and interaction with celebrities. For the first time, social media presents the opportunity for two-way, direct contact with celebrities, enabling followers to initiate conversations and even develop close relationships with previously unreachable and exclusive celebrities. This in turn fosters a potential to achieve higher levels of favorability and trust (Lee et al. 2011; Ranaweera & Prabhu, 2003). It is important to note that all extant studies of celebrity endorsement on social media examine conventional human celebrities, while research on VIs' endorsement is nonexistent.

2.2.3 Spokes-Characters as Brand Spokespeople

Brands' history of leveraging spokes-characters possesses strong similarities to that of celebrity endorsers. Spokes-characters—fictional characters devised by brands to promote products or services (Callcott & Lee, 1996)—date back centuries. For example, Quaker Oats trademarked its famous spokes-character in 1877 (Kelly, 2017) and the iconic Michelin Man first appeared in 1898 (Sinclair, 2014). During the 1950s, as James Dean's celebrity status boosted sales of Lee jeans, Marlboro debuted its now-legendary Marlboro Man (Bendix, 2020). The public's fondness for personified spokes-characters has yet to wane; to this day, they serve as endorsers, cherished company symbols, and nostalgic artifacts (Callcott & Lee, 1995).

Callcott and Phillips (1996) officially define spokes-characters as any caricatured real human, fictional human, mythological figure, animal, or object that acts as a spokesperson for a brand. In the overwhelming majority of cases described in literature, brands own their supporting spokes-characters; however, some literature explores brands' partnerships with external spokes-characters like Hello Kitty or Miss Piggy, which invites comparison to celebrity endorsement (Sheehan, 2020). Morgan (1986) adds that brands personify their spokes-characters in a way that makes them easily relatable, though this doesn't require spokes-character homophily with the brand's consumers per se—it simply refers to endowing a spokes-character with familiar and attractive human traits. Spokes-characters possess a recognizable personality of their own that is distinct from the brand's overarching personality, and they fulfill at least one of two key functions: advancing brand narrative and conveying brand personality. Furthermore, in order to attain optimal success, brands must utilize spokes-characters frequently in conjunction with products; as with many marketing tactics, infrequent exposure has little impact on influencing consumer behavior (Callcott & Lee, 1995; Vandebosch, Smits, & Van Stevens, 2009). In summary, these characteristics come as no surprise—as in the cases of opinion leaders and celebrity endorsers, successful spokes-characters leverage differentiation, brand expertise and alignment, and social visibility to systematically influence public opinion.

Regarding the outcomes of leveraging brand spokes-characters, the literature predictably illuminates further parallels with opinion leaders and celebrity endorsers: all three types of individual serve to augment favorability, trust, and purchase intent (Callcott & Lee, 1995; Callcott & Lee, 1996; LaBel & Cooke, 2008; Lin & Wang, 2012). However, the benefits to utilizing brand spokes-characters differentiate them from their human counterparts; while brands at best exert some control over opinion leaders and celebrity endorsers, they exercise full control over their owned spokes-characters (Erdogan, 1999). Since spokes-characters are imaginary, non-autonomous entities, there is no threat of personal controversy that might negatively impact the brand. In conjunction with this, spokes-characters constitute a less expensive marketing opportunity for brands—unlike celebrity endorsers, brand spokes-characters cannot negotiate higher rates or spark costly public relations scandals. Additionally, brands can craft maximum brand alignment with and demand unequivocal dedication from their owned spokes-characters in a way that is not feasible with even the most well-aligned and well-intentioned celebrity endorsers (Tom, 1992).

As in the case of celebrity endorsers, extant literature ties use of branded spokes-characters to the practice of emotional branding (LeBel & Cooke, 2008). As brand assets, often based on a key figure in a brand's history, spokes-characters' primary purpose always centers around brand-storytelling. As such, spokes-characters occupy an ideal position to communicate authentic brand stories—even more so than celebrity endorsers, whose endorsement of multiple brands and products undermines their credibility (Tripp, Jensen, & Carlson, 1994). This review did not uncover any studies comparing the effectiveness of celebrity endorsers to spokes-characters, though the established and continued success of brand spokes-characters and celebrity endorsers suggests that both tactics are effective in supplying consumers with valuable and relatable brand personality.

2.3 Social Media Influencing

As defined previously, opinion leaders are individuals who leverage their differentiation, expertise, and social ties in order to modify opinion seekers' attitudes or behaviors (Rogers & Cartano, 1962). However, this general definition applies regardless the context in which opinion leaders operate. In the past decade, a new type of opinion leader specific to social media contexts appeared: the social media influencer (SMI). Two broad shifts in media enabled the rise of SMIs. First, reality television shows like *American Idol* and *Survivor*—in which ordinary people rose to stardom—demonstrated everyday individuals' capacity to capitalize on the popularity of their personalities and use this power to impact public opinion. Second, the social media boom of the 2010s provided ordinary people with a means of spreading content and opinions to a limitless internet audience (Khamis, Ang, & Welling, 2017). Businesses quickly moved to capitalize on social media marketing and the power of influencers. Over ninety percent of United States-based businesses use at least one social media site for marketing purposes, and the global social media influencer market experiences substantial year-over-year growth (Statista, 2019a; Statista, 2020).

Typically referred to simply as "influencers," academics define social media influencers (SMIs) as a novel type of third-party endorsers who possess the ability to impact their audiences' attitudes across social media platforms like blogs and networking sites (Freberg et al. 2011). de Veirman, Cauberghe, and Hudders (2017) add that social media users regard influencers as trusted "tastemakers" in niche fields, echoing the influential potentials of differentiation and expertise from previously reviewed literature. Influencers establish clear online personalities and amass substantial followings and engagement levels in order to attract partnerships with brands for endorsement and outreach (Brown & Hayes, 2008; Hearn & Schoenhoff, 2016; Ranga & Sharma, 2014).

While the term "social media influencer" technically encompasses any individual influencing public opinion on a social networking site (from internationally famous celebrities to ordinary people), the term's use in popular culture overwhelmingly tends to refer to an ordinary person who rose to fame through social media (Abidin, 2015). It bears close relationship to the slightly broader concept of "micro-celebrity," which spans offline and online influencing contexts, and refers to individuals who lack the resources and recognition of traditional celebrities and leverage new technology to establish their fame (Senft, 2008). The unprecedented reach potential of these ordinary people points to a shifting power dynamic in the media (Khamis, Ang, & Welling, 2017). In the past, individuals relied upon traditional institutions like Hollywood and Broadway to support their self-promotion. Now, social media users wield their self-made online reputations and entrepreneurial business expertise as miniature versions of celebrity endorsers. In stark contrast to the opinion leaders of the past, influencers extend their opinion leadership outside of the realm of hobbies, in some cases transforming their online presence into a full-time profession (Khamis, Ang, & Welling, 2017).

As in the cases of opinion leaders and brand spokespeople, differentiation, expertise, and social ties retain their importance, arguably assuming even greater significance in today's hyper-personal social media context (Khamis, Ang, & Welling, 2017). Given the overwhelming attention economy—characterized by an unprecedented proliferation of internet content that competes for individuals' attention—and the resulting rise of hyper-personalization, clear differentiation and above-average expertise enable influencers to address the specific, niche interests of their increasingly selective followers (Freberg et al. 2011; Marwick, 2015).

Unsurprisingly, a clear alignment between a promoted brand or product and the influencer endorsing it results in greater marketing efficacy (Carrillat, d'Astous, & Lazure, 2013; Fleck-Dousteyssier, Korchia, & Le Roy, 2012; Till & Busler, 1998). Content shared by influencers experiences less success if it appears forced, robotic, or scripted to the target audience (Russell, 2002). Influencer accessibility and the timeliness and relevance of their content also take on greater importance in a social media context than in traditional opinion leadership or spokesperson endorsement contexts (Abidin, 2015; Khamis, Ang, & Welling, 2017; Thomson, 2006). The intimacy achieved through influencers' frequent, down-to-earth interactions with their followers constitutes a key aspect of influencers' persuasive power and represents a significant departure from the exclusivity of celebrity endorsers (Chung & Cho, 2017; Senft, 2008). Communicating on social media, the relationship between influencers and their followers approaches friendship, defined as a horizontal, dyadic relationship based on mutual affection and reciprocity (Bagwell & Schmidt, 2013; Hartup & Stevens, 1997). As mentioned in **Section 2.1.3**, the social media environment offers enhanced ability to quantify an influencer's social ties by providing clear metrics like following size and post engagement levels. Studies find that individuals form connections with the people who they perceive to be more popular, so clearly delineating an influencer's connections and reach provides followers with a greater capacity to evaluate their opinions' value (Bukowski & Newcomb, 1984; Parker & Asher, 1993). Previous literature connects attractiveness and relatability to successful influencing contexts, and research on social media influencers does the same. Social media users gravitate towards following attractive individuals with whom they share physical, behavioral, or demographic traits and tend to trust messages transmitted by a similar individual more (Briñol, Petty, & Tormala, 2004; Sokolova & Kefi, 2020).

As noted with other interpersonal influencing contexts reviewed, the outcomes of social media influencing for marketing purposes include increased brand recall, favorability, credibility, and purchase intent (Djafarova & Rushworth, 2017; Freberg et al. 2011; Hearn & Schoenhoff, 2016; Jin & Phua, 2014; Kim, Sung, & Kang, 2014; Lee & Watkins, 2016; Ranga & Sharma, 2014). Similar to celebrity endorsers and brand spokes-characters, influencers are well-positioned to effectively support an emotional branding strategy. Multiple attributes supported by social media platforms—emphasis on both text and multimedia content, real-time updates, chronological post listings, interactivity between influencers and other users—enable the rich storytelling and relatable yet aspirational narratives that underpin an effective emotional branding strategy. Social media influencing stands out among other methods of impacting opinion: it is quicker than relying on organic opinion leadership from brand loyalists, more cost-effective than partnering with a celebrity endorser, and less effort-intensive than developing a brand spokes-character (Phua, Jin, & Kim, 2017). Since influencers typically operate externally to brands, some of the same concerns that apply to celebrity endorsers remain in the case of influencers; personal scandals, multiple product endorsement, and misalignment between an influencer and the brand or products they promote pose challenges and risks for brands.

2.4 Perspectives on Virtual Influencing

In keeping with the popular, social media-focused usage of the term, The Oxford Advanced Learner's Dictionary (2020) defines an influencer as "a person or thing with the ability to influence potential buyers of a product or service by recommending it on social media." Earlier definitions mentioned in this review refer to influential entities solely as *people*, with the exception of niche literature on spokes-characters. As stated in the introduction, VIs approximate human characteristics, but they are not human beings—they are simply computer-generated avatars created for marketing purposes (Nolan, 2018). By specifying that *things* can wield influence as well, this Oxford definition addresses the evolving nature of influencing and allows for a broader conception of the tactic that encompasses emerging VIs. Since no formal consensus exists on the official definition of VIs' parameters, the authors of this study synthesized media coverage like Nolan's, Oxford's broad definition of "influencer," and related literature reviewed in this paper to develop a working definition for "virtual influencer." It is important to note that, while the definition of "social media influencer" is social media-specific, the definition of "virtual influencer" is not specific to a social media—or even online—context, and the following definition is intentionally broad to encompass future offline, experiential situations incorporating VIs.

> ***Virtual influencer***: a computer-generated avatar with a recognizable personality and an established personal narrative; created for marketing purposes.

While both the media and practitioners report on developments in virtual influencing, the coverage rarely extends beyond the novelty or ethical implications of their existence and typically focuses on only a few pivotal VIs—few articles offer a comprehensive synthesis on the state of virtual influencing as a whole (Forsey, 2019; Hsu, 2019; Nolan, 2018; Powers, 2019; Sokolov, 2019). Academics are understandably slower to cover emerging phenomenon; to date, no academic journal articles address the concept of virtual influencing in any capacity, and this review did not uncover any formal studies on the effectiveness of leveraging VIs to achieve marketing objectives. Without any VI-specific research to refer to, it is impossible to draw precise conclusions regarding the characteristics of effective VIs or outcomes of successful virtual influencing. However, the previously reviewed literature on concepts related to influencing illuminates common attributes and outcomes associated with using personal entities to impact opinion, which inform the framework of this research and are discussed in detail in subsequent chapters. The following sub-section incorporates para-social interaction literature that bears strong relation to virtual influencing.

2.4.1 Para-Social Interaction

While the phenomenon of para-social interaction spans all communication situations that are not face-to-face, it carries even greater weight in a virtual influencing context. Coined by Horton and Wohl in 1956, the term "para-social interaction" refers to the paradoxically close relationship between well-known media personalities (message senders) and their audiences (message receivers). They demonstrate that media personalities (such as television presenters or radio hosts) address their audiences fairly directly, and that audiences come to think of prominent personalities as friends, despite the medium-based constraints limiting their actual degree of interaction (Horton & Wohl, 1956).

Since its inception, many academics have contributed to the body of research on para-social interaction, though definitions show an overwhelming lack consensus. Some authors use the term to refer to the one-sided process—the receiver's perception of a media exposure—while others use the term to refer to the two-sided, cross-situational relationship between the receiver and the media personality (Klimmt, Hartmann, & Schramm, 2006). Other authors combine both views and refer to the two concepts interchangeably (Auter, 1992; Rubin & McHugh, 1987).

Additionally, some authors conceptualize para-social interaction in a more contemporary manner, excluding the media personality from the definition and framing para-social interaction as the relationship between a receiver and the media being consumed, regardless if that media centers around a key personality (Rubin, Perse, & Powell, 1985). More recent studies modify the definition of para-social interaction to broadly constitute a relationship between a receiver and the internet environment (Hoerner, 1999), which is most pertinent for this particular paper.

The internet revolution of the past two decades and the increasing intellectual capacity of computers laid a foundation for new fields into para-social interaction, as detailed in two particularly relevant studies from the 1990s. The first study demonstrated that the interaction between humans and computers is fundamentally social, paralleling the interaction between individuals and media personalities. This finding assumes particular significance to studying VIs because it shows that individuals interact socially with computer personalities, even though they are fully aware of the "fakeness" of the message sender (Nass, Steuer & Tauber, 1994). To build upon these findings, a second study the following year added to the discourse on para-social interaction between humans and computers (Nass et al. 1995). This subsequent research found that compelling computer personalities capable of inspiring human interaction are easily created; simply providing minimal, relatable cues—such as communicating dominance and submissiveness—make humans more inclined to engage with a computer personality. As with the previous study, this research by Nass et al. (1995) found that humans' responses to computer-generated personalities parallel humans' responses to interaction with other humans. Additional research built upon these findings, showing that—as in cases of opinion leadership, brand spokespeople, and social media influencers—a likeable, attractive, and trusted personality leads to more effective and influential interaction in a para-social context (Hoerner, 1999). The closer that a para-social interaction comes to embodying real life, face-to-face interaction, the more likely the message receiver will perceive it as pleasant and memorable (Cohen, 2001; Klimmt, Hartmann, & Schramm, 2006).

Since 2000, the literature surrounding para-social interaction focuses increasingly on new media applications. Research on para-social interaction between humans and virtual characters in a videogame context brings para-social interaction research even closer to the realm of VIs. In this context, players interact with functional avatars that either represent other human gamers or virtual personalities with whom an interpersonal interaction can occur (Lewis, Weber, & Bowman, 2008). More recently, the cultural dominance of social media inspired further research on para-social interaction. Research establishes that engaging para-social interaction on the internet does not require an actual person to fulfill the role of message sender (Hoerner, 1999), though the more thoroughly a para-social interaction imitates a real life experience, the more enjoyable and memorable it becomes (Cohen, 2001; Klimmt, Hartmann, & Schramm, 2006). Yuksel and Labrecque (2016) add that social media personalities leverage the accessible, communicative nature of social media platforms to give their followers and message receivers the impression of a particularly strong para-social interaction. This tactical employment of para-social interaction results in an acutely effective means of influencing opinion (Yuksel & Labrecque, 2016). Horton's and Wohl's original definition in 1956 specified the social distance and limited communication at the heart of para-social interactions, but the level of communication that social media enables extends the para-social interaction between message senders and receivers into more of a para-social relationship.

With research streams on computer-animated personalities and social media, literature on para-social relationship approaches application to a virtual influencing context. However, research combining these two streams to focus on computer-generated influencers on social media platforms does not yet exist.

3 Theoretical Framework

This section first introduces the problem definition, specifies the research question, and defines key terms used throughout this paper. Then, researchers identify and review applicable theories that guided the development of this study and formulate the research hypotheses.

3.1 Key Definitions

The subsequent chapters use a mix of conventional, specific, and researcher-created terminology. While some terms—such as "human influencer"—are universally understood, other terms require definition within the context of this particular study. The below table outlines these terms for ease of reference.

Table 3-1. *Key definitions of specific and researcher-created terms.*

Term	***Definition***
Reality level	A researcher-created identifier that distinguishes between human and virtual influencers. Among virtual influencers, reality level includes *hyperrealistic* and *cartoon* virtual influencers.
Virtual influencer	A computer-generated avatar with a recognizably personality and an established personal narrative; created for marketing purposes; includes *hyperrealistic* and *cartoon* physical appearances.
Hyperrealistic virtual influencer	A researcher-created categorization classifying virtual influencers that approach humanoid presentation. See **Figure 4-1**.
Cartoon virtual influencer	A researcher-created categorization classifying virtual influencers that embrace non-humanoid presentation. See **Figure 4-1**.
Longevity	Number of months elapsed since date of first public post, as measured on April 1.
Engagement rate	Calculated per post by: (Likes + Comments) ÷ Total Follower Count. Individual engagement rates of ten posts averaged for overall engagement rate by influencer.
Following size	Classifies influencer into commonly-accepted categories (*mega*, *macro*, *micro*, or *nano*) based on total follower count.
Mega-influencer	Influencer with 1,000,000+ followers.
Macro-influencer	Influencer with 100,000 - 999,999 followers.
Micro-influencer	Influencers with 10,000 – 99,999 followers.
Nano-influencers	Influencers with < 10,000 followers.
*Race**	Defined as "white" or "non-white" for the purposes of this study.
*Gender**	Defined as "male-appearing" or "female-appearing" for the purposes of this study.
Sentiment	In this study, a textual expression of a positive, neutral, or negative affective position. See **Section 4.5.4** for details.

Skepticism	In this study, a textual expression of doubt, mistrust, incredulity, uncertainty, or criticism. See **Section 4.5.5** for details.

*In line with this study's positivist approach, researchers employed reductionism to obtain binary variables in the cases of race and gender. These simplifications do not reflect researchers' personal definitions of those variables and were undertaken in consideration of limited sample size and ease of classification.

Figure 3-1. *Example of hyperrealisitc VIs (@lilmiquela, far left; @koffi.gram, center left) and cartoon VIs (@noonoouri, center right; @johnpork, far right).*

3.2 Problem Definition

While academic research on opinion leadership, brand spokespeople, and social media influencing abounds, academia has yet to apply these phenomena to virtual influencing—in fact, no peer-reviewed academic journal articles address the emerging concept of virtual influencing at all. As covered extensively in the literature review, research findings across situations related to influencing opinion for marketing purposes establish a clear progression from a satisfactory experience with an influential individual, to favorability and trust towards that individual and the product, service, or idea they promote, to increased adoption, purchase, or recommendation intent based on the individual's opinions.

Across the literature reviewed, no streams wholly address virtual influencing. Opinion leadership literature focuses on organic and hobby-based opinion-sharing, conceptualizing the practice as a one-way relationship that has the power to affect business outcomes, but does not possess marketing origins. Celebrity endorsement literature deals primarily with traditional celebrities and largely leaves the rise of endorsements by more ordinary social media users and micro-celebrities unaccounted for. Spokes-character literature arguably comes closest to encompassing VIs, but little research exists on influential spokes-characters external to (not owned by) the brands they promote, and this paper's review did not uncover any research regarding spokes-characters' applications on social media. Furthermore, the body of research on computer-animated spokes-characters is well overdue for an update. Finally, literature on social media influencers solely encompasses the influential impact of human beings.

Considering the complete absence of virtual influencing from academic literature to date, it is critical to note that this dearth does not imply a lack of interest among academics or an expected scarcity of theoretical contributions—quite the opposite. Academia understandably experiences a lag with regards to publishing research on emerging tactics like virtual influencing, which makes a study on the practice particularly timely and valuable to the discourse on influencing. In presenting novel findings, new research on influencing in a virtual context encourages revision of outdated concepts and theories, lays the groundwork for future research, and sparks a dialogue among academics.

Assuming a practical perspective, high financial and skill-based barriers to creation and adoption of VIs contribute to sparse employment of VI partnerships in support of marketing objectives. Given VIs' lack of mainstream awareness and industry penetration, managers currently lack in-depth understanding of best practices regarding virtual influencing. As a result, academic research into consumer attitudes towards virtual influencing is essential to reducing uncertainty surrounding this new promotional vehicle and encouraging future adoption.

3.2.1 Research Question and Rationale

With extensive options for contributing virtual influencing research to the academic discourse, this study elects to focus more narrowly on studying the favorability (as measured by sentiment) and trustworthiness (as measured by skepticism) expressed in social media users' comments on influencers' posts. These aspects of influencing arise frequently throughout related literature, enabling the results of this study to contribute to the academic dialogue across multiple research streams. The abundance of parallel HIs—many of whom possess the same fashion, beauty, lifestyle, and wellness focuses as their virtual counterparts—provides a valuable benchmark for this study, enabling comparisons and contrasts between the two groups. This comparative data will be beneficial both in contributing to the academic foundations of emerging influencing tactics and in guiding immediate management decisions regarding influencer strategy. As a result, this study seeks to answer the broad question: Do social media users perceive virtual and human influencers differently? To expand this question to situate it within Instagram—one of the most rapidly growing social media platforms (Sheldon & Bryant, 2016)—and enable potential links between research findings and business concerns such as brand loyalty and purchase intent, this study seeks to answer the more specific question:

Do social media users' perceptions of favorability (as measured by comment sentiment) and trustworthiness (as measured by comment skepticism) towards influencers differ across reality levels?

In exploring if and to what extent reality level affects sentiment and skepticism, this study aims to provide valuable and actionable insights to both guide academics in further studies and help managers better understand nuances of influencer perceptions.

3.3 Theories on Favorability and Trustworthiness

Research on the favorability and trustworthiness of influential individuals is well-established in literature. These aspects assume extra importance in marketing and advertising contexts, inspiring substantial research on the two properties and the publication of a myriad of theories and scales that attempt to understand and assess the situations in which they occur.

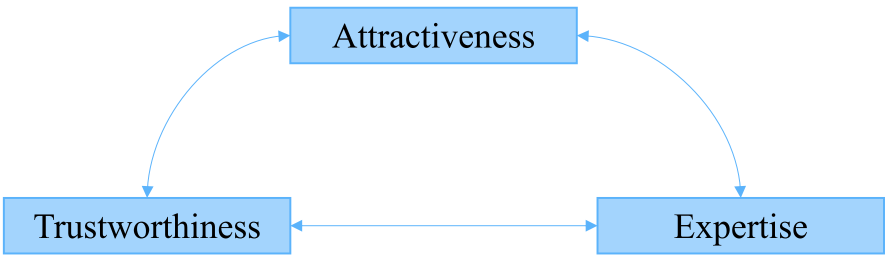
The Source-Credibility Model helps measure the credibility of a message sender based on their personal characteristics; a message sender's positive characteristics affect a receiver's acceptance of the message (Ohanian, 1990). Although authors generally agree on this terminology and the importance of the source-credibility phenomenon, researchers across decades employed a plethora of approaches to define the model's underlying dimensions. Resulting from a study on attitudinal and behavioral change based on communication styles, Hovland and Weiss (1951) developed the original Source-Credibility Model. Their study determined two factors that impact the credibility of a communicator: expertise and trustworthiness. They define expertise as the degree to which a communicator is perceived as a valid source of information and trustworthiness as a message receiver's degree of confidence in the sender's intent to communicate the most valid assertions (Hovland & Weiss, 1951). Additional iterations of the model expanded upon the dimensions of credibility, contributing new dimensions such as safety, qualification, and dynamism (Berlo, Lemert, & Mertz, 1969), authoritativeness and character (McCroskey, Holdridge, & Toomb, 1974), and objectivity (Whitehead, 1968).

An additional study by Giffin (1967) attempted to enrich the scope of the Source-Credibility Model by relating it to the theory of interpersonal trust. In this model, the author related Aristotle's "ethos" to what Hovland & Weiss (1951) call "credibility." He also supplied the aggregating term of "trust," defining it as the reliance upon the communication of another person in order to achieve a desired objective in a risky situation (Giffin, 1967). The outcome of this study constituted the addition of reliability, intentions, activeness, majority opinion of the message receiver, and personal attractiveness as dimensions contributing to the credibility of a message sender. After this, additional researchers began incorporating trust into their models. Rotter (1967) defined interpersonal trust as the expectancy from an individual that another individual's statement can be relied upon. He examined his definition of trust in relation to traditional conceptualizations of humor, friendship, popularity, gullibility, and trustworthiness to develop an interpersonal trust scale. Meanwhile, Larzelere and Huston (1980) developed a simpler trust measurement scale, the Dyadic Trust Scale, which assesses level of trust based on benevolence and honesty. Emphasizing the attractiveness dimension introduced by Giffin (1967), McGuire (1985) developed the Source-Attractiveness Model, which considered a different set of dimensions focused on the appeal of the message sender. This model theorized that a message's effectiveness depends upon its sender's familiarity, likeability, similarity, and attractiveness as perceived by the receiver (McGuire, 1985). The abundance of different interrelated models, which use different terminology and dimensions to approximate the same conceptual understand, creates a complicated framework for the reproduction of existing studies and development of new studies. In order for researchers to advance this stream of research in a consistent manner, and to simplify these phenomena for practitioners, Ohanian (1990) revisited all previous research on source-credibility and reframed the model.

3.4 Ohanian's Source-Credibility Model

Ohanian (1990) developed her iteration of the Source-Credibility Model (**Figure 3-1**) to provide a consistent, valid, and reliable framework for marketing and advertising professionals to use when assessing the credibility of a spokesperson for advertising activities, where credibility denotes the overall likelihood of a message receiver to modify attitudes or behaviors encouraged by a message sender. Previous iterations of the Source-Credibility Model uncover inconsistent definitions surrounding the model's terminology, and with the exception of McCroskey (1966), none of the scales were validated, so could not be considered as reliable measures for assessing the extent of a message sender's trustworthiness, attractiveness, or expertise. In her model, Ohanian (1990) combines the most well-established underlying dimensions of credibility—trustworthiness, attractiveness, and expertise—and provides a consistent and reliable blueprint for measuring them. First, she reviewed the existing definitions of the chosen dimensions and redefined them. In this model, "attractiveness" refers to the likeability of an individual's facial and physical characteristics. This dimension can be expressed using terminology like "attractive," "beautiful," "classy," and "elegant." Ohanian defines "trustworthiness" as a message receiver's level of confidence in or acceptance of a message sender. This dimension is typically associated with terminology like "trustworthy," "dependable," "honest," "reliable," and "sincere." Finally, "expertise" constitutes a message sender's level of knowledge about a focal topic, and is typically described using terminology like "experienced," "knowledgeable," "qualified," and "skilled" (Ohanian, 1990). The relationships between these dimensions is considered multidirectional, and all dimensions combine to produce one overall perception of the credibility of a message sender.

Figure 3-2. *Source-Credibility Model, Ohanian (1990)*

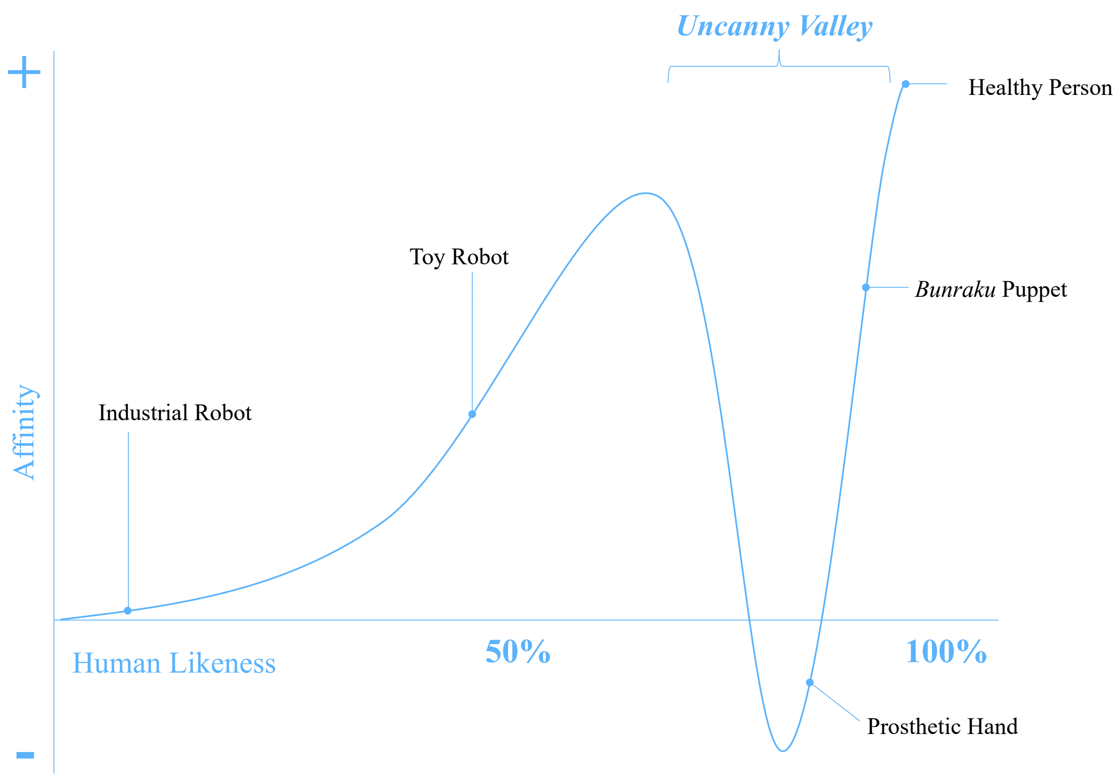


3.5 Mori's Uncanny Valley Effect

The main tenets of the Source-Credibility Model still maintain their relevance and applicability thirty years after Ohanian's refinements, and its dimensions are well-suited to exploring a novel iteration of influential spokesperson. However, the model predates the explosion of the internet and the rise of media social influencers. Thus, it fails to account for nuances exposed by new technology and new communication methods. Furthermore, the literature review for this study uncovered no instances in which a non-human entity was assessed using the Source-Credibility Model.

To augment the theoretical framework of this study with a theory addressing both new technology and non-human, computer-generated entities, researchers leveraged the Uncanny Valley Effect (Mori, 1970) alongside Ohanian's Source-Credibility Model (1990) when developing hypotheses. The Uncanny Valley Effect originated in the field of robotics during the late 1960s and posited that the degree of realism or human likeness perceived in a robot conditions an individual towards a positive or negative overall impression when interacting with that robot (Mori, 1970). According to Mori's research, the perceived positivity of a robot interaction generally increases as human likeness becomes more realistic. However, robot interactions that very closely approximate real life—but not quite—expose a certain degree of abnormality, causing the level of affinity that an individual experiences with a robot to plummet and resulting in feelings of unpleasantness or eeriness towards the robot interaction. To conceptualize this theory visually, Mori (1970) plotted degree of affinity present in a robot interaction against degree of human likeness of the robot involved (**Figure 3-2**).

Figure 3-3. *The Uncanny Valley Effect, Mori (1970)*



Kept in the shadows for decades, academics in the field of robotics (Seyama & Nagayama, 2007) and technology journalists reporting on virtual influencing (Bradley, 2019; Tiffany, 2019) have revived Mori's work in recent years, finding renewed applicability for the roboticist's framework with the rise of humanoid, computer-generated entities. Due to the gaps it bridges in the literature and Source-Credibility Model and its clear applicability to a virtual influencing context, researched deemed the Uncanny Valley Effect essential to incorporate into this research.

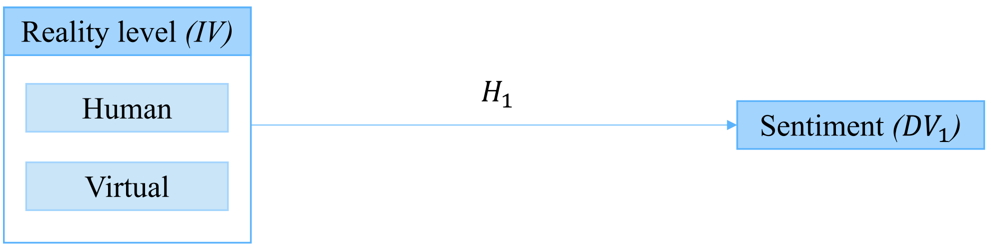
3.6 Notes on Adjustments to Selected Theories

Ohanian's (1990) Source-Credibility Model constitutes the most established and reliable model to assess the credibility of an influencer, and Mori's (1970) Uncanny Valley Effect layers in valuable insight regarding interactions with human beings versus virtual beings. In order to leverage these frameworks within our study, two slight adjustments are necessary. First, the social media context in which this study takes place and the research design's reliance on secondary data offer limited capability to assess an influencer's attractiveness, expertise, and trustworthiness separately. Since the relationships between these dimensions are conceptualized as multidirectional, it follows that they can be grouped for ease of study without compromising the validity of the model. As such, researchers measure Ohanian's Source-Credibility Model dimensions of attractiveness and expertise together via the dependent variable *sentiment*, and measure trustworthiness via the dependent variable *skepticism*. Additional information is provided in **Chapter 4**. Second, researchers extend Mori's (1970) Uncanny Valley Effect from robot-human applications, substituting VIs for the spectrum of realistic robots and HIs for the "healthy person" position in Mori's original model.

3.7 Theoretical Framework for Independent Variables

As detailed, for the purposes of this study, researchers combine attractiveness and expertise from Ohanian's (1990) model and infer that both of these aspects affect a dependent variable, sentiment. Based on these two dimensions, it follows that if an Instagram user perceives an influencer as physically attractive and knowledgeable or skilled on a topic, then that influencer will attain more positive sentiment in their post comments. However, if Mori's (1970) Uncanny Valley Effect holds true in this specialized social media context, then the reality level of an influencer can drastically impact the sentiment expressed in an influencer's post comments. Thus, researchers hypothesize that reality level will impact sentiment, such that HIs' Instagram activity will achieve higher degrees of positive commenter sentiment, while VIs' Instagram activity will achieve lower degrees of positive commenter sentiment. This interaction is depicted in **Figure 3-3**.

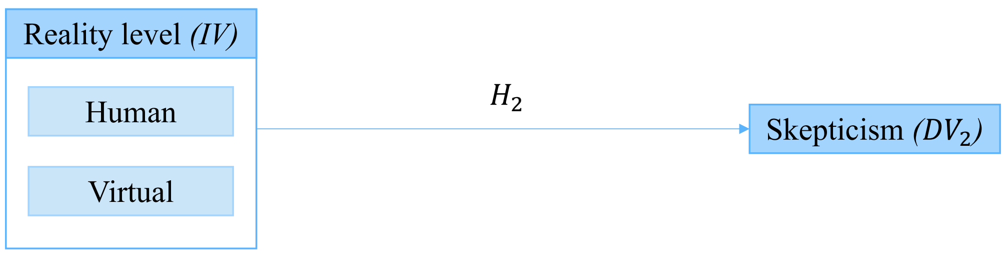
Figure 3-4*. Relationship between reality level and sentiment.*



H1: **Reality level** (IV) has an effect on **sentiment** (DV_1) such that human influencers' Instagram activity will achieve higher degrees of positive commenter sentiment, while virtual influencers' Instagram activity will achieve lower degrees of positive commenter sentiment.

Additionally, based on the trustworthiness dimension in Ohanian's (1990) model, it follows that if an Instagram user perceives an influencer as more trustworthy, honest, or sincere, then that influencer will attain lower rates of skepticism in their post comments. Again, if Mori's (1970) Uncanny Valley Effect holds true in this specialized social media context, then the reality level of an influencer can drastically impact the skepticism expressed in an influencer's post comments. Thus, researchers hypothesize that reality level will impact skepticism, such that HIs' Instagram activity will achieve lower levels of commenter skepticism, while VIs' Instagram activity will possess higher levels of commenter skepticism. This interaction is depicted in **Figure 3-4**.

Figure 3-5*. Relationship between reality level and skepticism.*



H2: **Reality level** (IV) has an effect on **skepticism** (DV_2) such that human influencers' Instagram activity will achieve lower levels of commenter skepticism, while virtual influencers' Instagram activity will possess higher levels of commenter skepticism.

3.8 Theoretical Framework for Moderating Variables

The two aforementioned hypotheses attempt to uncover the impact that an influencer's reality level exerts on the level of credibility other social media users perceive (as constituted by sentiment and skepticism). The existing literature suggests that additional variables may moderate the relationships between reality level and sentiment and skepticism, impacting the overall extent to which social media users perceive an influencer as credible. These rationale for including these moderating variables and the resulting hypotheses are detailed in the following sub-sections.

3.8.1 Theoretical Framework for Longevity

The first moderating variable proposed is longevity, or the extent to which an individual is used to interacting or familiar to another person (Styczynski & Langlois, 1977). This study defines longevity as the lifespan of an influencer's account, measured in the number of months elapsed since their first post. Academics tend to agree that the more familiar a face is, the more likeable it becomes (Gordon & Holyoak, 1983; Styczynski & Langlois, 1977; Verhulst, Lodge, & Lavine, 2010). Similar findings occur in the case of relatively inaccessible entities like celebrities (Lunardo, Gergaud, and Livat, 2015) and non-human entities like consumer products (Hekkert, Thurgood, & Whitfield, 2013). In their study on celebrities, Lunardo, Gergaud, & Livat (2015) found that television and film celebrities seem to be more appealing over the correlated dimensions of both time elapsed and number of exposures. These studies imply a clear interrelationship between time elapsed, familiarity level attained, and perceived attractiveness, laying a clear groundwork for longevity's incorporation into this study. It follows that the longer the amount of time that an influencer has been active on social media, the more exposure other social media users likely have to their content, and literature shows a precedent for this exposure leading to increased perceptions of likeability and attractiveness. Additionally, researchers expect Mori's (1970) Uncanny Valley Effect to negatively impact VI sentiment. Considering this, researchers developed the following hypothesis:

H3: The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **longevity** (MV) such that influencers with greater longevity will achieve higher sentiment. Therefore, virtual influencers with low longevity will experience the lowest levels of sentiment, while human influencers with high longevity will experience the highest levels of sentiment.

Furthermore, literature supports the proposition that longevity affects social media users' perceived trustworthiness towards an influencer, as well. Studies on interpersonal relationships find that the length of the relationship impacts the level of trustworthiness between the individuals (Alarcon, Lyons & Christensen, 2016; Levin, Whitener & Cross, 2006). This phenomenon also extends to well-established public figures, where the absence of an influential person's track record can lead to decreased trustworthiness and greater skepticism (Levin, Levin, & Edward Heath, 1997; Peskin & Newell, 2004). It follows that the longer the duration of an influencer's public activity, the more familiar and trustworthy this influencer will be perceived in the minds of social media users. Additionally, researchers expect Mori's (1970) Uncanny Valley Effect to result in higher rates of skepticism for VIs. Thus, researchers developed the following hypothesis:

H4: The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **longevity** (MV) such that influencers with greater longevity will achieve lower skepticism. Therefore, virtual influencers with low longevity will experience the highest levels of skepticism, while human influencers with high longevity will experience the lowest levels of skepticism.

3.8.2 Theoretical Framework for Engagement Rate

Engagement rate represents another variable that may moderate the relationship between reality level and the dependent variables, sentiment and skepticism. In this study, the way in which researchers define engagement rate includes both other social media users' engagement on an influencer's post, and any engagement from the influencer themselves. Existing literature suggests that high levels of engagement in online settings signal social acceptability and endorsement from other users. Specific to business contexts, consumers' preference for products sold online increases as the volume of reviews increases (Park, Lee, & Han, 2007; Viglia, Furlan, & Ladrón-de-Guevara, 2014). Powell et al. (2017) name this phenomenon the "love of large numbers," suggesting that consumers fixate on numbers to infer quality, oftentimes overlooking textual content of commentary. Furthermore, research on branded customer service in online settings highlights the importance of brand-to-consumer interaction and transparency in fostering perceptions of favorability and trust (Stevens et al. 2018). These precedents in the literature clearly possess similarities to the ways social media users interact with influencers. It follows that the higher an influencer's engagement rates, the greater social acceptability and trustworthiness social media users will infer in evaluating an influencer's posts. As detailed in the previous subsection, researchers expect Mori's (1970) Uncanny Valley Effect to result in less positive sentiment and higher rates of skepticism for VIs. Thus, researchers introduced the following hypotheses:

H5: The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **engagement rate** (MV) such that influencers with higher engagement rates will achieve higher sentiment. Therefore, virtual influencers with low engagement rates will experience the lowest levels of sentiment, while human influencers with high engagement rates will experience the highest levels of sentiment.

H6: The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **engagement rate** (MV) such that influencers with lower engagement rates will experience higher skepticism. Therefore, virtual influencers with low engagement rates will experience the highest levels of skepticism, while human influencers with high engagement rates will experience the lowest levels of skepticism.

3.8.3 Theoretical Framework for Following Size

Following size—a categorization based on the total number of followers an influecner possesses—is among the most widely-used measures to evaluate an influencer's popularity. Like engagement rate, following size is also subject to the effects of the love of large numbers (Powell et al. 2017) in the sense that influencers boasting larger following sizes will likely experience higher levels of sentiment and lower rates of skepticism. Research showing that consumers prefer products with larger volumes of reviews (Park, Lee, & Han, 2007; Viglia, Furlan, & Ladrón-de-Guevara, 2014) and studies demonstrating that individuals with more friends tend to be more likable people (Bukowski & Newcomb, 1984; Parker & Asher, 1993) also inform researchers' understanding of following size. These precedents in the literature hold substantial relevance in conceptualizing social media users' interaction with influencers given the concept of para-social interaction, which argues for strong similarities between real-life, face-to-face human interactions and social media interactions between influencers their audiences (Yuksel & Labrecque, 2016). It follows that, similar to the case of engagement rate, the larger an influencer's following size, the greater social acceptability and trustworthiness social media users will infer in evaluating an influencer's posts. Once again, researchers expect Mori's (1970) Uncanny Valley Effect to manifest in less positive sentiment and higher rates of skepticism for VIs. Thus, researchers propose the following hypotheses:

H7: The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **following size** (MV) such that influencers with higher numbers of followers will achieve higher sentiment. Therefore, virtual influencers with low numbers of followers will experience the lowest levels of sentiment, while human influencers with high numbers of followers will experience the highest levels of sentiment.

H8: The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **following size** (MV) such that influencers with higher numbers of followers will achieve lower skepticism. Therefore, virtual influencers with low numbers of followers will experience the highest levels of skepticism, while human influencers with high numbers of followers will experience the lowest levels of skepticism.

3.8.4 Theoretical Framework for Race

Literature identifies racial similarity as a key factor in the development of interpersonal relationships. Existing studies show that individuals tend to mistrust and avoid other individuals who are dissimilar to themselves (Dent, 2004), while individuals in the same racial or ethnic group possess higher levels of affinity for each other, inspiring favorable perceptions based on demographic similarities (Lord, Putrevu, & Collins, 2019). Race is incredibly understudied in an influencing context, particularly with regards to social media influencing, but abundant news articles and blog posts link disparities in brands' utilization and treatment of influencers to race (Perkins, 2019; Graham, 2019; Chen, 2019). These disparities manifest as higher compensation for white influencers and increased likelihood of their selection for brand campaigns, complimentary merchandise, and other benefits. This begs the question of whether brands choose to partner with white influencers over non-white influencers due to white influencers' increased ability to meet campaign objectives, or if this choice lies in an unwarranted racial bias. It follows that, since Instagram is a public platform available to users of all racial groups, and since individuals equally gravitate towards influential people similar to them (and tend to avoid people dissimilar to them), no differences in levels of sentiment and skepticism towards influencers should exist across racial groupings, but brands' relatively overwhelming utilization of white influencers suggests that they believe otherwise. Assuming the viewpoint of the brands in question solely for the purpose of hypothesis testing, researchers developed the following hypotheses, accounting for Mori's (1970) Uncanny Valley Effect in specifying lower sentiment and higher rates of skepticism for VIs:

H9: The effect of **reality level** (IV) on **sentiment** (DV1) is moderated by **race** (MV) such that white influencers will achieve higher sentiment. Therefore, non-white virtual influencers will experience the lowest levels of sentiment, while white human influencers will experience the highest levels of sentiment.

H10: The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **race** (MV) such that white influencers will achieve lower skepticism. Therefore, non-white virtual influencers will experience the highest levels of skepticism, while white human influencers will experience the lowest levels of skepticism.

3.8.5 Theoretical Framework for Gender

Lastly, literature on interpersonal opinion-sharing contexts illuminates clear gender-based differences in perceptions of and behavior toward influential individuals (Awad & Ragowsky, 2008; Cook & Corey, 1991; Martínez-Sanz & González Fernández, 2018; Palmer & Bejou, 1995; Sun & Qu, 2011). For example, Cook and Corey (1991) find that consumers trust saleswomen and perceive them more positively than salesmen. Furthermore, evidence shows that male and female influencers possess marked differences in the ways in which they approach influencing and communication (Martínez-Sanz & González Fernández, 2018). Male influencers tend to prioritize selling through social media, while their female counterparts tend towards relatable, narrative storytelling. Interpreting this through the lens of emotional branding, the rich and complex content female influencers tend to share points towards more enduring and positive reception and higher levels of trust among social media users. Furthermore, influencers on Instagram tend to be women (indaHash Labs, 2017). In alignment with the Mere Exposure Effect (Hekkert, Thurgood, & Whitfield, 2013), social media users' predominant exposure to female influencers should result in greater familiarity—and eventually higher levels of favorability and trust towards—female influencers. Thus, researchers specified the following hypotheses, accounting for Mori's (1970) Uncanny Valley Effect in proposing lower sentiment and higher rates of skepticism for VIs:

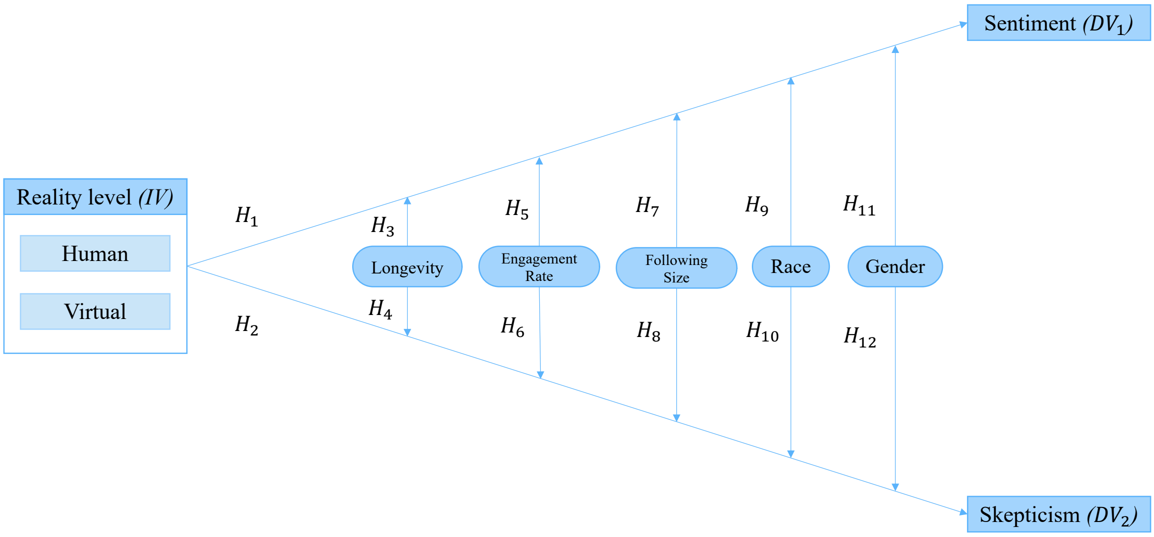
H11: The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **gender** (MV) such that female influencers will achieve higher sentiment. Therefore, male virtual influencers will experience the lowest levels of sentiment, while female human influencers will experience the highest levels of sentiment.

H12: The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **gender** (MV) such that female influencers will achieve lower skepticism. Therefore, male virtual influencers will experience the highest levels of skepticism, while female human influencers will experience the lowest levels of skepticism.

3.9 Original Model Introduction

In light of the problem research question and theoretical framework, researchers developed an original model to explain the relationships among variables examined in this study. The research question clearly dictated designating reality level as the independent variable for manipulation, and sentiment and skepticism as the two dependent variables hypothesized to diverge in correlation with diverging independent variables (Burns & Burns, 2008). Given Instagram's public, online context, the abundance of user-facing data allows for the possibility that moderating variables interact with independent variables to affect dependent variable outcomes. Malhotra (2010) specifies that an interaction effect arises when the effect that an independent variable has on a dependent variable differs depending upon levels of another additional variable. In this model, for example, an interaction effect would occur if humans experienced different levels of sentiment correlated with short-term versus long-term account longevity. While Instagram's rich data pool presented opportunities for including many moderating variables, researchers reviewed relevant literature and selected the five most salient moderating variables in order to maintain conciseness.

Figure 3-6. *Original model showing relationship between all variables studied.*



3.10 Chapter Summary

This study seeks to gain insight into social media users' perceptual differences when approaching VIs and HIs, as framed within Ohanian's (1990) Source-Credibility Model and Mori's (1970) Uncanny Valley Effect. The independent variable—reality level—addresses Mori's (1970) theory of the differences between human beings and humanlike (but ultimately non-human) entities. Researchers borrow the trustworthiness dimension from Ohanian's (1990) model to conceptualize the dependent variable *skepticism*, and combine Ohanian's (1990) attractiveness and expertise dimensions to conceptualize the dependent variable *sentiment*. Finally, researchers introduce five additional variables based upon precedents in literature that indicate these variables may moderate the relationship between reality level and the dependent variables. These moderating variables are: longevity, engagement rate, following size, race, and gender. To capture all these relationships, the researchers developed twelve hypotheses that explore main effects and interaction effects between reality level, sentiment and skepticism, and the five moderating variables.

4 Methodology

This chapter explains the methodological approach to collecting and analyzing both objective and subjective data from Instagram accounts. It begins by defining study-specific terminology essential to understanding the research design. Next, an overview of the selected research philosophy explains the ontological and epistemological approaches to this study. The subsequent problem definition and research question introduce the study's aims, and the research design offers an in-depth explanation of methods utilized in data collection and analysis.

4.1 Research Philosophy

Research methodology depends heavily upon researchers' distinct academic backgrounds and philosophies, specifically regarding selected ontological and epistemological approaches that frame a particular study. Therefore, a review of pertinent research philosophies and their resultant assumptions is critical to conceptualizing any study.

According to Easterby-Smith, Thorpe, and Jackson (2015), ontology outlines conventions for conceptualizing reality. In seeking findings that augment understanding of a universal reality of social media users' behaviors across diverging influencing contexts, this study leverages a realist perspective. Specifically, researchers adopt an internal realist approach, which states that a single reality exists but concedes that researchers cannot attain direct access to or full understanding of that reality. The indirect nature of observation and data collection limits researchers' ability to fully comprehend reality, so internal realists lean on facts and scientific law to reduce variance and potential for multiple explanations (Easterby-Smith, Thorpe, & Jackson, 2015).

The internal realist ontology aligns closely with a positivist epistemology. Epistemology deals with the theory of knowledge itself and defines best practices in research; in the case of positivism, theory posits that the social world exists independently of the researcher, and that measuring properties of reality objectively is a more effective method than subjective judgment (Easterby-Smith, Thorpe, & Jackson, 2015). This study primarily espouses a positivist perspective, though its descriptive nature and small, non-random sample size lend it elements of social constructionism (namely, the aim to augment general understanding necessarily prevails over demonstrating causality and achieving generalizability).

Certain assumptions of positivism dictate capacity for only approximate understanding of a phenomenon rather than a complete and wholly truthful understanding. In this study, operationalization (the translation of study elements into measurable variables) and reductionism (the simplification of study elements) are both contingent upon researcher judgment and potentially exclude valuable information critical to full understanding. A common criticism of the positivist perspective rests in its inflexibility and artificialness, particularly when faced with complex concepts. As expected, complicated, subjective concepts used in this study—such as sentiment and skepticism—present challenges when incorporated into a positivist research design. However, internal realists embrace the perspective that even the most attentive and well-designed research is naturally imperfect and incomplete, and that unavoidable imprecisions in research design do not wholly preclude the validity of statistically significant findings (Easterby-Smith, Thorpe, & Jackson, 2015).

4.2 Research Design

The relatively small extant quantity of VIs and the lack of peer-reviewed academic research on the virtual influencing phenomenon necessitates a quasi-experimental study to uncover aspects of the relationship between human and virtual reality levels of influencers and resulting levels of sentiment and skepticism that followers espouse. An experimental study aiming to establish causal links is neither feasible nor appropriate at this time given the small population of VIs and inability to sample randomly for a normal distribution (Burns & Burns, 2008). This research design relies on secondary data collection for two reasons. First, primary data collection from social media users via questionnaire or observation would severely limit the study's sample size and data volume due to sparse mainstream knowledge of VIs and researchers' relatively small community networks. In this case, a secondary approach allows for access to data from tens of thousands of unique users and ensures that users with knowledge of VIs are not underrepresented. Second, time constraints associated with this master thesis necessitated a cross-sectional data collection—collection occurred at a single point in time—rather than a longitudinal collection (Burns & Burns, 2008). Notably, a benefit of using publicly available data lies in its easy replication, either by original researchers or by a new research body. As a result, this secondary data-based design presents a fruitful opportunity for expanded research going forward.

4.2.1 Target Group Definition

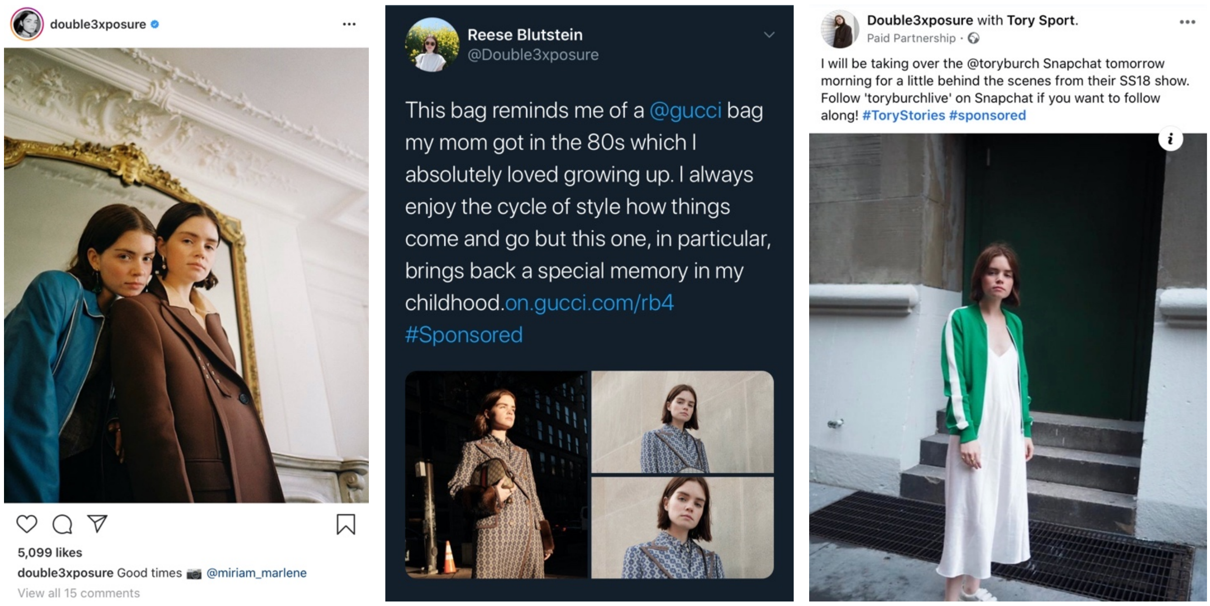
Contrary to VIs' limited mainstream awareness and absence from academic literature, human influencers (HIs) experience widespread awareness and acceptance among the general public and serve as a well-established touchpoint framing society's conceptualization of novel VIs (Influencer Marketing Hub, 2020a). The two influencer groups share key environmental and functional traits: they both operate primarily within the online social media sphere and cultivate distinct online personalities with the aim of impacting public opinion on concepts, products, brands, and more. These similarities enable robust comparison research between the two groups and allow for preliminary investigation into consumers' converging and diverging perceptions on influencers across reality levels.

4.2.2 Social Network Selection

In selecting a social media network within which to situate this study, Instagram emerged as most appropriate. Of all social media networks, Instagram is both the most widely used and the most effective network for influencing (Influencer Marketing Hub, 2020b; Mediakix, 2019). Accordingly, Instagram provides the richest opportunity for data collection from influencers, and studying Instagram influencers constitutes the most relevant and valuable influencer research for academics and practitioners alike. Furthermore, VIs overwhelmingly leverage Instagram as their primary means of communication. While ample HIs exist across multiple social networks, the relatively small quantities of VIs and the need for a sufficient sample size necessitated utilizing the social network most heavily saturated by VIs. Most importantly, Instagram's layout prioritizes post images and renders post copy as secondary, both sequentially (regarding the order in which elements appear on the page) and proportionally (regarding the relative size of elements). The premise of this study relies upon a user's ability to assess an influencer's physical appearance and form a determination of their reality level. Instagram's image-first format is most conducive to the visual demands of this study (see **Figure 3-2**).

Public Instagram accounts provide numerous opportunities for data collection. Objective account attributes include follower and followed account counts, number of likes, number and frequency of posts and comments, account longevity, engagement rate, frequency of certified branded partnerships, and verification status (indicating confirmed authenticity of a public figure's account). Subjective account data can be derived from the style and content of post images, captions, and comments. Both objective and subjective account attributes contribute to user judgments of sentiment and skepticism at the post and account levels.

Figure 4-1*. Examples of social media networks' layouts featuring HI Reese Blutstein (@double3xposure). Left to right: Instagram (hero image primary, copy secondary), Twitter (hero copy primary, images secondary), Facebook (copy primary, hero image secondary).*



4.3 Research Hypotheses

The following table outlines the full research hypotheses for this study put forth in **Chapter 3**. Researchers employ abbreviations denoting variable type for clarity, with "IV" referring to independent variables, "MV" referring to moderating variables, and "DV" referring to dependent variables.

Table 4-1. *Research hypotheses.*

Hypothesis	***Description***
Main hypotheses (independent variable – dependent variable)	
H1	**Reality level** (IV) has an effect on **sentiment** (DV_1) such that human influencers' Instagram activity will achieve higher degrees of positive commenter sentiment, while virtual influencers' Instagram activity will achieve lower degrees of positive commenter sentiment.
H2	**Reality level** (IV) has an effect on **skepticism** (DV_2) such that human influencers' Instagram activity will achieve lower levels of commenter skepticism, while virtual influencers' Instagram activity will possess higher levels of commenter skepticism.
Moderating effects (independent variable – moderating variable – dependent variable)	
H3	The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **longevity** (MV) such that influencers with greater longevity will achieve higher sentiment. Therefore, virtual influencers with low longevity will experience the lowest levels of sentiment, while human influencers with high longevity will experience the highest levels of sentiment.
H4	The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **longevity** (MV) such that influencers with greater longevity will achieve lower skepticism. Therefore, virtual influencers with low longevity will experience the highest levels of skepticism, while human influencers with high longevity will experience the lowest levels of skepticism.
H5	The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **engagement rate** (MV) such that influencers with higher engagement rates will achieve higher sentiment. Therefore, virtual influencers with low engagement rates will experience the lowest levels of sentiment, while human influencers with high engagement rates will experience the highest levels of sentiment.
H6	The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **engagement rate** (MV) such that influencers with lower engagement rates will experience higher skepticism. Therefore, virtual influencers with low engagement rates will experience the highest levels of skepticism, while human influencers with high engagement rates will experience the lowest levels of skepticism.
H7	The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **following size** (MV) such that influencers with higher numbers of followers will achieve higher sentiment. Therefore, virtual influencers with low numbers of followers will experience the lowest levels of sentiment, while human influencers with high numbers of followers will experience the highest levels of sentiment.

H8	The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **following size** (MV) such that influencers with higher numbers of followers will achieve lower skepticism. Therefore, virtual influencers with low numbers of followers will experience the highest levels of skepticism, while human influencers with high numbers of followers will experience the lowest levels of skepticism.
H9	The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **race** (MV) such that white influencers will achieve higher sentiment. Therefore, non-white virtual influencers will experience the lowest levels of sentiment, while white human influencers will experience the highest levels of sentiment.
H10	The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **race** (MV) such that white influencers will achieve lower skepticism. Therefore, non-white virtual influencers will experience the highest levels of skepticism, while white human influencers will experience the lowest levels of skepticism.
H11	The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **gender** (MV) such that female influencers will achieve higher sentiment. Therefore, male virtual influencers will experience the lowest levels of sentiment, while female human influencers will experience the highest levels of sentiment.
H12	The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **gender** (MV) such that female influencers will achieve lower skepticism. Therefore, male virtual influencers will experience the highest levels of skepticism, while female human influencers will experience the lowest levels of skepticism.

4.4 Operationalization of Variables

4.4.1 Overview of Sentiment and Skepticism

Ohanian's (1990) Source-Credibility Model identifies attractiveness, expertise, and trustworthiness as the critical components impacting the credibility of an influencer's communications. As previously mentioned, this study condenses these three concepts into two dimensions, labeling them as "sentiment" and "skepticism." Attractiveness and expertise combine to yield positive, negative, or neutral sentiment in a social media user's interactions with an influencer. Similarly, trustworthiness translates to a presence or lack of skepticism in a social media user's interactions with an influencer.

Given the abstract, subjective natures of sentiment and skepticism, single, standardized measures of each do not exist. Understanding that influencers' relationships with other social media users are interpersonal, researchers reviewed existing methods for measuring sentiment and skepticism, focusing on interpersonal methods used within a social media context, in order to develop scales appropriate for this study.

4.4.2 Operationalizing Sentiment

As a subjective measure, sentiment analysis typically examines polarity (positive, neutral, or negative sentiments) and strength (extent of positivity or negativity) of written text, and refrains from assigning distinct emotions like happiness, anger, or sadness to textual utterances (Taboada et al. 2011; Bae & Lee, 2012; Gonçalves, Benevenuto, & Cha, 2013). Two prevailing streams of sentiment analysis exist: the lexicon-based approach and the text classification approach. The lexicon-based approach relies on the semantic orientation of individual words and phrases, and utilizes either a traditional dictionary or a specialized dictionary manually or automatedly compiled by researchers for a specific project. The text classification approach depends upon development of machine learning programs and typically is highly specialized to a specific project, impeding appropriation in different contexts (Taboada et al. 2011).

Considering the immense volume of comments involved, a swift and simple means of classifying sentiment was necessary. Furthermore, given the time constraints and academic backgrounds of the researchers, neither creation of specialized dictionaries nor development of automated machine learning tools was feasible. Researchers first explored using a free, internet-based sentiment analysis tool, but an initial review of sentiment scores uncovered pervasive inaccuracies. Reasons for these inaccuracies included the tool's inability to interpret emojis, slang, misspellings, sarcasm, and foreign languages present in comments. As a result, employing researcher judgment enabled more accurate sentiment representations in the dataset.

Table 4-2. *5-point Likert scale used to measure sentiment.*

1	2	3	4	5
Very Negative	*Somewhat Negative*	*Neutral*	*Somewhat Positive*	*Very Positive*

Researchers leveraged a simple, 5-point Likert scale to assign numerical ratings to sentiment (**Table 4-2**). Ratings depended upon individual researchers' judgment of the direction and strength of comment sentiment. Researchers considered both conventional semantic definitions and colloquial connotations of comment terminology when assigning ratings. Direction defines the overall affective impression of a comment as negative, neutral, or positive. For example, terms like "hate" and "dislike" would be categorized as negative, while terms like "love" and "like" would fall into the positive category. Strength defines the relative extremity of a comment as somewhat or very. For example, terms like "love" and "hate" would be categorized as very strong, while terms like "like" and "dislike" would be categorized as somewhat strong. While individual terms with clear direction and strength assisted researchers in assigning sentiment ratings to whole comments, researchers used judgment to ensure that overall comment ratings reflected true perceived sentiment of whole comments. For example, though it includes the word "love," the comment "Love how her finger is going through ur hand" on a post from VI @knoxfrost was interpreted by both researchers as directionally ambiguous sarcasm meant to draw attention to image rendering inconsistencies. As such, the comment score was recorded as neutral (3) based on overall comment meaning rather than as very positive (5) based on the strong, positive term "love."

Reflecting on the choice to leverage researchers' individual judgment rather than an automated tool, the selected method proved particularly helpful in this study across multiple areas. First, an overwhelming majority of comments collected contain emojis. The automated tools considered did not support sentiment analysis for non-text characters, so researchers' first-hand knowledge of emojis' conventional interpretations within a millennial and Gen-Z online environment facilitated more effective interpretation of comment data. Second, automated tools struggle to accurately recognize slang terms and sarcasm, since both techniques tend to reappropriate conventional semantic definitions. Slang such as "Such a sick fit 🔥" and "Can you get yo foot off necks so we can breath!!!! Obsessed with this!!!! 😍 [sic]" or sarcasm such as "Stop being such an icon queen k thanks 💖" would likely receive negative sentiment ratings from an automated tool, while researchers interpreted all three comments to be positive. Third, researchers frequently encountered apparent spam comments in the dataset (for example, "I made amazing returns of $5650 through the help of @annekenricky on my bitcoin investment thanks @annekenricky"). An automated tool would likely award this comment a positive rating due to words like "amazing" and "thanks," but researchers employed judgment regarding spam comments' sentiment towards influencers and ultimately rated most spam comments as neutral (3). Extending this practice to collaboration-related comments, researchers also assigned neutral (3) ratings to generic collaboration requests absent of particular influencer relevance (for example, "Hey! DM us for collaboration 💕💕" but awarded positive ratings to more specific, complimentary collaboration requests such as "Amazing instagram Marcos. loving your style. Wanna collab with us? DM @kenzustreetwear and let's make it happen. 🔥"

4.4.3 Operationalizing Skepticism

When exploring scales for measuring skeptical attitudes towards influencers, scales measuring trust levels were first examined. Rotter (1967) defines interpersonal trust as the expectancy from an individual or group that another individual's statement can be relied upon, and measures trust in relation to other elements such as humor, friendship, popularity, gullibility, and trustworthiness. The Dyadic Trust Scale (Larzelere & Huston, 1980) assesses benevolence and honesty as components of trust in close relationships. Another scale by Rempel, Holmes, and Zanna (1985) evaluates trust in close relationships based on faith, predictability, and dependability. Three issues emerged in using trust scales. First, the aforementioned scales assess trust between individuals in the context of close relationships. Second, they focus more on identifying the variables that precede trust, rather than identifying how individuals express their trust towards others. Third, the contextual ambiguity of social media interactions makes it difficult to infer a complicated concept like trust. For example, would researchers be justified in inferring trust or distrust from a comment like "Who is this model? Is this digitally generated?" when its content is closer to basic skepticism?

Examining scales and models specific to skepticism proved more helpful for this study. Though often correlated with sentiment, skepticism exists as a distinct attribute. Merriam-Webster defines "skepticism" as "an attitude of doubt or a disposition to incredulity either in general or toward a particular object" and "the doctrine that true knowledge or knowledge in a particular area is uncertain; the method of suspended judgment, systematic doubt, or criticism" (Merriam-Webster, 2020). Multiple studies utilize scales for examining skepticism towards electronic WOM (Zhang, Ko, & Carpenter, 2016; Boerman et al. 2018). Though their proposed scale is complex, Zhang, Ko, and Carpenter (2016) simplify the concept of skepticism in an online environment by delineating three distinct sources: message truthfulness, message senders' motives, and message senders' identities. Boerman et al. (2018) leverage 7-point semantic differential scales, averaging scores to achieve a single skepticism rating.

Once again considering the immense volume of comments and the time constraints associated with this study, a swift and simple means of classifying skepticism was critical. The skepticism scales uncovered during the literature review were either unnecessarily complicated given this study's parameters, depended upon primary data collection, or were otherwise incompatible with this study's design. Furthermore, no free, automated tools for categorizing skepticism exist, likely due to the broad, subjective understanding of the concept and the same semantic challenges present in automated sentiment analysis tools. In light of these challenges, this study necessitated incorporating researchers' judgment to delineate skepticism. As mentioned, the vast majority of comments collected for this study were conceptually simple and straightforward. Most contained a single idea and clear presence or absence of skepticism, such as "Is he real???" or "Very beautiful 🌹." Researchers employed the three aforementioned sources of skepticism delineated by Zhang, Ko, and Carpenter (2016) to facilitate binary classification of individual comments, categorizing each as either containing skepticism ("1") or absent of skepticism ("0"), and drew on Boerman et al. (2018) in averaging the scores of all comments to achieve a single skepticism rating for each influencer.

Table 4-3. *Binary scale used to measure skepticism.*

0	1
No skepticism detected	*Skepticism detected*

Researchers leveraged a simple, binary scale to assign numerical ratings to skepticism (**Table 4-3**). Ratings depended upon individual researchers' perception of the presence or absence of skepticism. While researchers generally felt comfortable interpreting skepticism of comments figuratively, certain words with conflicting meanings required defaulting to a literal interpretation. For example, the term "unreal"—which spans multiple meanings such as critical skepticism, complimentary incredulity, and neutral uncertainty in this online context—occurred in multiple comments across reality levels. Examples include comments like "Unreal!! 💙💙" and "Looks unreal!!!!" on HIs' posts and "Unreal ❤️" and "UNREAL" on VIs' posts. Contextual clues like emojis, stylistic deviations, and other words hint at intended meaning, but researchers concluded that assuming a literal approach to rating skepticism (in this case, assuming all instances of the word "unreal" could potentially convey skepticism) would provide the most consistent results unbiased by reality level context or skepticism and sentiment of other post comments.

4.4.4 Operationalizing Longevity

Within the scope of this research, longevity refers to the lifespan of an influencer on Instagram, as measured in months elapsed since that influencer's first public post. This metric is not directly accessible within the Instagram platform, and required researchers to gather the dates of influencers' first posts to manually calculate the months elapsed since their initial posting. Longevity values used for this study are all based upon a cutoff date of April 1, 2020.

4.4.5 Operationalizing Engagement Rate

For the purpose of this research, engagement rate for each post is defined as (Likes + Comments) ÷ Total Follower Count. Engagement rate by influencer is based on the average engagement rate across ten posts from that influencer. For consistency and timely relevance, the researchers limited data collection to influencers' ten most recent posts, dating backwards from the cutoff date of April 1, 2020.

4.4.6 Operationalizing Following Size

Following size is a category grouping based on an influencer's total number of followers. Researchers leveraged categories rather than raw follower numbers for two main reasons. First, marketing practitioners widely accept classification of influencers into nano-, micro-, macro- and mega- groupings based on the number of followers they have (detailed in **Table 3-1**), as followers in each of these categories share common characteristics that are important to bear in mind when choosing an influencer to work with (Influencer Marketing Hub, 2020c). Second, the use of categories allows this data to be included in statistical tests. Given that VIs are a novel concept and that the small total population constrained sampling, the distribution across categories is not even. While large populations of nano- and micro- influencers exist, there are few virtual macro- and mega-influencers. Therefore, with the aim to perform comparisons across categories in the fairest manner, researchers combined macro- and mega- influencers under the same category, called "Macro/Mega." These two types of particularly popular influencers are conceptually and functionally close, so their fusion under the same category does not bias the implications of the obtained results. The remainder of influencers in the sample adhered to traditional micro- and nano- classifications.

4.4.7 Operationalizing Race

Race is a term utilized to distinguish major groups of people based on their ancestors and a distinctive combination of physical characteristics such as blood, skin color and general body complexion (Edwards, Fillingim, & Keefee, 2001). This term is not exempt of controversy and several researchers in a breadth of different academic fields attempt to deepen in the understanding of race and its implications (Outlaw, 1996; Sagas, 2000). However, the aim of this research is not to contribute to the definition of race, but to gain some understanding of the possible impact it may have on the perception of social media influencers. In keeping with the positivist research approach to this study, researchers employ a simplified, binary definition of race based on the physical appearance influencers exhibit in their posts. This study uses the classification "white" when an influencer's skin tone is light and their appearance approximates traditionally European features, and "non-white" when their appearance does not meet this criteria.

4.4.8 Operationalizing Gender

Gender refers to the prevailing norms of what is expected from women and men in terms of role in society, activities, attitudes, and behaviors (Subrahmanian, 2005). This topic has been covered by researchers in different fields and recently, attempts on redefining gender beyond the binary traditional conceptualization of male-female roles have emerged (Richards et al. 2016). As with race, the aim of this research is not to contribute to a new definition of gender, but to obtain some insights on the impact of this variable in para-social interactions across influencer reality levels. For that reason, the traditional binary classification of gender has been utilized, and influencers have been categorized as ‘male’ or ‘female’ based on their appearance.

4.5 Data Collection Method

Data collection spanned two phases: simple and complex. Simple data collection occurred in conjunction with sample compilation and involved recording easily accessible, surface-level descriptive data. Complex data collection involved more time-intensive processes to mine complex objective and subjective data from Instagram accounts. Methods are detailed below.

The extant influencer climate defined construction of a sample comprising target populations of human and virtual influencers. Given VIs’ novelty and their relatively small volume compared to HIs, this study necessitated incorporating as many VIs as possible to achieve a sample size sufficient for analysis. Considering this, researchers began by cataloging extant VIs.

First, researchers applied non-probability judgment sampling to compile a list of well-known VIs that emerged frequently in our preliminary research (for example, @lilmiquela, @bermudaisbae, @blawko22, and @noonoouri). Next, researchers leveraged a comprehensive directory of VIs compiled by VirtualHumans.org to augment the VI sampling frame. Finally, additional VIs were sourced using an informal snowball sample in which researchers manually searched comments on the posts of VIs already included in the study to uncover additional VIs. In multiple cases, researchers noted instances of lesser-known VIs commenting on well-known VIs’ posts to boast about their own digital origins (see **Figure 4-5**). Through these sampling methods, this study achieved a near-perfect sampling frame of virtual influencers, accounting for nearly all VIs in possession of baseline volumes of followers, posts, and follower engagement to be valuable to this study. VIs with fewer than 1,000 followers, fewer than ten posts, or fewer than fifteen total follower comments across ten posts provided too little meaningful data and therefore did not meet selection criteria for this study. For each VI cataloged, researchers recorded the influencer’s username, reality level, follower count, race, gender, and general content type (for example, “fashion” or “beauty”). **Table 4-4** details the collection procedure for each element.

Table 4-4. *Data points compiled during simple data collection phase and collection procedures utilized.*

Data point	***Collection procedure***
Account username	Publicly available on influencer profile.
Reality level	Subject to researcher judgment based on assessment of account images and/or categorization from news coverage or directories.
Follower count	Publicly available on influencer profile.
Following size	Derived from follower count according to the ranges specified in **Table 3-1**.
Race	Subject to researcher judgment based on assessment of account images and/or categorization from news coverage or directories.
Gender	Subject to researcher judgment based on assessment of account images and/or categorization from news coverage or directories.

General content type	Subject to researcher judgment based on assessment of account images and/or categorization from news coverage or directories.

Figure 4-2*. VI @viola.nuova (567 followers) comments on @shudu.gram's (199,000 followers) post, saying, "I'm digital like you."*

To compile the sample of HIs, researchers leveraged non-probability judgment sampling in conjunction with quota sampling to create matched pairs based on quotas derived from VI sample attributes: follower count (18 mega- and macro-influencers, 24 micro-influencers, and 23 nano-influencers), gender (18 men, 46 women), race (30 white, 35 non-white), and content type (a mix of fashion, beauty, lifestyle, and fitness accounts). As with VIs, researchers applied judgment sampling based on exploration of influencer-related news articles and influencer directories to compile a sample of HIs. While the large population of HIs allowed for probability random sampling, the small sample size of VIs and narrow parameters regarding number of followers and content type meant non-probability judgment sampling delivered a cleaner sample for comparison between HIs and VIs. Data collection procedure for the elements in **Table 4-4** remained consistent across VI and HI sampling. To minimize variance in influencers' follower counts (which tend to increase gradually over time), researchers compiled the full sample of VIs and HIs within a short timeframe spanning April 9, 2020 to April 16, 2020.

The second, more complex phase of data collection comprised time-intensive collection, calculation, and rating methods. As with collection of the data points previously outlined, researchers sought to minimize variance in sample data like engagement rate and post comments, so data collection in this phase was restricted to a short timeframe spanning April 16, 2020 to May 9, 2020.

First, researchers compiled longevity for all influencer accounts. This simply involved scrolling through each account's full feed of posts to view the date associated with the account's first public post; the complexity arose solely from the amount of time involved to access this data.

Second, researchers collected engagement rate components from ten posts per account. Posts were subject to multiple criteria to ensure integrity of data and relevance to this study. Most importantly, posts required at least one comment each by an Instagram user other than the influencer themselves in order to facilitate sentiment and skepticism analysis. Furthermore, researchers mandated that all selected posts show each influencer's distinguishing characteristics so that reality level, race, and gender could be feasibly deduced by other Instagram users. Finally, researchers selected the ten most recent posts compliant with the above criteria dating from April 1, 2020 and prior. This allowed the study to incorporate recent posts, and the time buffer between original posting date and data collection date helped achieve an accurate representation of post activity since the rate of new likes and comments on posts tends to peak in the first days after posting and flatten over time. As mentioned, the engagement rate formula used for each post was: (Likes + Comments) ÷ Total Follower Count. After recording engagement rates for each of the ten posts per account, researchers averaged individual post rates to obtain a single overall engagement rate for each influencer.

Using the ten posts per influencer selected according to the aforementioned criteria, researchers used web scraping tools to download comments on each individual post. The free web scraping tools that researchers first encountered possessed limits on number of comments extracted, and number of unique comment exports per day. In the cases of InstaLoadGram and The Raffler, researchers noted that neither tool limited comment exports per day at the beginning of this study, but over the course of data collection, both tools updated their terms to restrict the frequency of data exports, likely due to the influx of site requests associated with this particular study. The limitations of each tool considered dictated a data collection process that leveraged different tools given post metrics. For example, researchers utilized a tool with stricter limitations for virtual micro-influencer @aliona_pole (whose individual post comments never exceeded 30), while virtual mega-influencer @lilmiquela (whose individual post comments regularly exceeded 1,000) required a tool with laxer limitations and greater processing ability. Tools and their limitations are outlined below in **Table 4-5**. Considering these limitations, researchers included up to 100 comments per post, meaning that for each influencer, the maximum number of comments collected could not exceed 1,000. In cases where over 100 comments were collected for a single post (specifically, data from Export Comments and Apify Instagram Scraper), researchers selected the 100 earliest comments. After exporting, researchers utilized Google Translate to translate any non-English comments to English. Comment collection yielded 41,382 individual post comments across all influencers.

Table 4-5*. Web scraping tools used to export Instagram comments, with each tool's limitations detailed.*

Tool name	***Limitations on free exports***
Export Gram	Supports posts with unlimited comments, but only exports 200 comments per post
Export Comments	Supports posts with unlimited comments, but only 100 comments per post; 5 exports per day
InstaLoadGram	Supports only posts with fewer than 100 comments; exports all comments for supported posts; 5 exports per day (unlimited at start)

The Raffler	Supports posts with unlimited comments, but only exports 100 comments per post; 3 exports per day (unlimited at start)
Apify Instagram Scraper	Supports posts with unlimited comments*; 10 compute units total supported

*Researchers observed that the tool did not function properly for posts with over 400 comments.

Upon recording comments for each influencer in the sample, researchers proceeded to rate each comment for sentiment and skepticism according to the criteria set out in **Section 4.4.2** and **Section 4.4.3**. Each researcher input initial ratings completely blind to the ratings of the other researcher in order to minimize cognitive biases related to groupthink and the bandwagon effect. It is important to note that researchers were not blind to other elements of influencer data when rating individual comments (specifically account username, reality level, and other comments). Researchers opted not to blind themselves to this information because they viewed context as necessary for determining sentiment and skepticism. For example, the meaning of a simple comment like "The Flash🤤🤤" is difficult to deduce in the absence of contextual cues. Given Instagram's image-based format, a reference to "flash" along with drooling emoji faces could indicate a commenter's admiration of the influencer's photographic techniques, resulting in a positive sentiment score. However, context provided clues implying this comment actually refers to *The Flash*, a Netflix series, thus warranting a neutral sentiment score.

After inputting all sentiment and skepticism ratings, researcher scores were averaged to achieve a single score for each individual comment. In the case of sentiment, total individual comment scores per influencer were averaged to obtain a single overall sentiment score for each influencer in the dataset. As a binary metric, researchers treated skepticism differently. In cases of inconsistent skepticism ratings across researchers, comments were examined and discussed to agree on a single rating. This helped researchers adhere to consistent rating procedures and reinforced uniformity with the skepticism parameters used for this study. Upon finalizing skepticism for each comment, the scores per influencer were averaged to obtain a single overall skepticism score for each influencer in the dataset.

4.6 Data Analysis Methods

The data collection was split between the two researchers in this analysis, so a review of the gathered details and scrutiny to guarantee that all data were collected consistently and accurately was conducted. Afterward, the data was analyzed using Independent-Samples T-Tests, Linear Regression Models, Factorial ANOVA Tests, and Correlation Analyses.

4.6.1 Data Preparation

After obtaining all information needed for analysis, researchers took two measures to clean the dataset. First, any comments that influencers made on their own posts were removed from the data. Researchers felt that including influencers' own comments was appropriate in the case of engagement rate because unique users' comments and influencers' own comments both contribute to users' perceptions of post engagement. However, in measuring sentiment and skepticism, this study is only concerned with how other social media users view influencers, not with how influencers view themselves. Furthermore, influencers' commentary on their own posts typically manifests as responses to other users, so these influencer replies provide little meaningful, novel content. In consideration of this, researchers chose to omit ratings of influencers' own comments in final sentiment and skepticism scores.

Second, researchers removed influencers incompatible with this study. In total, 130 influencer profiles were scrutinized. However, researchers removed three VIs from the final sample due to study incompatibility. Two VIs, @fnmeka and @teflonsega, possessed private accounts incompatible with the web scraping tools used for comment extraction. Manual data extraction, while technically possible, was not feasible in the context of this study due to its time-intensiveness and the ethical concerns raised by data collection from private accounts. Researchers removed an additional VI, @magazineluiza, when a preliminary inspection of post data uncovered that the comments primarily posed company- and product-related questions and concerns rather than focusing on the company's virtual avatar, Lu. As such, @magazineluiza's atypical customer service focus represented an outlier among all other VI accounts studied and was inappropriate to include within the sample. Ultimately, 127 influencers qualified for inclusion in the sample, and all relevant data collected on these influencers was transferred to a final summary data file used as the basis for the studies in Jamovi (**Appendix A**).

4.7 Data Analysis Methods

4.7.1 Independent-Samples T-Test

The two main hypotheses exploring whether the means of influencer scores in sentiment and skepticism differ based on their reality level. Each hypothesis focuses on the study of one variable (sentiment or skepticism) in relationship with an influencer's reality level. Thus, researchers deemed univariate techniques to be most appropriate, as they are used to analyze variables in isolation (Malhotra, 2012). Within this group and given that the collected data for sentiment and skepticism were measured on a ratio scale, a test for metric data was the best fit in this study (Malhotra, 2012). Lastly, given that the intention was to analyze two different samples and determine whether they belong to the same population or if their mean scores are statistically significantly different (Burns & Burns, 2018), an Independent Samples T-Test emerged as the most appropriate univariate metric test to run.

4.7.2 Multivariate Techniques

The remainder of the hypotheses proposed in this research explore the interaction between several variables, so examine several variables simultaneously. For this reason, multivariate techniques were more appropriate in these cases (Malhotra, 2012).

Factorial ANOVA Tests

This study examined the effects of several independent and moderating variables on the dependent variables of sentiment and skepticism. Given that each hypothesis only takes one of these two dependent variables into account, dependence techniques for one dependent variable were the most appropriate (Malhotra, 2012). Within this group, Factorial ANOVA Tests allowed researchers to study two factors of interest simultaneously and explore each of these factors' main effects on the dependent variable as well as the interaction effect between the two variables on the dependent variable (Burns & Burns, 2018). However, this technique requires variables data expressed at the nominal or ordinal level, which makes it inappropriate for testing ratio measurements like longevity and engagement rate. Thus, Factorial ANOVA Tests were employed for all moderating variables *except* longevity and engagement rate.

Linear Regression Analysis
An alternative technique to ANOVA testing that is compatible with ratio level data is Linear Regression Analysis. The different regression models allow the researchers to predict likely values of the dependent variable from known values of one or several independent variables. In this case, as two variables are of interest and the focus is to determine if the presence of one of these variables has a moderating effect on the interaction between the independent and dependent variables, the Multiple Linear Regression technique was appropriate (Burns & Burns, 2018).

Correlation Analysis
A Correlation Analysis enables identification of correspondence between variables. It helps to illuminate relationships across variables, but does not specify the direction of the relationships (Burns & Burns, 2018). Added to this study in the absence of significant findings, the Correlation Analysis helps to obtain a broader understanding of the relationships between the selected variables for this study and their bearings on the hypotheses proposed.

4.8 Research Quality

Assessing the quality of research is essential to ensuring the integrity of the findings (Onwuegbuzie, 2000). Thus, concepts such as reliability, validity, and ethics should take into consideration throughout the data collection and analysis processes. The following sections cover the actions taken in this study to ensure reliability, validity, and ethical approach.

4.8.1 Reliability

Reliability refers to the stability and consistency of findings that enables replication by future researchers (Burns & Burns, 2008). The capacity to provide a thorough framework for a study such that it offers consistent and stable results across research contexts demonstrates a research project's quality.

According to Burns and Burns (2008), the reliability of a research methodology can be evaluated using multiple different approaches. One approach involves assessing if the obtained data is consistent with the data that would be obtained in the instance of future testing. The data obtained for this study are publicly available on the Instagram platform. Researchers obtained influencers' account metrics (longevity, engagement rate, and following size) from readily available account information and explained all calculations and nuances involved in finalizing these metrics. The collection of these data in the future is generally considered replicable as influencers are public personalities and all data originated from public accounts, though changes in personal privacy policies may restrict access to Instagram accounts in the future. The categorizations of race and gender follow literary precedents for defining binary groupings of these variables. The parameters of these variables have been thoroughly defined so that a similar categorization can be replicated in the future. However, differences in the understanding of race and gender exist across cultures and generations. With that in mind, future research should ensure that the definitions of race and gender employed in a study are relevant for the specific context. Additionally, researchers thoroughly detailed the comment rating procedures for skepticism and sentiment and assigned ratings in the most objective and consistent manner possible. In addition to the extensive coverage of sentiment and skepticism rating procedures provided in **Chapter 4**, **Appendix C** includes an example showing VI @xx_uca_xx's post comments and researcher ratings for sentiment and skepticism. As previously mentioned, utilization of an automated rating tool will enhance the replicability of this process and eliminate potential differences in the measurement of these two variables based on the cultural background of the researchers. However, no reliable tool exists at present, so the proposed scales set forth in this study approach the most reliable means of assessment possible. Finally, the Source-Credibility Model (Ohanian, 1990) that researchers utilized as a basis for identifying key underlying dimensions of influencer credibility for this study was tested for reliability by its author. Basing the research design around this model thus enhances the quality of this research.

The accuracy of the selected variables is another means of justifying the reliable nature of this study. This research primarily examined the relationships between the independent variable reality level and dependent variables sentiment and skepticism. These three dimensions have been designed and discussed in a simple, clear way to ensure that the key aspects of this study can be accurately conceptualized. Firstly, reality level designates whether an influencer is a human being or a computer-generated entity. This distinction was made looking at the visual cues in the influencers' content that allowed the researchers identify their nature. Furthermore, in some cases, VIs disclose their computer-generated origins, which simplifies the task of differentiating them from human beings. Finally, use of publicly available online directories helped corroborate researcher judgments on reality level. As such, reality level classifications present in this study are corroborated on multiple levels to ensure as much accuracy as possible. As mentioned, the sentiment and skepticism scales constructed for this study clearly aim at being objective, consistent, and reliable, and are based on previously developed reliable and established models and scales. For that reason, the authors of this study consider that they are accurate in capturing social media users' perceptions of sentiment and skepticism towards influencers.

4.8.2 Validity

Reviewing the internal and external validity of research also serves to enhance the quality of study results. By ensuring that the observed differences on the dependent variables are direct results of the independent variable—and not affected by anything else—this study contributes findings that are more reliable and therefore of high quality.

Keeping external validity in mind, researchers undertook measures to guarantee a generalizable sample. As the sample included different age, race and following size groups, the sample was not homogeneous and reflected the diversity present in the studied populations for these categories. Conversely, non-probability methods were applied in sampling. This allowed researchers to cover nearly the entire population of VIs with the sample, although this technique comes with some faults, as sampling theory is intended to be used in conjunction with probability sampling and can lead to errors when misused. Nevertheless, it is also true that normality is a mathematical abstraction, and not a reflection of a real-world event (Burns &

Burns, 2008). For this reason, and given that the data displayed a distribution close enough to normality, researchers elected to pursue parametric testing. Ultimately, the decision to use non-probability sampling was driven by the novelty of this topic and small population of VIs, and allowed researchers to collect enough data to address the research question. Given the limitations on time and resources, this was the best approach for this study.

Researchers also undertook measures to ensure internal validity. For example, influencer data—including comments, engagement rate and number of followers—was collected over a limited time period. Furthermore, all posts studied were shared on influencers' accounts on or before April 1, 2020, and only the comments up to that date were included in the assessment. These decisions were made to avoid threats to internal validity; however, influencers' and social media users' revisions or deletions of posts, captions, and comments understandably may impact this study's dataset. To avoid internal validity threats associated with researcher judgment, sentiment and skepticism scores were assigned to each comment using a clearly defined and objective score method. Researchers were also blind to each other's inputs until the culmination of the study. It is critical to note that differences in cultural backgrounds of future researchers or evolutionary changes in society's perceptions of sentiment and skepticism may impact these scores and the research outcome in the future. As mentioned, using an automated tools to assign ratings could help combat this concern, though no such reliable tools exist at this time.

4.8.3 Ethical Considerations

Ethical research involves applying moral principles to research design and data collection and analysis (Burns & Burns, 2008). Ethics play a vital role in governing research, as the application of moral standards to a project ensures research is amiably and respectfully conducted. An ethical approach underscoring a research project also helps to curtail any misbehavior on behalf of the researchers and protects all parties involved.

The researchers of this study commit to being objective in this research. This involves providing the full results of this study, regardless of their outcome as positive, negative, insightful, or irrelevant. Furthermore, the authors of this study commit to the right to anonymity and confidentiality of individuals. Hence, the design focused only on influencers with publicly available profiles, and only publicly available comments of other social media users were included in this study. Researchers did not collect any personal data on the commenters aside from their usernames, and limited data collection for influencers to only the metrics necessary for conducting this study. Instagram's terms and conditions provide that all users of the platform grant Instagram the right to publicly display their posts, comments, and any other information unless they opt to make their account private, so all data collection for this study was implicitly agreed to by all parties involved.

5 Analysis and Results

This chapter presents the empirical findings of this research. The hypotheses of this study were tested employing Independent-Samples T-Tests, Linear Regression Models, and Factorial ANOVA Tests. Upon examining initial results, researchers undertook a Correlation Analysis to provide additional understanding regarding the interrelationship of variables.

5.1 Analysis Approach

The first step of data analysis in this study involved ensuring that the values met statistical standards. Therefore, researchers checked the statistical significance of the full dataset using Levene's Test of Homogeneity of Variance before testing the hypotheses outlined in **Chapter 3**. In order to facilitate this, researchers stated null and alternative hypotheses for testing. Typical null and alternative hypotheses are demonstrated below (Burns & Burns, 2008).

H0: The finding was simply a chance occurrence (*null*)
H1: The finding did not occur by chance (*alternative*)

The hypothesis testing process begins assuming that the null hypothesis is true. If the findings of a study are unable to support the null hypothesis, then the alternative hypothesis is considered more likely to be correct. Based on Burns and Burns (2008), an alpha of 0.05 constitutes a reasonable threshold to prove significance; when the significance level is 5% or lower ($p < 0.05$), the null hypothesis is rejected, whereas if the significance level is greater than 5% ($p > 0.05$), the null hypothesis is accepted. Strong significant results may reach the 1% ($p \approx 0.01$) threshold.

Once testing identifies the significance of relationships, conducting further testing is needed to measure effect size, or the strength of the association between the independent and dependent variables (Burns & Burns, 2008).

5.2 Analysis of Results: Independent Variables

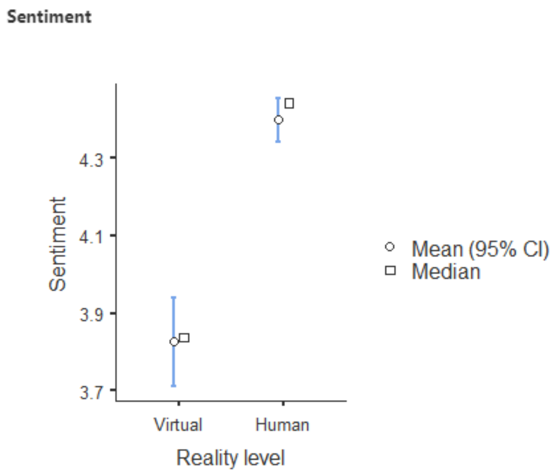
5.2.1 Reality Level and Sentiment

Researchers leveraged an Independent-Samples T-Test to evaluate the hypothesis (H1) that reality level has a significant effect on the sentiment expressed by Instagram users in influencers' post comments. Because the variances for the two groups were significantly unequal based on the Levene's Test for Homogeneity of Variance ($F = 57.0$, $p < 0.001$), researchers utilized the output for unequal variances. The mean sentiment recorded for HIs (M

= 4.39, SD = 0.23) was statistically significantly different (t = 8.90, df = 125, $p < 0.001$) from that of VIs (M = 3.826, SD = 0.46). The effect size d = 1.58 implies a very strong effect.

The error bar chart (**Figure 5-1**) supports a strong difference in sentiment across reality levels, showing a high degree of separation of the 95% confidence intervals of sentiment for HIs and VIs:

Figure 5-1*. Error bar chart for H1.*



These data encourage rejection of the null hypothesis that the difference in sentiment across reality levels occurred by chance, and supports acceptance of researchers' alternative hypothesis.

H1 (*supported*): **Reality level** (IV) has an effect on **sentiment** (DV_1) such that human influencers' Instagram activity will achieve higher degrees of positive commenter sentiment, while virtual influencers' Instagram activity will achieve lower degrees of positive commenter sentiment.

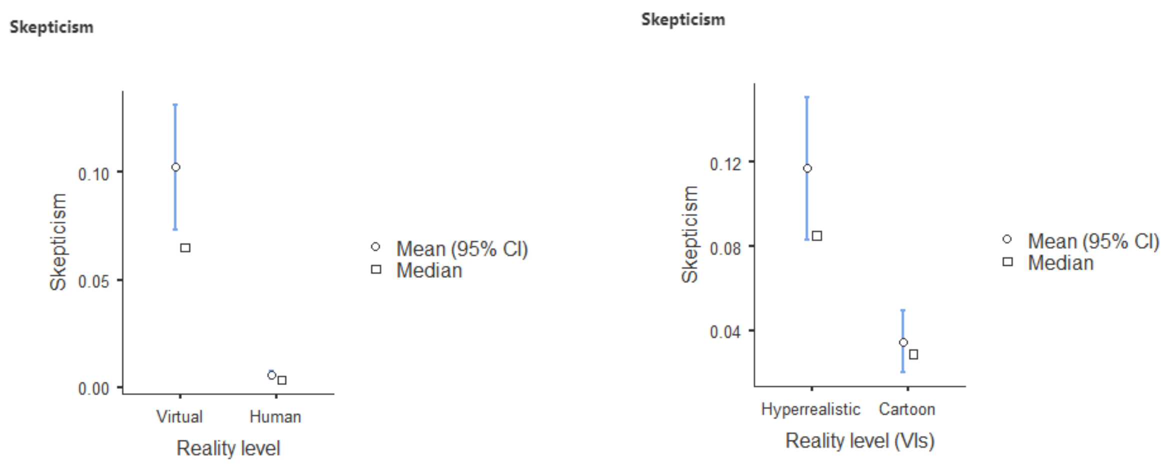
Though not outlined in an official research hypothesis due to the unreliability associated with the uneven distribution of sample sizes (51 hyperrealistic VIs versus 11 cartoon VIs), researchers sought to examine sentiment across the two VI reality levels. Applying the aforementioned analysis techniques, researchers attempted a second Independent-Samples T-Test, but the variances for the two virtual groups were *not* significantly unequal based on the Levene's Test for Homogeneity of Variance (F = 0.138, p = 0.712), indicating a lack of significant results for the Independent-Samples T-Test.

5.2.2 Reality Level and Skepticism

Following the same procedure for sentiment, researchers leveraged an Independent-Samples T-Test to evaluate the hypothesis (H1) that reality level has a significant effect on the skepticism expressed by Instagram users in influencers' post comments. Because the variances for the two groups were significantly unequal based on the Levene's Test for Homogeneity of Variance (F = 25.3, $p < 0.001$), researchers utilized the output for unequal variances. The mean skepticism recorded for HIs (M = 0.005, SD = 0.007) was statistically significantly different ($t = -6.68$, $df = 125$, $p < 0.001$) from that of VIs (M = 0.102, SD = 0.116). The effect size $d = -1.19$ implies a very strong effect.

As in the case of sentiment, the error bar chart (**Figure 5-2**, **left**) supports a strong difference in skepticism across reality levels, showing a high degree of separation of the 95% confidence intervals of sentiment for HIs and VIs:

Figure 5-2. *Error bar charts for H1. Left: error bar chart for HIs and VIs; right: error bar chart for hyperrealistic VIs and cartoon VIs.*



These data encourage rejection of the null hypothesis that the difference in skepticism across reality levels occurred by chance, and supports acceptance of the researchers' alternative hypothesis.

H2 (*supported*): **Reality level** (IV) has an effect on **skepticism** (DV_2) such that human influencers' Instagram activity will achieve lower levels of commenter skepticism, while virtual influencers' Instagram activity will possess higher levels of commenter skepticism.

Though not outlined in an official research hypothesis due to the unreliability associated with the uneven distribution of sample sizes (51 hyperrealistic VIs versus 11 cartoon VIs), researchers sought to examine skepticism across the two VI reality levels. Applying the aforementioned analysis techniques, researchers ran a second Independent-Samples T-Test. Because the variances for the two groups were significantly unequal based on the Levene's Test for Homogeneity of Variance ($F = 7.35$, $p = 0.009$), researchers utilized the output for unequal variances. The mean skepticism recorded for hyperrealistic VIs (M = 0.117, SD = 0.123) was statistically significantly different ($t = 2.19$, $df = 60.0$, $p = 0.032$) from that of cartoon VIs (M = 0.0347, SD = 0.0249). The effect size $d = 0.729$ implies a very strong effect.

The error bar chart (**Figure 5-2**, **right**) supports a strong difference in skepticism across VI reality levels, showing a high degree of separation of the 95% confidence intervals of sentiment for hyperrealistic VIs and cartoon VIs.

5.3 Analysis of Results: Moderating Variables

To broaden the understanding of the drivers influencing differences in sentiment and skepticism between HIs and VIs, researchers conducted additional analyses to explore the effects of longevity, engagement rate, following size, influencer race, and influencer gender in moderating the relationships between reality level and sentiment and skepticism. Different levels of measurement used for variables necessitated employing two different methods of analysis. Following size (degraded from number of followers, a ratio-level measure), race, and gender constitute nominal measurements, allowing for the utilization of ANOVA testing to explore possible interactions between variables. Longevity and engagement rate, on the other hand, are ratio measurements, and therefore incompatible with ANOVA testing. For these variables, researchers leveraged a simple slope analysis instead. The results of these tests are presented in the following sections.

5.3.1 Longevity Moderating Reality Level and Sentiment

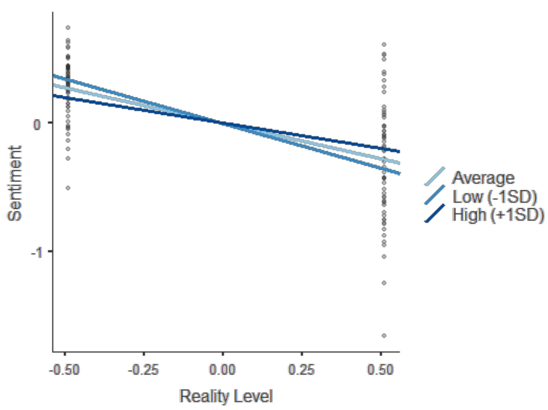
In order to examine the potential moderating effect of influencers' longevity on the relationship between reality level and sentiment, researchers conducted a Simple Slope Analysis.

Figure 5-3. *Simple slope analysis moderation estimates for H3.*

Moderation Estimates

	Estimate	SE	Z	p
Reality Level	-0.54528	0.06331	-8.613	< .001
Longevity	4.29e-4	9.28e-4	0.462	0.644
Reality Level ✻ Longevity	0.00440	0.00280	1.574	0.116

Figure 5-4. *Simple slope plot for H3.*



The results of this analysis (**Figure 5-3**, **Figure 5-4**) show that the interaction between reality level and longevity has no significant effect on sentiment (p = 0.116). Furthermore, longevity does not have a significant main effect on sentiment, either (p = 0.644). These data support the acceptance of the null hypothesis and the rejection of researchers' alternative hypothesis.

H3 (*not supported*): The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **longevity** (MV) such that influencers with greater longevity will achieve higher sentiment. Therefore, virtual influencers with low longevity will experience the lowest levels of sentiment, while human influencers with high longevity will experience the highest levels of sentiment.

5.3.2 Longevity Moderating Reality Level and Skepticism

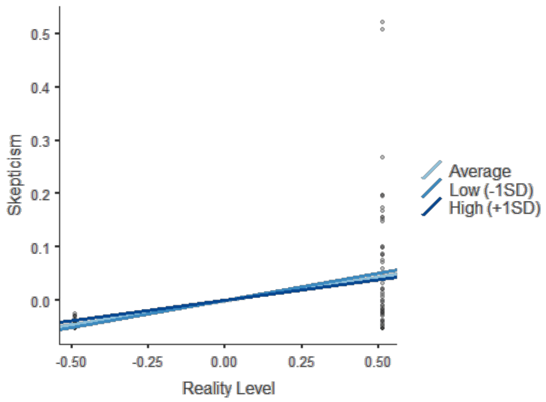
In order to examine the potential moderating effect of influencers' longevity on the relationship between reality level and skepticism, researchers conducted a Simple Slope Analysis.

Figure 5-5. *Simple slope analysis moderation estimates for H4.*

Moderation Estimates

	Estimate	SE	Z	p
Reality Level	0.0895	0.0144	6.233	< .001
Longevity	-1.34e−4	2.10e-4	-0.636	0.525
Reality Level ✻ Longevity	-3.88e−4	6.34e-4	-0.613	0.540

Figure 5-6. *Simple slope plot for H4.*



The results of this analysis (**Figure 5-5**, **Figure 5-6**) show that the interaction between reality level and longevity has no significant effect on skepticism (p = 0.540). Furthermore, longevity does not have a significant main effect on skepticism, either (p = 0.525). These data support the acceptance of the null hypothesis and the rejection of researchers' alternative hypothesis.

H4 (*not supported*): The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **longevity** (MV) such that influencers with greater longevity will achieve lower skepticism. Therefore, virtual influencers with low longevity will experience the highest levels of skepticism, while human influencers with high longevity will experience the lowest levels of skepticism.

5.3.3 Engagement Rate Moderating Reality Level and Sentiment

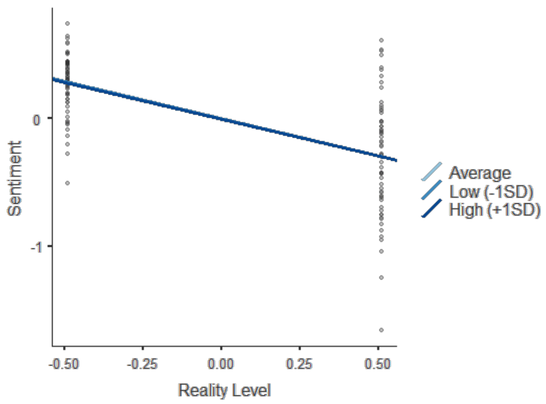
In order to examine the potential moderating effect of engagement rate on the relationship between reality level and sentiment, researchers conducted a Simple Slope Analysis.

Figure 5-7*. Simple slope analysis moderation estimates for H5.*

Moderation Estimates

	Estimate	SE	Z	p
Reality Level	-0.5808	0.0633	-9.178	< .001
Engagement Rate	0.6058	0.4371	1.386	0.166
Reality Level ✻ Engagement Rate	0.0879	0.8774	0.100	0.920

Figure 5-8*. Simple slope plot for H5.*



The results of this analysis (**Figure 5-7**, **Figure 5-8**) show that the interaction between reality level and engagement rate has no significant effect on sentiment ($p = 0.920$). Furthermore, engagement rate does not have a significant main effect on sentiment, either ($p = 0.166$). These data support the acceptance of the null hypothesis and the rejection of researchers' alternative hypothesis.

H5 (*not supported*): The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **engagement rate** (MV) such that influencers with higher engagement rates will achieve higher sentiment. Therefore, virtual influencers with low engagement rates will experience the lowest levels of sentiment, while human influencers with high engagement rates will experience the highest levels of sentiment.

5.3.4 Engagement Rate Moderating Reality Level and Skepticism

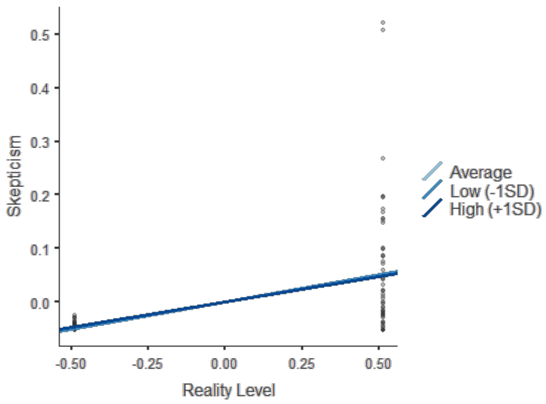
In order to examine the potential moderating effect of engagement rate on the relationship between reality level and skepticism, researchers conducted a Simple Slope Analysis.

Figure 5-9. Simple slope analysis moderation estimates for H6.

Moderation Estimates

	Estimate	SE	Z	p
Reality Level	0.0969	0.0143	6.752	< .001
Engagement Rate	-0.0114	0.0991	-0.115	0.909
Reality Level ✻ Engagement Rate	-0.0483	0.1990	-0.243	0.808

***Figure 5-10**. Simple slope plot for H6.*



The results of this analysis (**Figure 5-9**, **Figure 5-10**) show that the interaction between reality level and engagement rate has no significant effect on skepticism ($p = 0.808$). Furthermore, engagement rate does not have a significant main effect on skepticism, either ($p = 0.909$). These data support the acceptance of the null hypothesis and the rejection of researchers' alternative hypothesis.

H6 (*not supported*): The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **engagement rate** (MV) such that influencers with lower engagement rates will experience higher skepticism. Therefore, virtual influencers with low engagement rates will experience the highest levels of skepticism, while human influencers with high engagement rates will experience the lowest levels of skepticism.

5.3.5 Following Size Moderating Reality Level and Sentiment

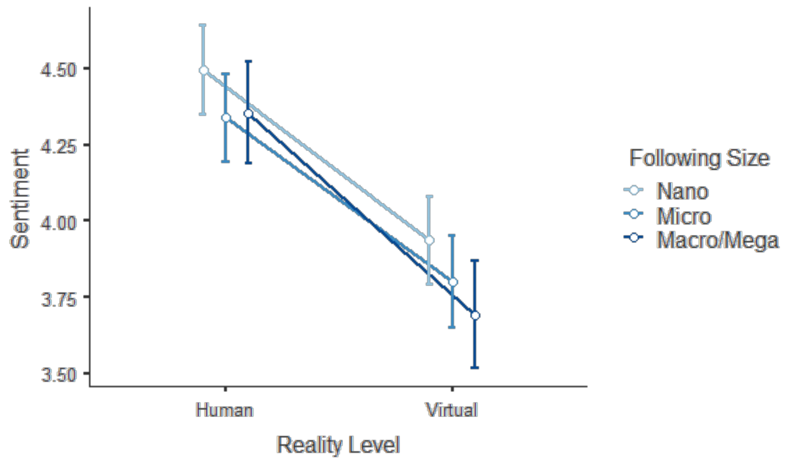
While ratio-level data enabled Independent-Samples T-Tests for the moderating variables previously described, the nominal categorization of following size, race, and gender necessitated analysis using an ANOVA test. To examine the potential moderating effect of following size on the relationship between reality level and sentiment, researchers conducted a Factorial ANOVA Test to investigate interaction effect between reality level and following size.

Figure 5-11. *Factorial ANOVA for H7.*

ANOVA - Sentiment

	Sum of Squares	df	Mean Square	F	p
Reality Level	10.6212	1	10.6212	83.109	< .001
Following Size	0.8402	2	0.4201	3.287	0.041
Reality Level ✻ Following Size	0.0845	2	0.0423	0.331	0.719
Residuals	15.4636	121	0.1278		

Figure 5-12. *Main effects plot for H7.*



The results of this analysis (**Figure 5-11**) reveal a main effect for reality level ($F = 83.1$, $p < 0.001$) and following size ($F = 3.287$, $p = 0.041$) separately, but show no significant effect for the interaction between the two variables ($F = 0.33$, $p = 0.719$). The main effects plot (**Figure 5-12**) reiterates the differences in sentiment towards influencers based on their reality level: overall, HIs received a substantially higher sentiment score than VIs. The plot also shows a main effect for following size which leads to substantial differences in sentiment across following size categories. A smaller following size clearly indicates higher sentiment, and vice versa. Though these results are statistically significant, since researchers' hypothesis specified a different relationship, these findings do not support H7; however, the main effect of following size is important to note. Ultimately, these data technically support the acceptance of the null hypothesis and rejection of researchers' alternative hypothesis since following size does not moderate the relationship between reality level and sentiment; it is a main effect.

H7 (*not supported*): The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **following size** (MV) such that influencers with higher numbers of followers will achieve higher sentiment. Therefore, virtual influencers with low numbers of followers will experience the lowest levels of sentiment, while human influencers with high numbers of followers will experience the highest levels of sentiment.

5.3.6 Following Size Moderating Reality Level and Skepticism

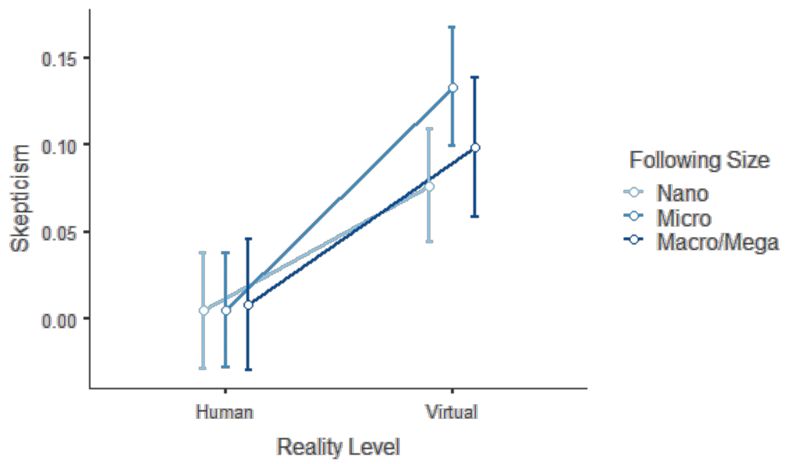
To examine the potential moderating effect of following size on the relationship between reality level and skepticism, researchers conducted a Factorial ANOVA Test to investigate interaction effect between reality level and following size.

Figure 5-13. *Factorial ANOVA for H8.*

ANOVA - Skepticism

	Sum of Squares	df	Mean Square	F	p
Reality Level	0.2914	1	0.29137	44.47	< .001
Following Size	0.0188	2	0.00942	1.44	0.241
Reality Level ✻ Following Size	0.0192	2	0.00958	1.46	0.236
Residuals	0.7927	121	0.00655		

Figure 5-14. *Main effects plot for H8.*



The results of this analysis (**Figure 5-13**) reveal a main effect for reality level (F = 44.47, p < 0.001), but not for following size (F = 1.44, p = 0.241) or the interaction between the two variables (F = 1.46, p = 0.236). The main effects plot (**Figure 5-14**) reiterates the differences in sentiment towards influencers based on their reality level: overall, HIs received a substantially higher sentiment score than VIs. Though no significant main or interaction effect of following size appears, it is interesting to note that while HIs possess relatively flat skepticism levels across following size, skepticism peaks for VIs with micro-influencers and tapers off at the following size extremes. These data support the acceptance of the null hypothesis and the rejection of researchers' alternative hypothesis.

H8 (*not supported*): The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **following size** (MV) such that influencers with higher numbers of followers will achieve lower skepticism. Therefore, virtual influencers with low numbers of followers will experience the highest levels of skepticism, while human influencers with high numbers of followers will experience the lowest levels of skepticism.

5.3.7 Race Moderating Reality Level and Sentiment

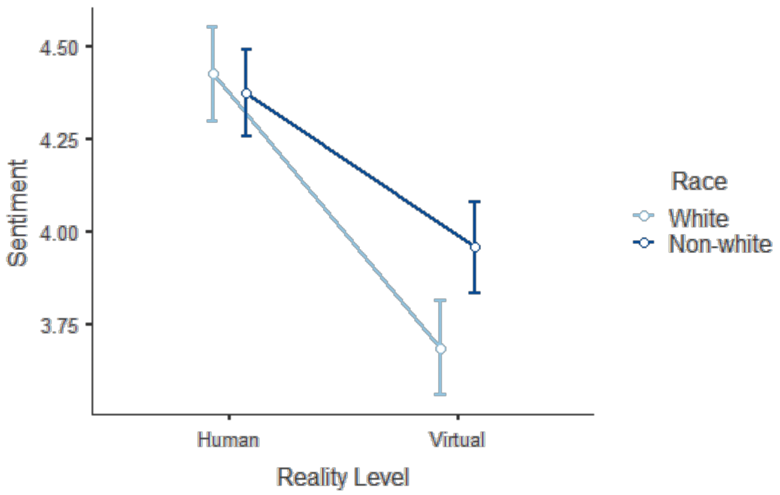
To examine the potential moderating effect of race on the relationship between reality level and sentiment, researchers conducted a Factorial ANOVA Test to investigate interaction effect between reality level and race.

***Figure 5-15**. Factorial ANOVA for H9.*

ANOVA - Sentiment

	Sum of Squares	df	Mean Square	F	p
Reality Level	10.585	1	10.585	85.70	< .001
Race	0.386	1	0.386	3.12	0.080
Reality Level ✻ Race	0.826	1	0.826	6.68	0.011
Residuals	15.192	123	0.124		

***Figure 5-16**. Main effects plot for H9.*



The results of this analysis (**Figure 5-15**) reveal a main effect for reality level (F = 85.7, p < 0.001) and an interaction effect between reality level and race (F = 6.68, p = 0.011), but show no significant effect for race alone (F = 3.12, p = 0.08). The main effects plot (**Figure 5-16**) reiterates the differences in sentiment towards influencers based on their reality level: overall, HIs received a substantially higher sentiment score than VIs. It also clearly demonstrates an interaction effect, as shown by the diverging lines in the plot. While sentiment is relatively flat across race categories in the case of HIs, there is a substantial difference in sentiment across race categories among VIs, with non-white VIs achieving higher sentiment than white VIs. Though these results are statistically significant, since researchers' hypothesis specified a different relationship, these findings do not support H9; however, the interaction effect demonstrated is important to note. Ultimately, these data support the acceptance of the null hypothesis and rejection of researchers' alternative hypothesis since the findings show a different relationship than researchers proposed.

H9 (*not supported*): The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **race** (MV) such that white influencers will achieve higher sentiment. Therefore, non-white virtual influencers will experience the lowest levels of sentiment, while white human influencers will experience the highest levels of sentiment.

5.3.8 Race Moderating Reality Level and Skepticism

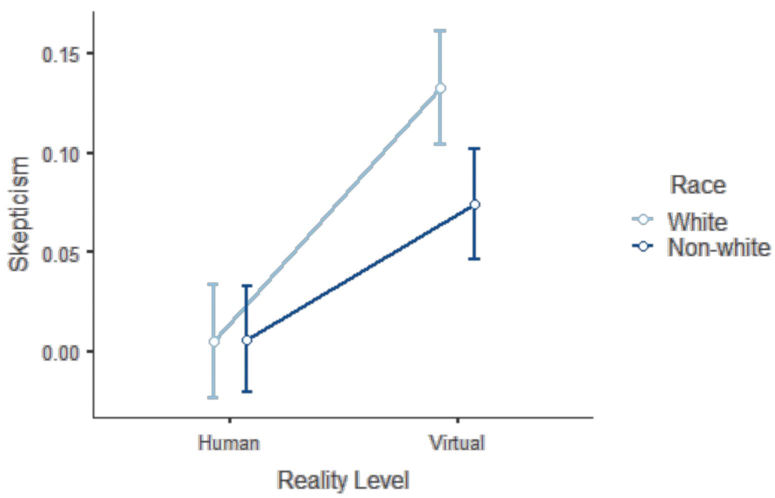
To examine the potential moderating effect of race on the relationship between reality level and skepticism, researchers conducted a Factorial ANOVA Test to investigate interaction effect between reality level and race.

Figure 5-17*. Factorial ANOVA for H10.*

ANOVA - Skepticism

	Sum of Squares	df	Mean Square	F	p
Reality Level	0.3018	1	0.30177	47.79	< .001
Race	0.0263	1	0.02633	4.17	0.043
Reality Level ✻ Race	0.0282	1	0.02822	4.47	0.037
Residuals	0.7768	123	0.00632		

Figure 5-18*. Main effects plot for H10.*



The results of this analysis (**Figure 5-17**) reveal a main effect for reality level ($F = 47.79$, $p < 0.001$), race ($F = 4.17$, $p = 0.043$), and the interaction effect for the two variables ($F = 4.47$, $p = 0.037$). The main effects plot (**Figure 5-18**) reiterates the differences in skepticism towards influencers based on their reality level: overall, HIs received a substantially lower skepticism score than VIs. It also shows the main effect for race, with non-white influencers generally receiving lower levels of skepticism. Furthermore, it clearly demonstrates an interaction effect, as shown by the diverging lines in the plot. While skepticism is relatively flat across race categories in the case of HIs, there is a substantial difference in skepticism scores across race categories for VIs, with non-white VIs achieving much lower levels of skepticism than white VIs. Though these results are statistically significant, since researchers' hypothesis specified a different relationship, these findings do not support H10; however, the main effect of race and the interaction effect demonstrated are important to note. Ultimately, these data support the acceptance of the null hypothesis and rejection of researchers' alternative hypothesis since the findings show a different relationship than researchers proposed.

H10 (*not supported*): The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **race** (MV) such that white influencers will achieve lower skepticism. Therefore, non-white virtual influencers will experience the highest levels of skepticism, while white human influencers will experience the lowest levels of skepticism.

5.3.9 Gender Moderating Reality Level and Sentiment

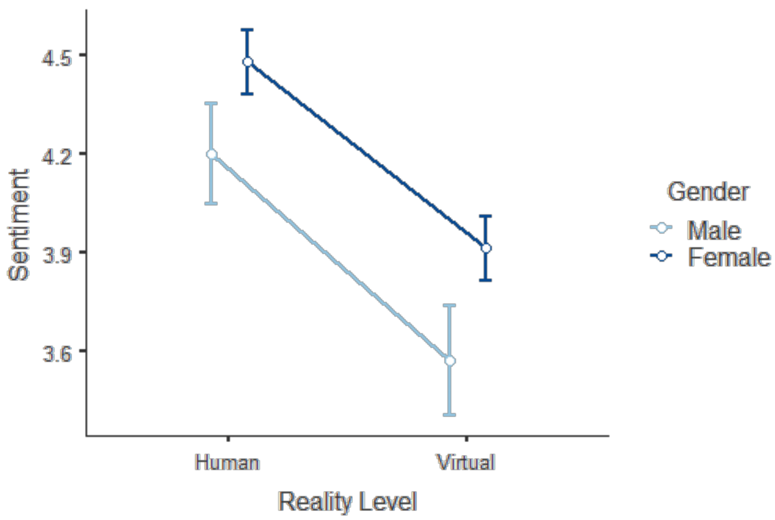
To examine the potential moderating effect of gender on the relationship between reality level and sentiment, researchers conducted a Factorial ANOVA Test to investigate interaction effect between reality level and gender.

Figure 5-19. *Factorial ANOVA for H11.*

ANOVA - Sentiment

	Sum of Squares	df	Mean Square	F	p
Reality Level	8.9977	1	8.9977	79.394	< .001
Gender	2.4360	1	2.4360	21.495	< .001
Reality Level ✻ Gender	0.0261	1	0.0261	0.230	0.632
Residuals	13.9395	123	0.1133		

Figure 5-20. *Main effects plot for H11.*



The results of this analysis (**Figure 5-19**) reveal a main effect for reality level ($F = 79.39$, $p < 0.001$) and gender ($F = 21.495$, $p < 0.001$) separately, but show no significant effect for the interaction between the two variables ($F = 0.230$, $p = 0.632$). The main effects plot (**Figure 5-20**) reiterates the differences in sentiment towards influencers based on their reality level: overall, HIs received a substantially higher sentiment score than VIs. The plot also clearly delineates the main effect for gender: females receive consistently higher sentiment scores than males across reality levels. Though the main effect for gender is statistically significant, since researchers' hypothesis specified an interaction relationship, these findings do not support H11; however, the main effect of gender is important to note. Ultimately, these data technically support the acceptance of the null hypothesis and rejection of researchers' alternative hypothesis since gender does not moderate the relationship between reality level and sentiment; it is a main effect.

H11 (*not supported*): The effect of **reality level** (IV) on **sentiment** (DV_1) is moderated by **gender** (MV) such that female influencers will achieve higher sentiment. Therefore, male virtual influencers will experience the lowest levels of sentiment, while female human influencers will experience the highest levels of sentiment.

5.3.10 Gender Moderating Reality Level and Skepticism

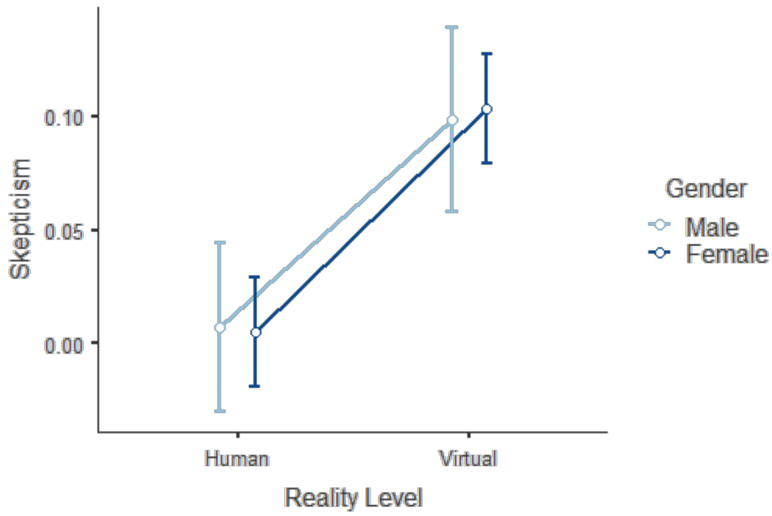
To examine the potential moderating effect of gender on the relationship between reality level and skepticism, researchers conducted a Factorial ANOVA Test to investigate interaction effect between reality level and gender.

Figure 5-21. *Factorial ANOVA for H12.*

ANOVA - Skepticism

	Sum of Squares	df	Mean Square	F	p
Reality Level	0.228	1	0.22801	33.79580	< .001
Gender	5.33e-5	1	5.33e-5	0.00790	0.929
Reality Level ✻ Gender	3.06e-4	1	3.06e-4	0.04530	0.832
Residuals	0.830	123	0.00675		

Figure 5-22. *Main effects plot for H12.*



The results of this analysis (**Figure 5-21**) reveal a main effect for reality level ($F = 33.79$, $p < 0.001$), but show no evidence of a main effect of gender on skepticism ($F = 0.007$, $p = 0.929$) or an interaction effect between reality level and gender ($F = 0.045$, $p = 0.832$). The main effects plot (**Figure 5-22**) reiterates that no clear interaction exists between reality level and gender in impacting skepticism level. Ultimately, these data support the acceptance of the null hypothesis and the rejection of researchers' alternative hypothesis.

H12 (*not supported*): The effect of **reality level** (IV) on **skepticism** (DV_2) is moderated by **gender** (MV) such that female influencers will achieve lower skepticism. Therefore, male virtual influencers will experience the highest levels of skepticism, while female human influencers will experience the lowest levels of skepticism.

5.4 Analysis of Results: Correlation of Variables

Upon viewing the initial results of hypothesis testing, researchers felt correlation tests might provide additional insight into the relationships between variables. Thus, they conducted three correlation tests: one for the full sample, one for HIs only, and one for VIs only.

***Figure 5-23**. Correlation matrix: full sample.*

Correlation Matrix

		Longevity	Engagement Rate	Following Size	Sentiment	Skepticism
Longevity	Pearson's r	—				
	p-value	—				
Engagement Rate	Pearson's r	-0.235	—			
	p-value	0.008	—			
Following Size	Pearson's r	0.262	-0.414	—		
	p-value	0.003	< .001	—		
Sentiment	Pearson's r	0.444	0.034	-0.147	—	
	p-value	< .001	0.701	0.098	—	
Skepticism	Pearson's r	-0.388	0.040	0.049	-0.682	—
	p-value	< .001	0.655	0.581	< .001	—

The correlation matrix for the full sample (**Figure 5-23**) shows some variable correlations. To specify, longevity is statistically significantly correlated with engagement rate ($r = -0.235$, $p = 0.008$), following size ($r= 0.262$, $p = 0.003$), sentiment ($r= 0.444$, $p < 0.001$), and skepticism ($r= -0.388$, $p < 0.001$). Engagement rate is statistically significantly correlated with following size ($r = -0.414$, $p < 0.001$). Most interestingly for this study, the matrix revels an incredibly strong and statistically significant correlation between sentiment and skepticism ($r = -0.682$, $p < 0.001$). When examining HIs only, the correlation matrix shows a slightly different output:

***Figure 5-24**. Correlation matrix: HIs only.*

Correlation Matrix

		Longevity	Engagement Rate	Following Size	Sentiment	Skepticism
Longevity	Pearson's r	—				
	p-value	—				
Engagement Rate	Pearson's r	-0.311	—			
	p-value	0.012	—			
Following Size	Pearson's r	0.484	-0.514	—		
	p-value	< .001	< .001	—		
Sentiment	Pearson's r	-0.206	0.172	-0.255	—	
	p-value	0.100	0.171	0.040	—	
Skepticism	Pearson's r	0.217	0.120	0.189	-0.112	—
	p-value	0.083	0.339	0.133	0.374	—

The correlation matrix for HIs only (**Figure 5-24**) shows parallels to the full sample with certain correlational relationships, while illuminating key differences in other relationships. Notably, sentiment ($r = -0.206$, $p = 0.100$) and skepticism ($r = 0.217$, $p = 0.083$) do not show statistically significant correlations with longevity when HIs are examined separately, which supports hypothesis findings that HIs enjoy consistently high sentiment and consistently low skepticism across the board. However, the correlation between longevity and engagement rate ($r = -0.311$, $p = 0.012$) and longevity and following size ($r = 0.484$, $p < 0.001$) hold true from the full sample to the HIs-only sample. Additionally, the strength of the correlation between longevity and following size ($r = 0.484$) is nearly double for HIs in comparison to that of the full sample ($r = 0.262$). Furthermore, skepticism and sentiment are not statistically significantly correlated for HIs alone. This finding is not surprising considering that, while HIs' sentiment scores vary across the positive sentiment range, their skepticism remains flat close to zero. The correlation between following size and engagement rate ($r = -0.514$, $p < 0.001$) remains true in the case of HIs, though is slightly stronger in this case than for the full sample. Interestingly, sentiment and following size are statistically significantly correlated for HIs ($r = -0.255$, $p = 0.040$) where they were not for the full sample, showing that a smaller following size correlates with higher sentiment. When examining VIs only, the correlation matrix again shows a slightly different output:

Figure 5-25*. Correlation matrix: VIs only.*

Correlation Matrix

		Longevity	Engagement Rate	Following Size	Sentiment	Skepticism
Longevity	Pearson's r	—				
	p-value	—				
Engagement Rate	Pearson's r	-0.161	—			
	p-value	0.211	—			
Following Size	Pearson's r	0.161	-0.313	—		
	p-value	0.212	0.013	—		
Sentiment	Pearson's r	0.099	0.106	-0.211	—	
	p-value	0.445	0.414	0.099	—	
Skepticism	Pearson's r	-0.049	-0.023	0.099	-0.603	—
	p-value	0.708	0.858	0.445	< .001	—

The correlation matrix for VIs only (**Figure 5-25**) shows noticeably fewer correlations between variables. This is understandable given the relative breadth and inconsistency of VI content in comparison to the more established output of HIs. Paralleling the full sample and HI-only sample, following size and engagement rate show a statistically significant correlation ($r = -0.313$, $p = 0.013$), but it's the weakest correlation for these variables across the three matrices. Departing from HIs but paralleling the full sample, sentiment and skepticism show an incredibly strong and statistically significant correlation ($r = -0.603$, $p < 0.001$); unlike HIs, VIs exhibit much broader ranges of both sentiment and skepticism.

5.5 Condensed Hypothesis Testing Results

The below table summarizes all hypotheses of this study and the results of testing. Cases when testing uncovered significant results that differed from researchers' hypotheses are noted.

Table 5-1*. Condensed hypothesis testing results.*

Hypothesis	***Description***	***Result***
Main hypotheses		
H1	Reality level influences sentiment: HIs will achieve highest sentiment, while VIs will achieve lowest sentiment.	*Supported*
H2	Reality level influences skepticism: HIs will achieve lowest skepticism, while VIs will achieve highest skepticism.	*Supported*
Moderating effects		
H3	The effect of reality level on sentiment is moderated by longevity: VIs with lowest longevity will experience lowest levels of sentiment, while HIs with highest longevity will experience highest levels of sentiment.	*Not supported*
H4	The effect of reality level on skepticism is moderated by longevity: VIs with lowest longevity will experience highest levels of skepticism, while HIs with highest longevity will experience lowest levels of skepticism.	*Not supported*
H5	The effect of reality level on sentiment is moderated by engagement rate: VIs with lowest engagement rates will experience lowest levels of sentiment, while HIs with highest engagement rates will experience highest levels of sentiment.	*Not supported*
H6	The effect of reality level on skepticism is moderated by engagement rate: VIs with lowest engagement rates will experience highest levels of skepticism, while HIs with highest engagement rates will experience lowest levels of skepticism.	*Not supported*
H7	The effect of reality level on sentiment is moderated by following size: VIs with smallest following size will experience lowest levels of sentiment, while HIs with largest following size will experience highest levels of sentiment.	*Not supported*[1]
H8	The effect of reality level on skepticism is moderated by following size: VIs with smallest following size will experience highest levels of skepticism, while HIs with largest following size will experience lowest levels of skepticism.	*Not supported*
H9	The effect of reality level on sentiment is moderated by race: non-white VIs will experience lowest levels of sentiment, while white HIs will experience highest levels of sentiment.	*Not supported*[2]
H10	The effect of reality level on skepticism is moderated by race: non-white VIs will experience highest levels of skepticism, while white HIs will experience lowest levels of skepticism.	*Not supported*[3]
H11	The effect of reality level on sentiment is moderated by gender: male VIs will experience lowest levels of sentiment, while female HIs will experience the highest levels of sentiment.	*Not supported*[4]
H12	The effect of reality level on skepticism is moderated by gender: male VIs will experience highest levels of skepticism, while female HIs will experience lowest levels of skepticism.	*Not supported*

[1] Following size has a main effect on sentiment, but no interaction effect with reality level.
[2] Reality level and race have an interaction effect on sentiment, but it is opposite what researchers hypothesized.
[3] Race has a main effect on skepticism, and reality level and race have an interaction effect on skepticism, but it is opposite what researchers hypothesized.
[4] Gender has a main effect on sentiment, but no interaction effect with reality level.

5.6 Chapter Summary

In conclusion, researchers conducted four different types of tests—Independent-Samples T-Tests, Linear Regression Models, Factorial ANOVA Tests, and Correlation Analyses—to test hypotheses for statistical significance.

First, Independent-Samples T-Tests were conducted to assess whether the relationships between reality level and sentiment and skepticism were statistically significant. Results support the relationships specified in H1 and H2. Second, in order to obtain greater insight into the nature of these relationships, the moderating effects of five identified variables were assessed using Linear Regression Models and Factorial ANOVA Tests. These tests allowed the researchers to understand the effects and directions of the moderating variables on the main relationships.

While all hypothesized relationships of moderating variables (H3 – H12) were not supported, 4 cases (H7, H9, H10, and H11) yielded statistically significant results that are of value to understanding the variables examined. Testing for H7 and H11 uncovered main effects for following size and gender, respectively, on sentiment. Testing for H10 illuminated a main effect for race on skepticism, and showed that, while an interaction effect between race and reality level exists, it manifests differently than researchers expected. H9 confirmed an interaction effect between race and sentiment, but again, this effect manifested differently than researchers hypothesized.

Authors expand upon and discuss these results in **Chapter 6**.

6 Discussion of Key Findings

This section discusses the empirical findings outlined in ***Chapter 5*** *by variable, synthesizing results in light of the literature review and theoretical framework.*

6.1 Discussion of Independent Variable Impact

This study aims to understand whether consumers perceive human and virtual influencers in the same way. To meet this aim, researchers operationalized the sentiment and skepticism expressed in influencers' comments, enabling data analysis of perceptual similarities and differences across the two reality levels.

6.1.1 Reality Level and Sentiment

Positive Sentiment Among Full Sample

As hypothesized, the results show that the reality level of an influencer clearly impacts the average sentiment expressed in post comments. To recap, researchers defined sentiment as positive, neutral, or negative affect expressed in influencers' post comments. Both HIs and VIs enjoyed positive sentiment—average sentiment scores for both groups (4.39 for HIs, 3.826 for VIs) were above the neutral sentiment ranking (3). First and foremost, all influencers included in the sample—regardless of reality level—demonstrate at least some degree of social media literacy through sharing compelling multimedia and textual content and/or demonstrating personable relationships with their following, which establishes the baseline level for inviting interactions from other social media users (Leung, Schuckert, & Yeung, 2013).

Furthermore, users on social media tend to surround themselves with content that they are interested in and enjoy by following or subscribing to certain account pages and positively engaging with content updates (Sprout Social, 2020). As such, users tend not to follow influencers whose content they find annoying or unsatisfactory. In supplying posts for users' main feeds, Instagram prioritizes displaying content from followed accounts, meaning that it is rare for a user to encounter content from an influencer who they do not follow. Synthesizing this knowledge, it makes sense that influencers' posts reflect positive sentiment: the users commenting on their posts have, in most cases, voluntarily elected to see their content. In other words, a social media user who finds @lilmiquela unfavorable is less likely to follow her account in the first place, and therefore less likely to potentially see or contribute negative comments to the content she posts.

One key aspect of enjoyable content that lends itself to positive sentiment in comments is relatability. Regardless of reality level, influencers in this study share appealing and relatable lifestyle, fashion, and beauty content that is easily understood by the other social media users that interact with their posts. Influencers post this content in the hopes that followers will ascertain shared characteristics between themselves and the influencer, perceive a stronger bond, and harbor increased engagement. Multiple theories support the connection between relatability and favorable sentiment. Emotional branding literature states that relatable storytelling can go so far as to inspire love for an influencer (Gobé, 2011). Instagram's support of visual and textual content makes it particularly apt for influencers' storytelling, and researchers deduced that all influencers sampled possessed distinct personal narratives that would enable effective emotional branding. Similarity-attraction theory also provides a rationale for relatable content driving more positive sentiment. The theory states that individuals feel more attracted to and hold more favorable perceptions for entities and objects that they perceive to be similar to themselves (Byrne, 1971). Though this study only examines influencers—and not the profiles of their commenters—the content of comments supports a strong degree of commenter relatability and therefore attitudinal and interest-based similarity between the two groups, which would lead to higher sentiment in comments across reality levels.

Furthermore, an influencer's friendliness, differentiation, and physical attractiveness can also contribute to positive sentiment (Gentina, Butori, & Heath, 2014; Hoerner, 1999; LeBel & Cooke, 2008; Till & Busler, 2000) Researchers noted that the influencers sampled almost always leverage a friendly attitude when communicating with their audiences, which naturally lays the groundwork for favorable perceptions among their followers. Literature on para-social interaction supports that interactions can be equally effective across reality levels (Nass et al. 1995), meaning that the friendliness extended by HIs and VIs alike helps to bridge the para-social interaction gap regardless of reality level, enabling social media users to view influencers as friends (Bagwell & Schmidt, 2013; Hartup & Stevens, 1997). Across reality levels, influencers represent a distinctly unique and physically attractive subset of social media users. This likely stems from the visibility associated with the influencing profession, which makes influencers particularly subject to public scrutiny on the visual content they post and inspires influencers to prioritize an appealing physical presentation to endear them to their audiences and differentiate them from the mainstream (Gentina, Butori, & Heath, 2014). The influencers sampled in this study are no exception; many of the comments collected positively attest to the above-average handsomeness and appealing physical characteristics of the influencers.

Differing Sentiment Levels Across Reality Levels

Extending beyond reasons explaining the positive sentiment achieved by both HIs and VIs, the results of this study support that HIs and VIs possess a statistically significant difference in the degree of positive sentiment expressed in their post comments.

With regards to relatability, the same two theories explored above carry significance when assessing differences between HIs and VIs. First, emotional branding offers an explanation for the discrepancy across reality levels. While both human and virtual influencers are capable of spinning the compelling narratives at the heart of effective emotional branding (Gobé, 2011), VIs are understandably less established in this regard. As non-humans necessarily lacking HIs' prolific lifetime of character developments and experiences, VIs cannot equal the degrees of complexity that their human counterparts are endowed with, which constricts the ability of their emotional branding strategies in garnering maximum positive sentiment. Byrne's (1971) similarity-attraction theory also sheds light on the differences in sentiment across reality level. While HIs and VIs share humanoid physical characteristics and/or personality traits, VIs represent a much greater departure from a typical human being, so they will naturally appear relatively dissimilar a typical social media user. For example, it is much easier for users to find similarities between themselves and an HI like @carodaur (a human girl who enjoys fashion and travel) than it is for a user to find similarities between themselves and a VI like @john.pork (a cartoon influencer with the head of a pig). While hyperrealistic VIs like @lilmiquela come closer to approximating a humanlike social media presence, the limitations in graphical rendering technology still expose her non-humanness and lead to perceptions of dissimilarity with human social media users.

Reality level-based differences in perceived friendliness also contribute to a difference in sentiment levels across the two groups. While para-social interaction literature establishes that individuals can come to regard computer-animated avatars as friends (Nass et al. 1995), VIs—by virtue of their singular marketing origins—are naturally lacking in their capabilities to establish and develop rich social connections. Research shows that in para-social interaction contexts, individuals gravitate more towards those personas that they perceive to be most true-to-life and human (Wan & Aggarwal, 2015). It follows that VIs' computer-based origins prevent them from attaining an elevated friendship status with—and therefore positive sentiment from—their followers on social media.

Additionally, an examination of physical attractiveness across reality levels uncovers a potential reason explaining VIs' lower sentiment scores. As computer-generated beings, creators can render VIs as infinitely "perfect"—no matter the beauty standards promoted by society, VIs can easily and equally be rendered to match these standards. However, research shows that humans don't necessarily gravitate towards physical perfection, and in some cases may even find it eerie and unsettling (Mori, 1970). People tend to find comfort in and relate to natural imperfections that they observe in other humans (Zaidel & Cohen, 2005). Since no aspect of VIs' creation can occur through happenstance, they naturally are incapable of possessing these endearing nuances.

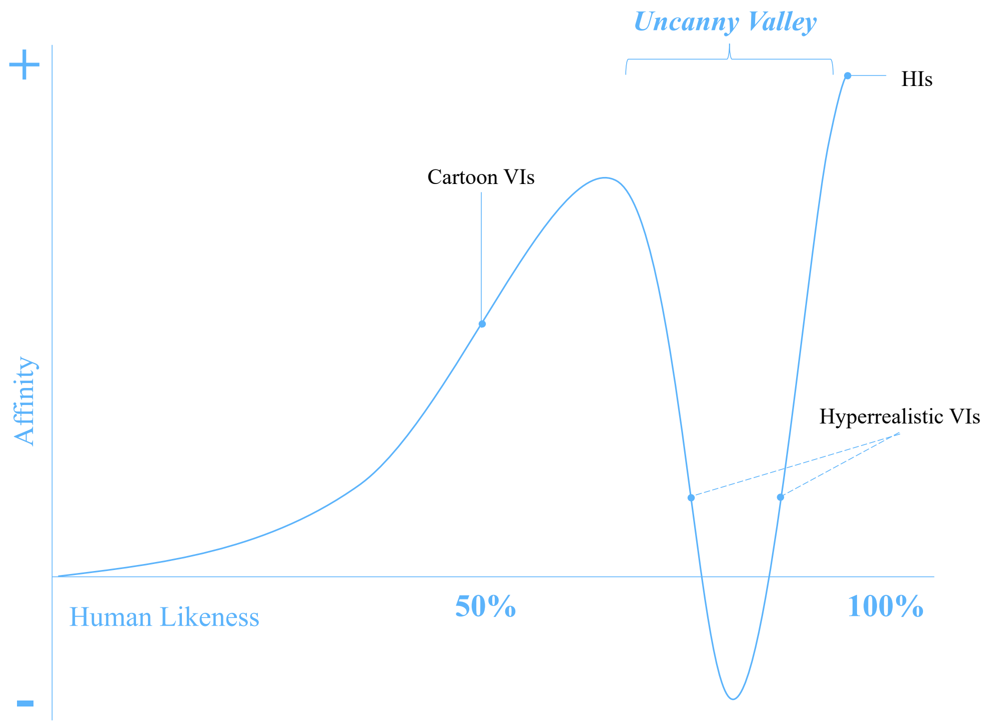
Finally, it is critical to note that online commentary tends towards extreme sentiments, so opinions shared online are typically more polarized in their nature than commentary shared in a face-to-face context (Chevalier & Mayzlin, 2006; Hong & Kim, 2016; Hu, Pavlou, & Zhang, 2006). As established in the preceding paragraphs, VIs experience lower sentiment than humans for a variety of reasons. Regarding this study specifically, the nature of sentiment polarization online serves to emphasize substantial divides between the two reality level groups, and is important to reflect upon when considering applications of VIs outside of an online context. In other words, while this social media-focused study shows a significant difference in sentiment levels across virtual and human influencers, the profoundness of this difference may be less pronounced in other contexts.

6.1.2 Reality Level and Skepticism

As hypothesized, the results show that the reality level of an influencer clearly impacts the average skepticism expressed in post comments. To recap, researchers defined skepticism as iterations of doubt, mistrust, incredulity, uncertainty, or criticism expressed in influencers' post comments. While HIs enjoyed borderline nonexistent levels of skepticism (M = 0.005), VIs experienced substantial levels of skepticism (M = 0.102). In other words, these results show that VIs experience over twenty times the level of skepticism that HIs do. To mine additional insights from the dataset, researchers examined the spectrum of skepticism within the VI category. Results showed a significant difference between skepticism experienced by hyperrealistic VIs (M = 0.117) and cartoon VIs (M = 0.0347). In short, hyperrealistic VIs garnered over three times more skepticism than their cartoon counterparts.

Returning to Mori's (1970) framework, the findings of this study are consistent with the Uncanny Valley effect he proposes: affinity towards non-human renderings increases a lifelike quality increases, but dips into a more skeptical domain at the points where non-human renderings closely approximate real life. Appropriating Mori's affinity and human likeness spectrum, researchers propose a version that incorporates HIs, hyperrealistic VIs, and cartoon VIs. As seen in **Figure 6-1**, HIs occupy the position associated with maximum affinity and human likeness (which human beings occupy in Mori's original framework). Because cartoon VIs bear some resemblance to humans, they occupy a moderate position in the framework (originally occupied by toy robots in Mori's version) that denotes some human likeness and a fairly positive reception. However, hyperrealistic HIs—with their remarkably high levels of skepticism and quasi-humanlike attributes—fall somewhere within the Uncanny Valley, a region in which their eerie human likeness fuels aspects of skepticism like uncertainty and distrust.

Figure 6-1. *The Uncanny Valley Effect (Mori, 1970) adjusted for influencers.*



The Uncanny Valley effect may be particularly pronounced among influencers due to the fear and uncertainty surrounding ever-improving rendering technologies. While HIs are fairly well-established and widely understood within the social media realm and cartoon VIs clearly exhibit their computer-based origins, hyperrealistic VIs represent a new frontier in media that the public does not yet understand. Two prominent psychological explanations also apply in this case. First, society's technophobia—the fear of and anxiety towards new technology—explains why hyperrealistic VIs are more difficult to trust than established entities like cartoon avatars and human marketers (Brosnan, 2002). Second, transparency likely plays a role in social media users' elevated skepticism towards hyperrealistic VIs. The Persuasion Knowledge Model supports this conclusion—as in the case of native advertising, a user's inability to recognize the origins of marketing content prevent the user from effectively coping with advertising messages and inspire feelings of distrust (Wojdynski & Evans, 2016). Marketing research further supports the importance of transparency in this context, showing that cartoons' transparency enables people to trust them more easily (Brunick et al. 2016). New laws require HIs to disclose marketing activity with post callouts and hashtags such as #ad and #sponsored, but the current legal environment surrounding VIs is much more ambiguous and less strict in its requirements. As such, VIs' lack of explicit disclose regarding their origins or marketing purposes can explain elevated levels of distrust and suspiciousness from social media users.

6.1.3 Correlation Between Sentiment and Skepticism

Findings show that sentiment and skepticism possess a strong negative correlation. The more positive the sentiment expressed towards influencers' content, the lower the level of skepticism expressed towards that influencer. The Mere Exposure Effect helps explain this correlation, stating that as a phenomenon becomes more familiar, individuals tend to behave in a more positive and unquestioning way towards it (Hekkert, Thurgood, & Whitfield, 2013). In other words, the more accustomed that individuals are to an influencer, the more likeable and trustworthy that influencer becomes in their mind (Verhulst, Lodge, & Lavine, 2010). VIs constitute a totally novel marketing tactic, which means that social media users generally are not accustomed to them conceptually. As such, VIs are more likely to encounter both negative sentiment and high levels of skepticism in their post comments. HIs, on the other hand, are fairly well-established on the platforms in which they operate and in the minds of social media users, making them more likely to experience positive sentiment and low rates of skepticism among their commenters.

6.2 Discussion of Moderating Variable Impact

To further this study's aim of understand consumers' perceptions of human and virtual influencers, researchers examined five moderating variables: longevity, engagement rate, following size, race, and gender.

6.2.1 Longevity

Researchers opted to study longevity to explore if the lifespan of an influencer's account impacts social media users' attitudes towards their content. The appeal of public personalities tends to increase over time and with more frequent contact (Chung & Cho, 2017; Lunardo, Gergaud, & Livat, 2015). Furthermore, repeated observation of and interaction with an influencer allows a social media user to collect a substantial amount of information about an influencer that results in an elevated evaluation of that influencer's trustworthiness (Rempel, Holmes, & Zanna, 1985). Despite these precedents in the literature, hypothesis testing uncovered neither a main effect nor an interaction effect, and neither longevity hypothesis was supported. This implies that—regardless of the reality level of an influencer—a lengthier account lifespan does not necessarily generate higher levels of sentiment or lower levels of skepticism.

One reason for the lack of significant findings in this case stems from the way the Instagram platform reports metrics. Unlike following size and engagement rate, longevity is difficult for social media users to deduce since it is not prominently displayed on account profiles or within posts. In fact, determining longevity is a time-intensive process that requires scrolling through a user's entire catalog of posts to reach the first chronological listing. As such, most social media users are wholly unaware of the specific longevities of the accounts they interact with. This nuance makes the insignificant findings understandable; considering the metrics Instagram displays, a readily available data point more visible to social media users, such as total number of posts, may better explore the relationships put forth in this study's longevity hypotheses.

In spite of the insignificant results of the Linear Regression Models, the Correlation Analysis uncovered significant results. Across the full sample of influencers, longevity is positively correlated with following size and sentiment, and negatively correlated with engagement rate and skepticism. The shorter the longevity of an account, the higher the engagement rate and the lower the following size. Naturally, all account following sizes begin at zero, so a positive correlation between longevity and following size is understandable. Additionally, it's valuable to consider following size when interpreting the correlation between longevity and engagement rate. Since following size is the denominator in the engagement rate formula, engagement rate decreases as following size increases. These correlations understandably extend to the HI-only sample; however, it is interesting to note that in the case of VIs, longevity shows no significant correlations with engagement rate and following size. One reason for this result could stem from the small sample size of this study—the novelty of VIs limited the quantity available for research. Another possible explanation arises from VIs' short lifespans compared to their human counterparts. While the range of longevity for HIs spanned 108 months, the range for VIs only spanned 64 months (with the exception of a single outlier). The constricted range of VIs' longevity may have limited the ability to deduce clear trends in the dataset.

The correlations between longevity and engagement rate and following size were mild in strength, but the correlation matrix illuminated strong correlations for longevity with sentiment and skepticism. This constitutes an especially interesting result, as the findings more closely align with the aforementioned rationales (Chung & Cho, 2017; Lunardo, Gergaud, & Livat, 2015; Rempel, Holmes, & Zanna, 1985) and come closer to uncovering the relationships approximated by the researchers' initial hypotheses. Given the significant results of the correlation matrix, it is clear that, across the full sample of influencers, sentiment increases with greater longevity, while skepticism decreases with greater longevity.

6.2.2 Engagement Rate

Researchers elected to study engagement rate based upon prior research connecting engagement rate on social media sites with consumer behaviors like purchase intent and loyalty (Barhemmati & Ahmad, 2015; Toor, Husnain, & Hussain, 2017). More interaction was expected to provide more relevant information to the followers, who need it to build trustworthiness towards influencers (Rempel, Holmes, & Zanna, 1985). Despite these precedents in the literature, hypothesis testing uncovered neither a main effect nor an interaction effect, and neither engagement rate hypothesis was supported. This implies that—regardless of the reality level of an influencer—a higher engagement rate does not necessarily generate higher levels of sentiment or lower levels of skepticism.

Researchers propose that a more specific design for measuring engagement rate more narrowly might have produced significant findings. As with the case of longevity, engagement rate is not easily visible to social media users. While its components—total likes and comments and number of followers—are readily available on account and post pages, arriving at an engagement rate from these inputs requires calculation. To simplify the design and leverage metrics more obvious to social media users (that therefore have a greater chance of impacting their behavior), the concept of engagement could be refined in one of two ways. To measure the engagement of a post in relation to all social media users, total likes may be a better data point to collect since social media users infer the engagement levels of an influencer by assessing their post likes. Since Instagram places the number of total likes directly below each image, social media users are much more likely to both observe and be impacted by this metric. Research by Powell et al. (2017) supports this, stating individuals' behavior is irrationally impacted by large numbers. To measure a specific influencer's level of engagement with their following, an influencer's reply rate in post comments or the frequency of their posts might better approximate this phenomenon. Research shows a strong foundation for positive sentiment and lower skepticism associated with direct interaction with an influencer (Rempel, Holmes, & Zanna, 1985), so in the case of this study, the engagement rate could be too broad since it incorporates both a selected influencer's engagement and other social media users' engagement.

In spite of the insignificant results of the Linear Regression Models, the Correlation Analysis uncovered significant results. Across the full sample of influencers, engagement rate maintains a significant negative correlation with following size. This relationship holds true in the cases of HIs and VIs, respectively. Though this correlation is the inverse of what researchers initially hypothesized, upon reviewing recent media coverage of influencer marketing, this finding makes sense. The success of nano-influencers is attributed to their small yet hyper-engaged followings, while macro- and mega-influencers cater to much larger and more disengaged audiences. As a result, influencers with smaller following sizes attain much higher rates of engagement (Influencer Marketing Hub, 2020b).

6.2.3 Following Size

Researchers chose to study following size since influencers with a large follower base are perceived as more likeable, socially acceptable, and trustworthy (de Veirman et al. 2017). As with engagement rate, research by Powell et al. (2017) supports this, stating individuals' behavior is irrationally impacted by large numbers, which in this case would mean that a larger following generates more positive sentiment and lower levels of skepticism. Despite these precedents in the literature, findings did not support either of researchers' initial following size hypotheses, and no significant interaction effect was uncovered. Once again, this lack of significance regarding following size could be due to metric visibility. While Instagram displays an influencer's number of followers prominently at the top of their account page, many followers view and interact with posts by way of their main feed, which does not contain following size information. As such, many followers may be unaware of an influencer's following size when interacting with their posts, in spite of the public availability of this metric. Just as with engagement rate, total likes may be a better data point to collect since social media users infer the popularity and reach potential of an influencer by assessing their post likes. Since Instagram places the number of total likes directly below each image, social media users are much more likely to both observe and be impacted by this metric.

It is valuable to note that hypothesis testing did reveal an unexpected main effect for following size on sentiment. This implies that—regardless of the reality level of an influencer—a smaller following size generates higher levels of sentiment. This finding constitutes the inverse of what researchers expected based on the literature reviewed, but aligns with industry best practices. As mentioned in **Section 6.2.2**, nano-influencers possess small followings typically representing passionate audiences with niche interests (Influencer Marketing Hub, 2020b). These small followings are particularly engaged with nano-influencers' content, generally leading to more enthusiastic, positive commentary.

Though analysis did not uncover a main effect for following size on skepticism, it is interesting to note the unusual results present with VIs. While HIs received consistently low levels of skepticism across following size categories, skepticism peaked for virtual micro-influencers and was lower at the following size extremes. As mentioned, nano-influencers experience high levels of passionate engagement and higher levels of sentiment. Given their niche appeal and the correlation between positive sentiment and low skepticism explained in **Section 6.1.3**, it makes sense that their skepticism levels would be lowest. In the cases of virtual mega- and macro-influencers, who receive hundreds—sometimes even thousands—of comments per post, there is naturally a higher likelihood that skeptical comments would swiftly be addressed by any of the numerous other social media commenters, solely based on the sheer number of post interactions that these hyper-popular influencers generate. Furthermore, rates of skepticism in the case of mega- and macro-influencers are easily diluted by the multitude of other, non-skeptical post comments. Virtual micro-influencers fall into a sweet spot between these extremes—they possess too large a following to command the devoted attention enjoyed by nano-influencers, and too small a following to quickly and extensively address skepticism in the way that their more popular mega- and macro- counterparts can.

Finally, the Correlation Analysis uncovered a significant negative correlation between following size and sentiment, but only in the case of HIs. This demonstrates the same effect previously discussed regarding sentiment and following size: nano-influencers boast enthusiastic followings and achieve consistently higher levels of sentiment than larger following size groupings (Influencer Marketing Hub, 2020b).

6.2.4 Race

Researchers decided to explore the relevance of race across reality levels due to the abundance of media coverage detailing the disparities in brands' treatment of white and non-white HIs (Chen, 2019; Deighton, 2020; Graham, 2019; LaSane, 2019; Perkins, 2019; Reid, 2019). This unequal treatment manifests as higher compensation, increased likelihood of selection for branded campaigns, and higher quantities of complimentary brand merchandise in the case of white influencers, among other benefits. Based on brands' preferential treatment of white influencers, researchers hypothesized that white influencers experience higher levels of sentiment and lower levels of skepticism.

Despite these precedents in the marketing practice, findings did not support either of researchers' initial race hypotheses. However, analysis uncovered other significant results. In the case of sentiment, results showed that, while there is no significant main effect for race, there is a significant interaction effect between reality level and race. Sentiment scores are negligibly different across race categories for HIs, but in the virtual realm, the difference becomes much more pronounced; non-white VIs substantially surpass white VIs in sentiment scores. This makes sense from the viewpoint that racial differences tend to affect relationships (Dent, 2004). Researchers observed that commenters on non-white VIs' posts expressed clear enthusiasm for the augmented racial representation they perceived the influencer as promoting. **Chapter 7** covers implications for practitioners in more depth.

In the case of skepticism, results showed both a significant main effect for race and a significant interaction effect between reality level and race. These effects translate to a much higher skepticism rate for white VIs than non-white VIs, while HIs across race categories experience skepticism levels close to zero. Knowing that sentiment and skepticism correlate, it makes sense to infer that the lower skepticism experienced by non-white VIs also stems from a general enthusiasm to the minority representation in this format.

6.2.5 Gender

Finally, researchers examined gender of influencers because literature establishes that differences in gender affect consumer perceptions. Male influencers tend to prioritize selling through social media, while their female counterparts tend towards relatable, narrative storytelling (Martínez-Sanz & González Fernández, 2018). Furthermore, consumers generally perceive female sellers more positively (Cook & Corey, 1991).

For both sentiment and skepticism, hypothesis testing did not uncover an interaction effect between reality level and gender, so neither hypothesis was supported. However, in the case of sentiment, testing illuminated the significant main effect of gender. Regardless of reality level, female influencers experienced higher sentiment than male influencers. This constitutes an particularly interesting result, as the findings closely align with the aforementioned rationales (Cook & Corey, 1991; Martínez-Sanz & González Fernández, 2018) and come closer to uncovering the relationship proposed in the initial hypothesis. Curiously, the main effect for gender did not extend to skepticism. In this study, the differences in skepticism across reality levels proved so pronounced that it makes sense that gender exerts little effect in comparison. HIs experienced almost no skepticism whatsoever, while VIs experienced a substantial amount. When social media users expressed their skepticism towards a VI, researchers observed that the commentary overwhelmingly focused on their reality level, and never associated skepticism with specifically gendered traits.

7 Conclusion

This chapter extends the key findings of this research and focuses on detailing this study's theoretical and practical implications. In addition, it discusses limitations present in the research and provides direction for future research in examining the phenomenon of virtual influencers as they relate to marketing outcomes.

7.1 Research Aims and Objectives

The purpose of this thesis was to analyze the affective sentiment and skepticism of social media users' comments on influencers' posts in an attempt to understand whether consumers perceive virtual influencers differently than human influencers. To achieve this purpose, researchers conducted a systematic literature review to understand the nature of influencing opinion historically and in modern, online contexts. Findings show that reality level indeed plays a critical role in social media users' perceptions towards and interactions with influencers. The following section outlines conclusions of this research, focusing on both theoretical and practical implications.

7.2 Theoretical Implications

One of the most important theoretical contributions of this study is the confirmation that Mori's (1970) Uncanny Valley Effect applies to social media influencers, as shown by the lower sentiment and higher skepticism in social media users' para-social interactions with VIs, which substantially diverge from the attitudes expressed towards HIs. This research demonstrates that, in cases when a VI comes incredibly close to embodying a humanlike appearance, social media users express more negative sentiment and higher levels of skepticism, indicating at best a relative dissatisfaction with VIs when compared to their human counterparts. Of additional importance, this study adjusts Ohanian's (1990) Source-Credibility Model framework so that it is more appropriate for examining the dimensions of attractiveness, expertise, and trustworthiness in a secondary, social media context (which is naturally less information-rich than a primary, qualitative study). Furthermore, researchers leverage this study as an opportunity to introduce their novel definition of virtual influencers, which provides a standard classification for the emerging phenomenon upon which future studies can be based.

Although previous studies covered both para-social interactions between humans and computer-generated animations (Nass, Steuer & Tauber, 1994; Bente, Krämer, Petersen, 2002) and para-social interactions occurring within the internet context (Hoerner, 1999), no prior study ever attempted to examine para-social interaction in the realm of virtual influencers, which means that this paper is the first of its kind.

In addition to demonstrating the strong relationship between an influencer's reality level and the resulting sentiment and skepticism expressed towards that influencer in para-social interactions, this study also achieves a high degree of understanding for additional variables that affect social media users' sentiment and skepticism. In the case of longevity, hypothesis testing provided no significant results, but significant results from the Correlation Analysis suggest that a more established presence on a social media platform (with regards to time) correlate with more positive sentiment and decreased levels of skepticism. This supports previous research that connects exposure over time—and its resulting familiarity—to heightened perceptions of favorability and trustworthiness (Gordon & Holyoak, 1983; Peskin & Newell, 2004; Styczynski & Langlois, 1977; Verhulst, Lodge, & Lavine, 2010). While several authors examined this phenomenon in the context of marketing and interpersonal relationships, no previous study attempted to understand the impact of the Mere Exposure Effect in a social media context regarding virtual influencers and their audiences. Once again, this study is the first to apply the Mere Exposure Effect to virtual influencers.

Literature presents a strong foundation for conceptualizing popularity as one of the factors that influences interpersonal relationships. Well-known, influential individuals tend to have more friends than others (Bukowski & Newcomb, 1984; Parker & Asher, 1993; Parmar & Patel, 2014). Significant results in this study illuminated a main effect for following size on sentiment, but the relationship is the inverse of what the literature proposes. As social media continues to develop and reach potential continues to increase, the finding that a smaller following engenders more positive sentiment provides valuable incentive for conducting additional research to examine other contexts in which these findings may apply. It is interesting to note that this finding aligns with studies showing that closeness to a message sender leads to a more positive perception of their messages (Freberg et al. 2011), implying that in this context, the importance of intimacy overpowers the importance of popularity. Practitioners already note this trend, as evidenced in the nano-influencer phenomenon discussed previously.

The topic of gender as a mediator in social relationships has also been broadly covered by previous research. Studies demonstrate that gender influences individuals' attitudinal and behavioral patterns (Barry et al. 1957; Erickson, 1964; Parson & Bales, 1955) and interactions between a message sender and receiver (Palmer & Bejou, 1995). There is a lack of research applicable to marketing contexts that delineates implications of gender when computer-generated personalities are involved. This research shows a clear relationship between gender and sentiment: females achieve consistently higher sentiment than males. This reinforces academic findings that saleswomen are more positively perceived than their male counterparts (Cook & Corey, 1991), and potentially demonstrates the effectiveness of emotional branding tactics, which females utilize more frequently than males (Martínez-Sanz & González Fernández, 2018). The insignificant findings on skepticism suggest that perhaps the gender dimension plays no vital role when interacting with non-human personalities, although further research is necessary to establish a clear understanding of this phenomenon.

In sum, this paper contributes to existing literature and theoretical discourse by laying the groundwork for new research on virtual influencers in a social media context and beyond.

7.3 Practical Implications

From a practical perspective, these research findings provide interesting and readily actionable insights for managers and marketers curious about experimenting with virtual influencers in their social media marketing activities. With the vast number of influencers available, the task of selecting the appropriate partner is not easy for brands. Assessing findings across the full dataset, this research supports that longevity and a large following correlate with greater sentiment, while illuminating that variables like engagement rate exert little impact. In the case of reality level, these findings clearly show that social media users approach virtual influencers with elevated levels of skepticism and generally express more negative sentiment towards this novel tactic, but that does not imply that virtual influencers do not possess relevance. For technology buffs or innovative early adopters, virtual influencers' novelty and futurism could inspire a more enthusiastic relationship with a brand's consumers. Ultimately, the decision to leverage a virtual influencer could depend heavily on target audience, product or service type, and influencing context. As such, future research in this vein would be incredibly valuable in shedding light on which virtual influencing contexts inspire the highest levels of sentiment and lowest levels of skepticism.

When evaluating influencers to work with, managers must consider characteristics like attractiveness, expertise, and trustworthiness, as well as the cost of the partnership, the brand-influencer alignment, and the risks of controversy associated with an influencer partnership. For example, the initial investment in virtual influencing may be large, but it might prove more cost-effective in the long-term as human influencers tend to negotiate higher rates as their popularity grows. VIs are wholly based on a marketer's goals, so achieving perfect brand and target audience alignment with a VI is much simpler than achieving an equal level of alignment with a human influencer. Furthermore, human influencers always present a risk of controversy or insecurity in their personal lives, which manifests as a direct or indirect threat to the brands they partner with. For example, brands including Sephora felt it necessary to cut ties with American influencer Olivia Jade Giannulli after news of her involvement in a massive college admissions scandal (Ilchi, 2019). More indirectly, influencers' personal issues can negatively impact their branded relationships—for example, almost half of human influencers admit to suffering from mental health issues associated with their profession, which are understandable given the intense public scrutiny of their appearances and lifestyles (Dodgson, 2019). These personal issues naturally limit HIs' abilities to take on demanding projects with brands, but VIs do not experience such challenges.

However, working with virtual influencers it not all roses. Their employment in brands' marketing is a novel concept, and brand-new virtual influencers are not considered a strong source of credibility since they possess no clear track record. Building awareness for and best practices surrounding a novel marketing tactic demands a considerable time investment, and brands should bear this in mind before launching their own VI campaigns. Furthermore, when attempting to achieve a humanlike appearance with the VIs they utilize, marketers should keep the Uncanny Valley Effect in mind to avoid unintentional eeriness and creepiness that may disturb potential consumers.

Cartoon VIs may constitute a better alternative, but their match with a brand and its advertising objectives needs to be evaluated. As mentioned, one of the primary benefits associated with collaborating with VIs is the avoidance of controversy risk, as the brands wield full control over the influencer's tone, behavior, and attitude. Yet the virtual nature of an influencer may be a source of controversy itself, given arguments surrounding transparency and proper disclosure or origins and marketing intent.

Furthermore, VIs represent a threat for human influencers' professional futures—and those of models, or any other human that can be replaced in media—which may lead to social movements against virtual influencing that parallel other movements sparked by widespread industry changes, as seen when Uber threatened the traditional jobs within the car service industry (Kyvrikosaios, 2018).

Ultimately, this paper provides practitioners with an understanding of the different levels of sentiment and skepticism inspired by human and virtual influencers. Both influencing alternatives present opportunities and downfalls, so brands must be thoughtful when selecting the most appropriate influencer type for their needs.

7.4 Limitations and Opportunities for Future Research

Although this research provides reliable insights on the different sentiment and skepticism exerted by influencers in relation to their reality level, it includes several limitations that are worth mentioning, in line with the researchers commitment of transparency and with the aim of identifying the opportunities to be captured by future research.

First, limitations on the data collection process are considered. The researchers attempted to collect all the information regarding the comments on the influencers' posts in the most standardized, consistent manner. Yet, the constraints in budget and time made this task challenging, and some problems were encountered. In total, 5 tools were used to retrieve the social media content. Although all of them allowed collect the same information items and the researchers could summarize every information consistently, the need to use so many tools is considered a limitation because it implied that time needed to be invested in understanding each tool and making sure all the information was consistent. Furthermore, the researchers only accessed these tools in their free version, given the budget constraints of the research. This brought in some limitations as comment number limit per download. In this regard, sentiment of mega influencers, whose posts enjoyed in some cases thousands of comments, was calculated considering a smaller number of comments. It would be best if future research can include every comment in the influencers' posts. Although the approach taken in this study has been thoroughly planned with a clear intention to capture the closest to reality information, including the full set of comments in the future will enrich the dataset. Furthermore, some influencers' accounts were private, and their posts could not be accessed. This can be considered a limitation, as the researchers needed to remove these influencers from their dataset. Although less likely for human influencers, in the case of virtual influencers it is feasible to assess the full population, since not that many exist. Thus, the possibility of entering all their profiles in the future can be an interesting opportunity to obtain better understanding on them.

Secondly, the levels of skepticism and sentiment expressed by each comment were given manually by the researchers. Although the scoring system was based on well-established scales and the process has been documented in detail to ensure transparency and consistency, some uncontrollable variables such as cultural background, different judgement and misunderstanding of the comment content may influence the scores provided. For the aim this study the researchers intended to use a scoring tool, yet it proved not to be as reliable as human judgement. Yet for future research, the availability of a reliable sentiment and skepticism scoring tool will allow for standardization of the scores and replicability of the study.

Thirdly, both hyperrealistic and cartoon VIs were assessed in comparison with HIs. Besides, an additional test was conducted to explore differences between different sublevels of reality within the VIs group. Yet, the uneven distribution of the sample units made the outcomes of this comparison not strongly reliable. Currently, the population of existing VIs is not even, and most of them attempt to resemble humanlike appearance. However, with the development of these characters, the possibility to compare equally sized groups of hyperrealistic and cartoon VIs will provide future research with the ability to obtain relevant insights.

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Appendix A: Full Analysis Dataset

Full Analysis Dataset

Influencer	Number of Followers	Following Size	Longevity	Engagement Rate	Race	Gender	Reality Level	Sentiment	Skepticism
carodaur	2,300,000	Macro/Mega	81	0.0204	White	Female	Human	4.7628	0.0078
lukasabbat	2,200,000	Macro/Mega	94	0.0748	Non-white	Male	Human	4.2094	0.0144
lilmiquela	2,100,000	Macro/Mega	47	0.0347	Non-white	Female	Virtual HR	3.3368	0.2506
ireneisgood	1,700,000	Macro/Mega	109	0.0157	Non-white	Female	Human	4.3704	0.0041
knoxfrost	1,100,000	Macro/Mega	13	0.0566	Non-white	Male	Virtual HR	2.8736	0.2470
vanessahong	641,000	Macro/Mega	101	0.0053	Non-white	Female	Human	4.3814	0.0163
thalasya_	530,000	Macro/Mega	17	0.0072	White	Female	Virtual HR	3.5688	0.2045
thegreylayers	445,000	Macro/Mega	81	0.0099	Non-white	Female	Human	4.4478	0.0013
yoox	442,000	Macro/Mega	15	0.0512	White	Female	Virtual HR	4.0583	0.0971
bradleysimmonds	369,000	Macro/Mega	88	0.0182	White	Male	Human	3.6083	0.0033
noonoouri	351,000	Macro/Mega	26	0.0122	Non-white	Female	Virtual C	4.7288	0.0276
guggimon	341,000	Macro/Mega	9	0.0456	Non-white	Male	Virtual C	3.4788	0.0531
justinliv	328,000	Macro/Mega	100	0.0310	Non-white	Male	Human	4.1297	0.0039
janky	310,000	Macro/Mega	9	0.0504	Non-white	Male	Virtual C	3.6058	0.0435
namvo	292,000	Macro/Mega	98	0.0333	Non-white	Female	Human	4.3577	0.0176
alatorreee	284,000	Macro/Mega	79	0.0266	Non-white	Female	Human	4.3070	0.0055
thebaduratwins	270,000	Macro/Mega	45	0.0628	Non-white	Female	Human	4.3903	0.0157
bee_nfluencer	267,000	Macro/Mega	11	0.1010	Non-white	Female	Virtual C	4.2008	0.0063
albertoortizrey	253,000	Macro/Mega	94	0.0236	Non-white	Male	Human	4.5010	0.0021
bermudaisbae	227,000	Macro/Mega	39	0.0803	White	Female	Virtual HR	3.6833	0.1526
shionat	206,000	Macro/Mega	103	0.0230	Non-white	Female	Human	4.4416	0.0101
bodybyralph	202,000	Macro/Mega	16	0.0296	White	Male	Virtual C	3.1932	0.0133
shudu.gram	199,000	Macro/Mega	35	0.0648	Non-white	Female	Virtual HR	4.1813	0.1018
imma.gram	175,000	Macro/Mega	20	0.0265	Non-white	Female	Virtual HR	4.3600	0.0756
ryanstylesnyc	172,000	Macro/Mega	69	0.0253	Non-white	Male	Human	4.4410	0.0033
luhshawnay	171,000	Macro/Mega	33	0.0559	Non-white	Female	Human	4.4681	0.0023
jessedriftwood	163,000	Macro/Mega	92	0.0725	White	Male	Human	4.0310	0.0114
trevor_stuurman	161,000	Macro/Mega	75	0.0259	Non-white	Male	Human	4.5613	0.0035
blawko22	158,000	Macro/Mega	26	0.0421	Non-white	Male	Virtual HR	3.3676	0.2078
mathiaslefevre	153,000	Macro/Mega	72	0.0247	White	Male	Human	4.4245	0.0015
epiphenus	142,000	Macro/Mega	10	0.0616	White	Male	Virtual C	3.1678	0.0288
realqaiqai	142,000	Macro/Mega	19	0.0597	Non-white	Female	Virtual C	3.7769	0.0240
astrolovesu	140,000	Macro/Mega	17	0.0677	Non-white	Male	Virtual C	3.5051	0.0442
hails_world	124,000	Macro/Mega	91	0.0081	Non-white	Female	Human	4.5511	0.0227
thora_valdimars	98,900	Micro	95	0.0129	White	Female	Human	4.6250	0.0000
itsbinxie	98,100	Micro	10	0.0603	White	Female	Virtual HR	3.3633	0.3201
annasarlvit	92,900	Micro	79	0.0508	White	Female	Human	4.5424	0.0034
rubyrubygloom	72,400	Micro	108	0.0084	Non-white	Female	Virtual HR	4.5175	0.0351
marcosfecchino	66,500	Micro	94	0.0548	Non-white	Male	Human	4.2399	0.0051
joeylondonstyle	54,600	Micro	91	0.0275	Non-white	Male	Human	4.0901	0.0116
iongottlich	54,500	Micro	61	0.0574	White	Male	Virtual HR	3.9734	0.0293
babythiagohendrix	47,400	Micro	26	0.0989	Non-white	Male	Human	3.9845	0.0133
veronicawi	42,800	Micro	62	0.0336	White	Female	Human	4.5542	0.0027
jedyvales	38,000	Micro	10	0.0086	White	Female	Virtual HR	3.8983	0.0678
tamirajarrel	37,700	Micro	72	0.0314	White	Female	Human	4.5675	0.0000
brontekingg	36,100	Micro	79	0.0611	White	Female	Human	4.4267	0.0267
soylivos	33,000	Micro	5	0.2689	White	Female	Virtual HR	4.6506	0.0088
zoedvir	29,600	Micro	14	0.0105	Non-white	Female	Virtual HR	4.3958	0.0167
thisis.kenna	29,300	Micro	4	0.0352	White	Female	Virtual HR	3.2386	0.5593
teovandenbroeke	27,300	Micro	83	0.0205	White	Male	Human	4.4688	0.0125
alizarexx	27,200	Micro	10	0.0305	Non-white	Female	Virtual HR	4.0000	0.0729
bushybroweth	25,600	Micro	58	0.0158	Non-white	Male	Human	4.3170	0.0000
punodostres	25,200	Micro	88	0.0343	Non-white	Female	Human	4.0953	0.0042
cinnamonryan	22,200	Micro	77	0.0501	Non-white	Female	Human	4.4242	0.0000
passporttofriday	21,800	Micro	101	0.0345	White	Female	Human	4.4028	0.0000
zeline_pov	20,100	Micro	11	0.1280	Non-white	Female	Virtual HR	3.3941	0.2196
aliona_pole	19,800	Micro	18	0.0753	White	Female	Virtual HR	3.9417	0.2083
maya_cgi	18,500	Micro	36	0.0050	White	Female	Virtual HR	3.5429	0.2000
ruby.economics	18,200	Micro	19	0.0275	White	Female	Virtual HR	3.6923	0.1282

adriengallo	17,500	Micro	93	0.1687	White	Male	Human	4.0755	0.0063
alex.kereszti	17,000	Micro	40	0.0653	White	Female	Human	3.8408	0.0029
lil_wavi	16,900	Micro	24	0.0503	Non-white	Male	Virtual HR	4.1642	0.0358
marquelleturner	16,800	Micro	99	0.1379	Non-white	Male	Human	4.3023	0.0033
shy.yume	16,600	Micro	10	0.0507	White	Female	Virtual HR	3.6927	0.0112
vixmeldrew	16,300	Micro	57	0.0219	White	Female	Human	4.3542	0.0000
teebabsy	15,100	Micro	65	0.0195	Non-white	Female	Human	4.3132	0.0000
liam_nikuro	14,900	Micro	12	0.0643	Non-white	Male	Virtual HR	4.0069	0.0000
labasrodo	14,700	Micro	40	0.1038	White	Female	Virtual HR	3.0758	0.1515
nicoleloher	14,100	Micro	100	0.0316	White	Female	Human	4.4098	0.0082
thealmachronicle	13,900	Micro	58	0.0404	Non-white	Female	Human	4.5573	0.0000
aoiprism	13,500	Micro	13	0.0439	Non-white	Female	Virtual HR	3.8333	0.0000
john.pork	13,100	Micro	21	0.2428	Non-white	Male	Virtual C	3.6493	0.0318
datcoolgaffy	13,100	Micro	35	0.0902	Non-white	Male	Human	4.1654	0.0110
phoenixmcewan	12,500	Micro	13	0.0480	White	Male	Virtual HR	2.4609	0.5739
adamantlyadler	11,600	Micro	93	0.0289	Non-white	Female	Human	4.5439	0.0000
koffi.gram	11,400	Micro	15	0.3022	Non-white	Male	Virtual HR	4.2453	0.1380
haley_stutzman	11,000	Micro	89	0.0177	White	Female	Human	4.5385	0.0000
agraceabbott	10,900	Micro	97	0.0728	White	Female	Human	4.2642	0.0033
pippapei	10,800	Micro	13	0.0219	Non-white	Female	Virtual HR	3.8190	0.0517
perl.www	10,200	Micro	23	0.1518	White	Female	Virtual HR	4.0928	0.0722
takeheartuk	10,000	Nano	47	0.0446	White	Female	Human	4.6277	0.0027
alicemikoni	10,000	Nano	8	0.0344	White	Female	Virtual HR	3.2931	0.1034
yameiionline	9,956	Nano	15	0.1670	Non-white	Female	Virtual C	4.0194	0.0129
bricelyliriano	9,622	Nano	23	0.1058	White	Female	Human	4.6258	0.0000
plusticboy	9,420	Nano	4	0.1189	Non-white	Male	Virtual HR	4.0861	0.0492
lewis_hiro_newman	8,500	Nano	5	0.1684	Non-white	Male	Virtual HR	3.9341	0.0586
amiyamato	8,463	Nano	68	0.0832	Non-white	Female	Virtual C	3.8298	0.0957
ria_ria_tokyo	8,231	Nano	12	0.0605	Non-white	Female	Virtual HR	4.0957	0.0851
michaelsabunii	8,019	Nano	37	0.0592	Non-white	Male	Human	4.2712	0.0000
bebiselis	8,000	Nano	5	0.0371	White	Female	Virtual HR	3.5331	0.0041
fauxnandes	7,771	Nano	77	0.0676	Non-white	Female	Human	4.7412	0.0235
freesoulmum	7,770	Nano	9	0.0781	White	Female	Human	4.4833	0.0000
ivaany.h	7,586	Nano	13	0.0132	Non-white	Female	Virtual HR	4.6471	0.0000
xx_uca_xx	7,109	Nano	9	0.0916	Non-white	Female	Virtual HR	4.5000	0.0357
bellwether_dario	6,948	Nano	95	0.0296	Non-white	Male	Human	3.9167	0.0076
theonshoremum	6,557	Nano	39	0.0404	White	Female	Human	4.5234	0.0000
dagny.gram	6,364	Nano	12	0.2534	White	Female	Virtual HR	3.5139	0.2253
candiceklubb	5,964	Nano	8	0.0439	White	Female	Virtual HR	3.8396	0.1509
christiancaro_	5,761	Nano	59	0.0715	White	Male	Human	4.0729	0.0208
amishbeauty	5,346	Nano	12	0.1314	Non-white	Female	Human	4.6997	0.0034
still_georgette	5,081	Nano	80	0.3080	Non-white	Female	Human	4.5522	0.0087
nelsy.ernst	4,998	Nano	92	0.0880	Non-white	Female	Human	4.5674	0.0000
monica_giglio	4,737	Nano	79	0.0374	White	Female	Human	4.4783	0.0000
cahaya.gram	4,498	Nano	8	0.1538	White	Female	Virtual HR	4.0123	0.1235
amanda_bims	4,467	Nano	12	0.0668	White	Female	Virtual HR	4.2195	0.0000
ameliadepippo	4,380	Nano	16	0.0947	White	Female	Human	4.8590	0.0038
polishboy08	4,352	Nano	23	0.0561	White	Male	Virtual HR	3.4250	0.0250
yona.obj	4,351	Nano	14	0.0419	White	Female	Virtual HR	4.1875	0.0625
ellie.blakeney	3,578	Nano	1	0.1049	White	Female	Human	4.5025	0.0000
cloe_benoliel	3,566	Nano	83	0.0166	White	Female	Human	4.4167	0.0000
alexisbakerrr	3,501	Nano	58	0.1050	Non-white	Female	Human	4.5074	0.0000
hey_mrs.stone	3,276	Nano	16	0.0184	White	Female	Virtual HR	4.6094	0.0313
the_hashtag_mama	3,161	Nano	61	0.0704	White	Female	Human	4.5480	0.0000
natasha_ivanchenko	2,532	Nano	46	0.2655	White	Female	Human	4.3726	0.0118
brenn.gram	2,521	Nano	20	0.2649	Non-white	Female	Virtual HR	4.0333	0.1394
lozzietravels	2,450	Nano	85	0.2178	Non-white	Female	Human	4.5356	0.0000
sara.kosmos	2,288	Nano	6	0.0858	White	Female	Virtual HR	3.3333	0.2500
meme.konichiwa	2,067	Nano	11	0.0820	Non-white	Female	Virtual HR	3.6852	0.1111
blondedges	1,973	Nano	35	0.1788	Non-white	Female	Human	4.4725	0.0000
milla_sakurai	1,944	Nano	6	0.0808	Non-white	Female	Virtual HR	4.4524	0.0000
pearlsandpencil	1,884	Nano	42	0.0630	Non-white	Female	Human	4.2400	0.0000
jenniferskma	1,751	Nano	19	0.2774	White	Female	Human	4.7135	0.0000
poka_pokaka	1,503	Nano	16	0.1644	Non-white	Female	Virtual HR	3.9048	0.0952
karolinxs	1,456	Nano	12	0.1948	White	Female	Virtual HR	3.5000	0.1370
asyastrike	1,351	Nano	17	0.2774	White	Female	Virtual HR	4.0570	0.0403
julesbaron_	1,312	Nano	77	0.2929	White	Female	Human	4.6371	0.0242
robinabree	1,188	Nano	26	0.0455	White	Female	Virtual HR	3.7353	0.0000

Appendix B: Outputs from Jamovi

Descriptives

Descriptives

	Reality Level	Longevity	Engagement Rate	Following Size	Race	Gender
N	Human	65	65	65	65	65
	Virtual	62	62	62	62	62
Missing	Human	0	0	0	0	0
	Virtual	0	0	0	0	0
Mean	Human	69.4	0.0696	0.923	0.538	0.708
	Virtual	18.8	0.0837	0.871	0.516	0.742
Median	Human	79	0.0446	1	1	1
	Virtual	13.5	0.0586	1.00	1.00	1.00
Minimum	Human	1	0.00530	0	0	0
	Virtual	4	0.00500	0	0	0
Maximum	Human	109	0.308	2	1	1
	Virtual	108	0.302	2	1	1

Frequencies

Frequencies of Following Size

	Reality Level	
Following Size	Human	Virtual
Nano	23	24
Micro	24	22
Macro/Mega	18	16

Frequencies of Race

	Reality Level	
Race	Human	Virtual
White	30	30
Non-white	35	32

Frequencies of Gender

	Reality Level	
Gender	Human	Virtual
Male	19	16
Female	46	46

Independent Samples T-Test Outputs

Sentiment

Independent Samples T-Test

Independent Samples T-Test

		Statistic	df	p
Sentiment	Student's t	8.90 [a]	125	< .001

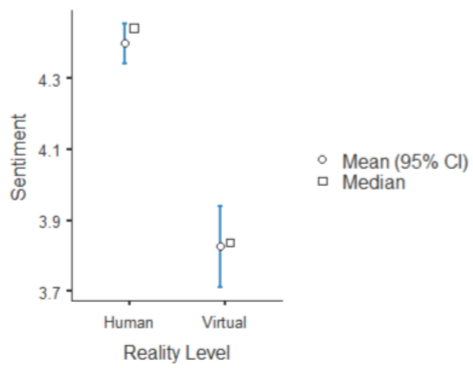
[a] Levene's test is significant (p < .05), suggesting a violation of the assumption of equal variances

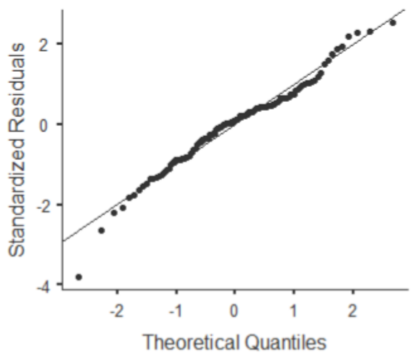
Group Descriptives

	Group	N	Mean	Median	SD	SE
Sentiment	Human	65	4.40	4.44	0.230	0.0285
	Virtual	62	3.83	3.84	0.461	0.0586

Plots

Sentiment





Skepticism

Independent Samples T-Test

Independent Samples T-Test

		Statistic	df	p
Skepticism	Student's t	-6.68 [a]	125	< .001

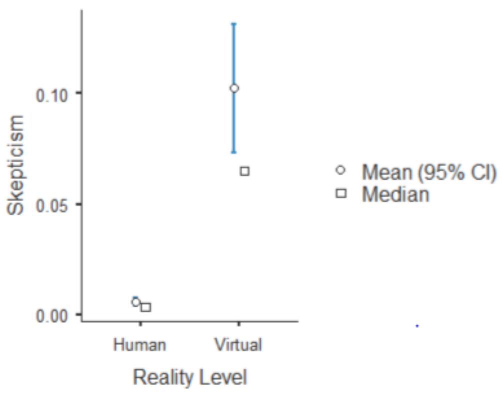
[a] Levene's test is significant (p < .05), suggesting a violation of the assumption of equal variances

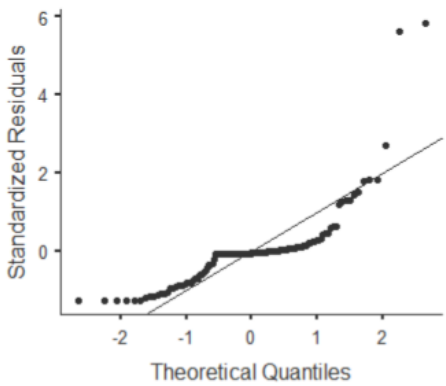
Group Descriptives

	Group	N	Mean	Median	SD	SE
Skepticism	Human	65	0.00566	0.00328	0.00712	8.83e-4
	Virtual	62	0.102	0.0651	0.116	0.0148

Plots

Skepticism





Linear Regression Models Outputs

Longevity – Sentiment

Moderation

Moderation Estimates

	Estimate	SE	Z	p
Reality Level	-0.54528	0.06331	-8.613	< .001
Longevity	4.29e-4	9.28e-4	0.462	0.644
Reality Level ✻ Longevity	0.00440	0.00280	1.574	0.116

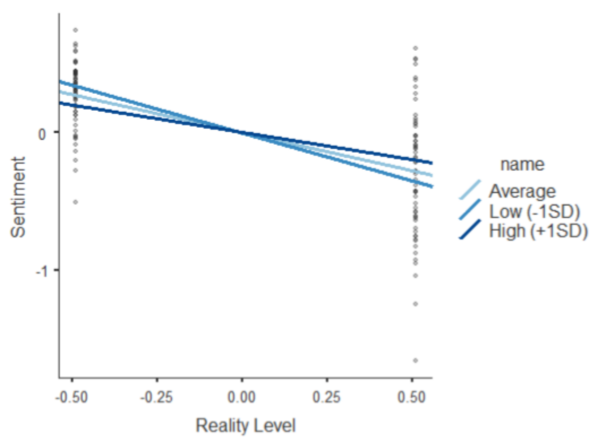
Simple Slope Analysis

Simple Slope Estimates

	Estimate	SE	Z	p
Average	-0.545	0.0647	-8.43	< .001
Low (-1SD)	-0.695	0.1128	-6.17	< .001
High (+1SD)	-0.395	0.1183	-3.34	< .001

Note. shows the effect of the predictor (Reality Level) on the dependent variable (Sentiment) at different levels of the moderator (Longevity)

Simple Slope Plot



Longevity – Skepticism

Moderation

Moderation Estimates

	Estimate	SE	Z	p
Reality Level	0.0895	0.0144	6.233	< .001
Longevity	-1.34e−4	2.10e-4	-0.636	0.525
Reality Level ✻ Longevity	-3.88e−4	6.34e-4	-0.613	0.540

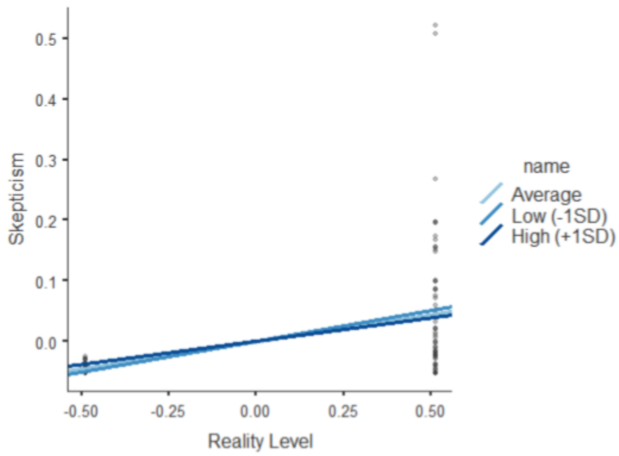
Simple Slope Analysis

Simple Slope Estimates

	Estimate	SE	Z	p
Average	0.0895	0.0144	6.21	< .001
Low (-1SD)	0.1027	0.0253	4.05	< .001
High (+1SD)	0.0762	0.0266	2.87	0.004

Note. shows the effect of the predictor (Reality Level) on the dependent variable (Skepticism) at different levels of the moderator (Longevity)

Simple Slope Plot



Engagement Rate – Sentiment

Moderation

Moderation Estimates

	Estimate	SE	Z	p
Reality Level	-0.5808	0.0633	-9.178	< .001
Engagement Rate	0.6058	0.4371	1.386	0.166
Reality Level ✻ Engagement Rate	0.0879	0.8774	0.100	0.920

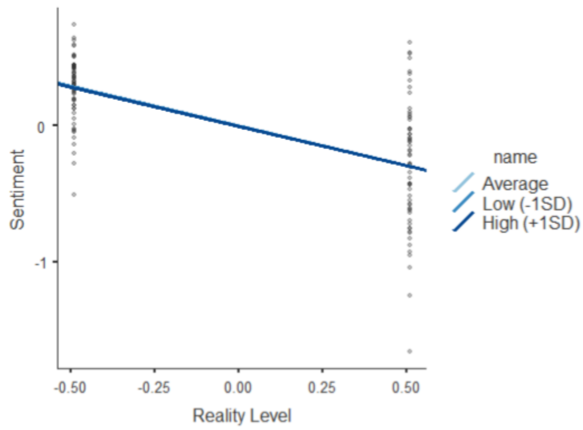
Simple Slope Analysis

Simple Slope Estimates

	Estimate	SE	Z	p
Average	-0.581	0.0633	-9.18	< .001
Low (-1SD)	-0.587	0.0898	-6.54	< .001
High (+1SD)	-0.574	0.0894	-6.42	< .001

Note. shows the effect of the predictor (Reality Level) on the dependent variable (Sentiment) at different levels of the moderator (Engagement Rate)

Simple Slope Plot



Engagement Rate – Skepticism

Moderation

Moderation Estimates

	Estimate	SE	Z	p
Reality Level	0.0969	0.0143	6.752	< .001
Engagement Rate	-0.0114	0.0991	-0.115	0.909
Reality Level ✻ Engagement Rate	-0.0483	0.1990	-0.243	0.808

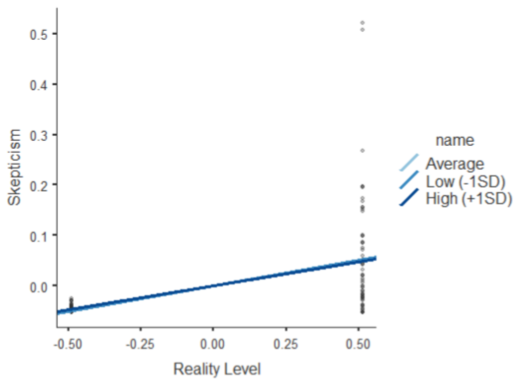
Simple Slope Analysis

Simple Slope Estimates

	Estimate	SE	Z	p
Average	0.0969	0.0144	6.75	< .001
Low (-1SD)	0.1004	0.0204	4.93	< .001
High (+1SD)	0.0934	0.0203	4.60	< .001

Note. shows the effect of the predictor (Reality Level) on the dependent variable (Skepticism) at different levels of the moderator (Engagement Rate)

Simple Slope Plot



Factorial ANOVA Outputs

Following Size – Sentiment

ANOVA

ANOVA - Sentiment

	Sum of Squares	df	Mean Square	F	p
Reality Level	10.6212	1	10.6212	83.109	< .001
Following Size	0.8402	2	0.4201	3.287	0.041
Reality Level ✻ Following Size	0.0845	2	0.0423	0.331	0.719
Residuals	15.4636	121	0.1278		

Assumption Checks

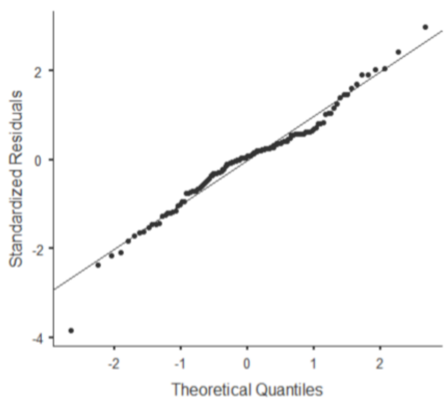
Homogeneity of Variances Test (Levene's)

F	df1	df2	p
5.14	5	121	< .001

Normality Test (Shapiro-Wilk)

Statistic	p
0.972	0.010

Q-Q Plot



Post Hoc Tests

Post Hoc Comparisons - Following Size

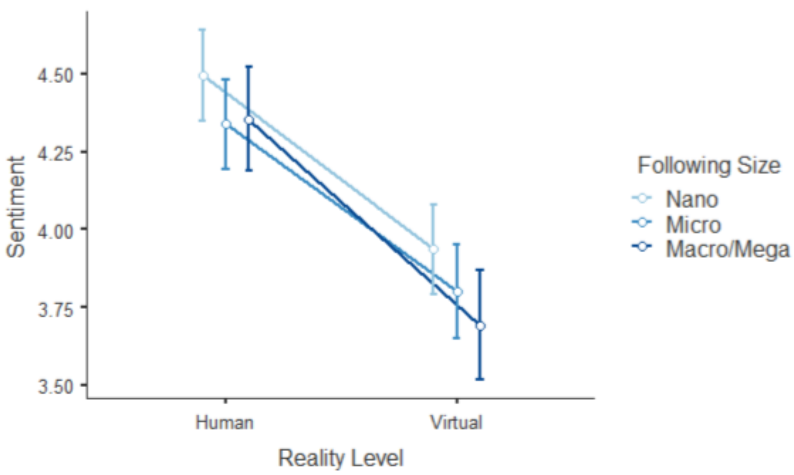
Comparison							
Following Size		Following Size	Mean Difference	SE	df	t	p_{tukey}
Nano	-	Micro	0.1448	0.0742	121	1.951	0.129
	-	Macro/Mega	0.1909	0.0806	121	2.369	0.050
Micro	-	Macro/Mega	0.0461	0.0810	121	0.570	0.837

Post Hoc Comparisons - Reality Level ✻ Following Size

Comparison									
Reality Level	Following Size		Reality Level	Following Size	Mean Difference	SE	df	t	p_{tukey}
Human	Nano	-	Human	Micro	0.1565	0.104	121	1.500	0.665
		-	Human	Macro/Mega	0.1394	0.113	121	1.239	0.817
		-	Virtual	Nano	0.5588	0.104	121	5.357	< .001
		-	Virtual	Micro	0.6919	0.107	121	6.490	< .001
		-	Virtual	Macro/Mega	0.8012	0.116	121	6.884	< .001
	Micro	-	Human	Macro/Mega	-0.0170	0.111	121	-0.153	1.000
		-	Virtual	Nano	0.4024	0.103	121	3.899	0.002
		-	Virtual	Micro	0.5354	0.106	121	5.074	< .001
		-	Virtual	Macro/Mega	0.6447	0.115	121	5.588	< .001
	Macro/Mega	-	Virtual	Nano	0.4194	0.111	121	3.763	0.003
		-	Virtual	Micro	0.5525	0.114	121	4.863	< .001
		-	Virtual	Macro/Mega	0.6618	0.123	121	5.388	< .001
Virtual	Nano	-	Virtual	Micro	0.1331	0.106	121	1.261	0.805
		-	Virtual	Macro/Mega	0.2424	0.115	121	2.101	0.294
	Micro	-	Virtual	Macro/Mega	0.1093	0.117	121	0.930	0.938

Estimated Marginal Means

Reality Level ✻ Following Size



Following Size – Skepticism

ANOVA

ANOVA - Skepticism

	Sum of Squares	df	Mean Square	F	p
Reality Level	0.2914	1	0.29137	44.47	< .001
Following Size	0.0188	2	0.00942	1.44	0.241
Reality Level ✻ Following Size	0.0192	2	0.00958	1.46	0.236
Residuals	0.7927	121	0.00655		

Assumption Checks

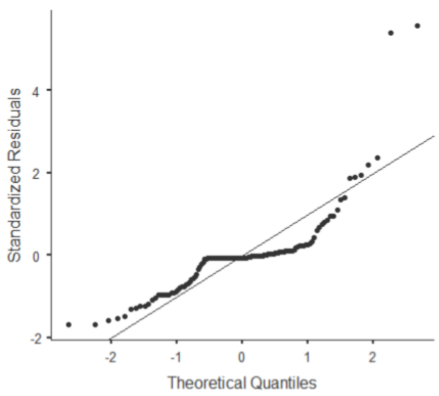
Homogeneity of Variances Test (Levene's)

F	df1	df2	p
17.6	5	121	< .001

Normality Test (Shapiro-Wilk)

Statistic	p
0.737	< .001

Q-Q Plot



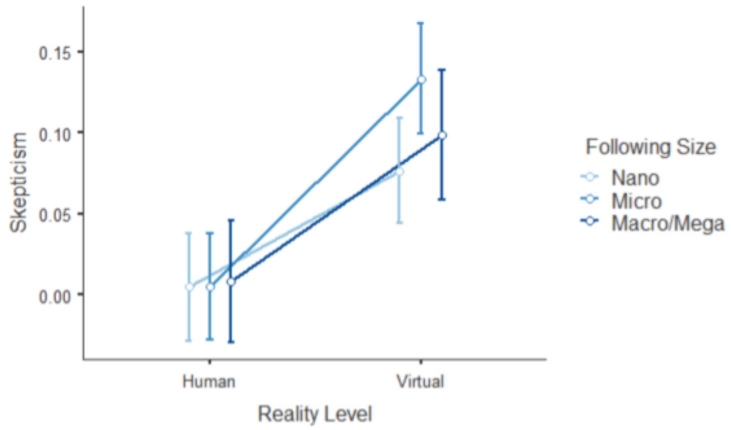
Post Hoc Tests

Post Hoc Comparisons - Reality Level ✻ Following Size

Comparison									
Reality Level	Following Size		Reality Level	Following Size	Mean Difference	SE	df	t	p_{tukey}
Human	Nano	-	Human	Micro	-1.40e−4	0.0236	121	-0.00592	1.000
		-	Human	Macro/Mega	-0.00352	0.0255	121	-0.13810	1.000
		-	Virtual	Nano	-0.07188	0.0236	121	-3.04341	0.033
		-	Virtual	Micro	-0.12865	0.0241	121	-5.32970	< .001
		-	Virtual	Macro/Mega	-0.09397	0.0264	121	-3.56639	0.007
	Micro	-	Human	Macro/Mega	-0.00338	0.0252	121	-0.13384	1.000
		-	Virtual	Nano	-0.07174	0.0234	121	-3.07033	0.031
		-	Virtual	Micro	-0.12851	0.0239	121	-5.37897	< .001
		-	Virtual	Macro/Mega	-0.09383	0.0261	121	-3.59191	0.006
	Macro/Mega	-	Virtual	Nano	-0.06836	0.0252	121	-2.70873	0.081
		-	Virtual	Micro	-0.12513	0.0257	121	-4.86419	< .001
		-	Virtual	Macro/Mega	-0.09046	0.0278	121	-3.25256	0.018
Virtual	Nano	-	Virtual	Micro	-0.05677	0.0239	121	-2.37613	0.173
		-	Virtual	Macro/Mega	-0.02209	0.0261	121	-0.84573	0.958
	Micro	-	Virtual	Macro/Mega	0.03467	0.0266	121	1.30382	0.782

Estimated Marginal Means

Reality Level ✻ Following Size



Gender – Sentiment

ANOVA

ANOVA - Sentiment

	Sum of Squares	df	Mean Square	F	p
Reality Level	8.9977	1	8.9977	79.394	< .001
Gender	2.4360	1	2.4360	21.495	< .001
Reality Level ✻ Gender	0.0261	1	0.0261	0.230	0.632
Residuals	13.9395	123	0.1133		

Assumption Checks

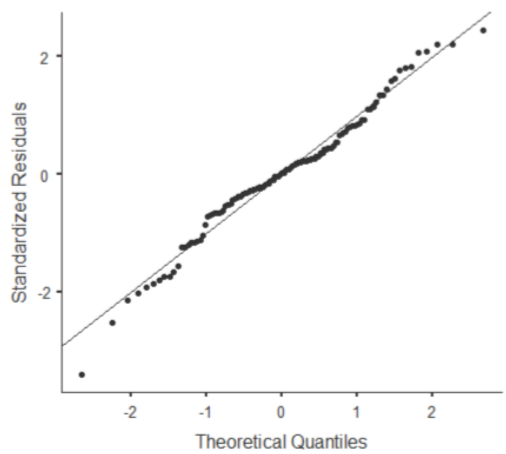
Homogeneity of Variances Test (Levene's)

F	df1	df2	p
12.7	3	123	< .001

Normality Test (Shapiro-Wilk)

Statistic	p
0.978	0.037

Q-Q Plot

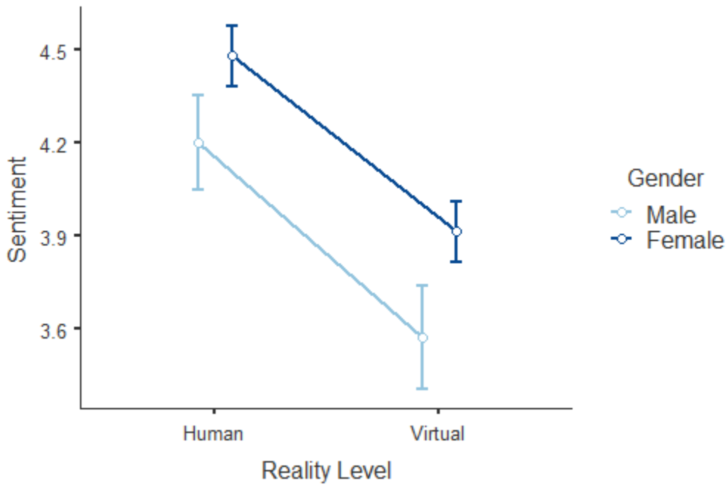


Post Hoc Comparisons - Reality Level ✻ Gender

Comparison									
Reality Level	Gender		Reality Level	Gender	Mean Difference	SE	df	t	p_{tukey}
Human	Male	-	Human	Female	-0.279	0.0918	123	-3.03	0.015
		-	Virtual	Male	0.629	0.1142	123	5.51	< .001
		-	Virtual	Female	0.287	0.0918	123	3.12	0.012
	Female	-	Virtual	Male	0.908	0.0977	123	9.29	< .001
		-	Virtual	Female	0.565	0.0702	123	8.05	< .001
Virtual	Male	-	Virtual	Female	-0.343	0.0977	123	-3.51	0.003

Estimated Marginal Means

Reality Level ✻ Gender



Gender - Skepticism

ANOVA

ANOVA - Skepticism

	Sum of Squares	df	Mean Square	F	p
Reality Level	0.228	1	0.22801	33.79580	< .001
Gender	5.33e-5	1	5.33e-5	0.00790	0.929
Reality Level ∗ Gender	3.06e-4	1	3.06e-4	0.04530	0.832
Residuals	0.830	123	0.00675		

Assumption Checks

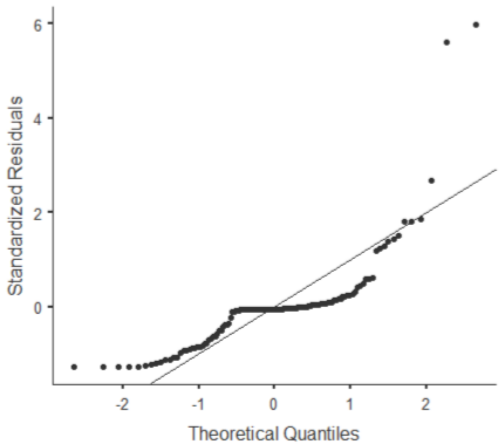
Homogeneity of Variances Test (Levene's)

F	df1	df2	p
19.2	3	123	< .001

Normality Test (Shapiro-Wilk)

Statistic	p
0.687	< .001

Q-Q Plot



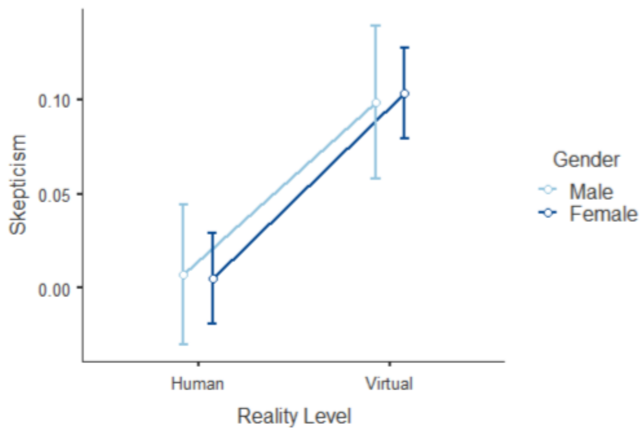
Post Hoc Tests

Post Hoc Comparisons - Reality Level ✻ Gender

Comparison									
Reality Level	Gender		Reality Level	Gender	Mean Difference	SE	df	t	p_{tukey}
Human	Male	-	Human	Female	0.00203	0.0224	123	0.0905	1.000
		-	Virtual	Male	-0.09160	0.0279	123	-3.2868	0.007
		-	Virtual	Female	-0.09654	0.0224	123	-4.3098	< .001
	Female	-	Virtual	Male	-0.09363	0.0238	123	-3.9275	< .001
		-	Virtual	Female	-0.09857	0.0171	123	-5.7550	< .001
Virtual	Male	-	Virtual	Female	-0.00494	0.0238	123	-0.2070	0.997

Estimated Marginal Means

Reality Level ✻ Gender



Race – Sentiment

ANOVA

ANOVA - Sentiment

	Sum of Squares	df	Mean Square	F	p
Reality Level	10.585	1	10.585	85.70	< .001
Race	0.386	1	0.386	3.12	0.080
Reality Level ✻ Race	0.826	1	0.826	6.68	0.011
Residuals	15.192	123	0.124		

Assumption Checks

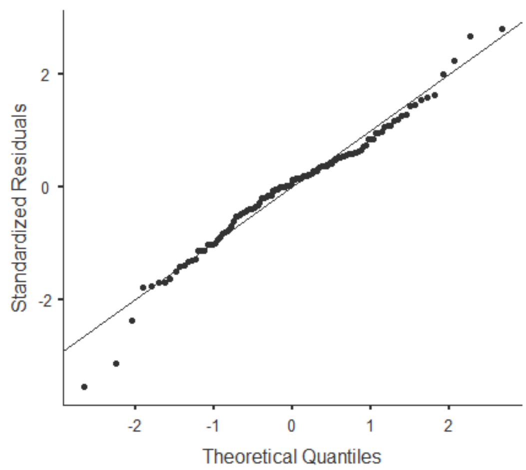
Homogeneity of Variances Test (Levene's)

F	df1	df2	p
7.20	3	123	< .001

Normality Test (Shapiro-Wilk)

Statistic	p
0.975	0.017

Q-Q Plot



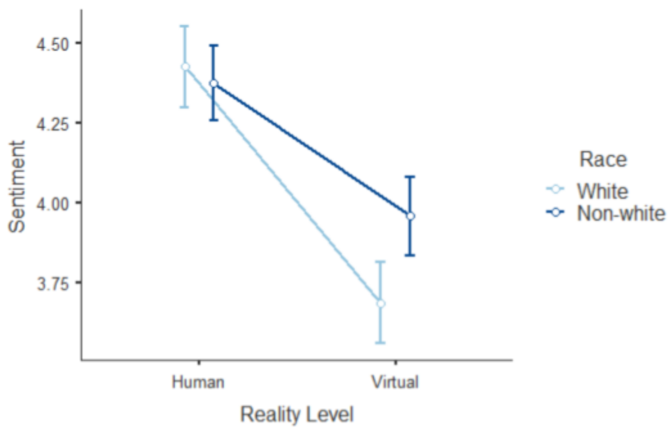
Post Hoc Tests

Post Hoc Comparisons - Reality Level ✻ Race

Comparison									
Reality Level	Race		Reality Level	Race	Mean Difference	SE	df	t	p_{tukey}
Human	White	-	Human	Non-white	0.0511	0.0874	123	0.585	0.937
		-	Virtual	White	0.7401	0.0907	123	8.157	< .001
		-	Virtual	Non-white	0.4681	0.0893	123	5.241	< .001
	Non-white	-	Virtual	White	0.6890	0.0874	123	7.880	< .001
		-	Virtual	Non-white	0.4170	0.0860	123	4.851	< .001
Virtual	White	-	Virtual	Non-white	−0.2720	0.0893	123	−3.046	0.015

Estimated Marginal Means

Reality Level ✻ Race



Race – Skepticism

ANOVA

ANOVA - Skepticism

	Sum of Squares	df	Mean Square	F	p
Reality Level	0.3018	1	0.30177	47.79	< .001
Race	0.0263	1	0.02633	4.17	0.043
Reality Level ✻ Race	0.0282	1	0.02822	4.47	0.037
Residuals	0.7768	123	0.00632		

Assumption Checks

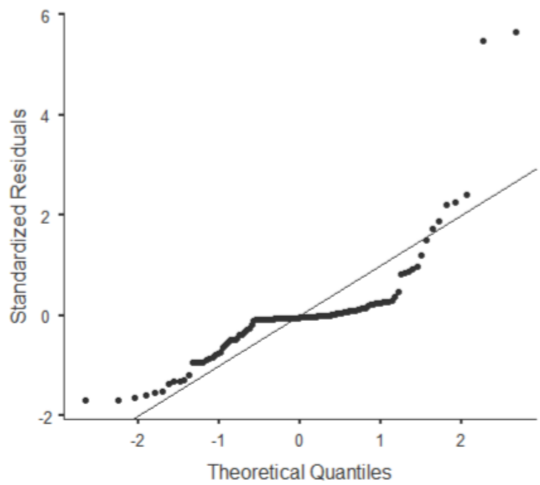
Homogeneity of Variances Test (Levene's)

F	df1	df2	p
22.9	3	123	< .001

Normality Test (Shapiro-Wilk)

Statistic	p
0.714	< .001

Q-Q Plot



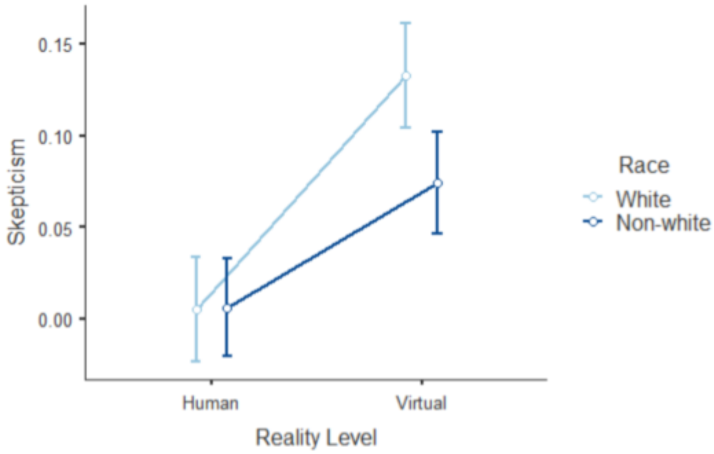
Post Hoc Tests

Post Hoc Comparisons - Reality Level ✻ Race

Comparison									
Reality Level	Race		Reality Level	Race	Mean Difference	SE	df	t	p_{tukey}
Human	White	-	Human	Non-white	−0.00102	0.0198	123	−0.0515	1.000
		-	Virtual	White	−0.12756	0.0205	123	−6.2168	< .001
		-	Virtual	Non-white	−0.06883	0.0202	123	−3.4083	0.005
	Non-white	-	Virtual	White	−0.12654	0.0198	123	−6.3999	< .001
		-	Virtual	Non-white	−0.06781	0.0194	123	−3.4889	0.004
Virtual	White	-	Virtual	Non-white	0.05873	0.0202	123	2.9079	0.022

Estimated Marginal Means

Reality Level ✻ Race



Correlation Matrix Outputs

Full Sample

Correlation Matrix

Correlation Matrix

		Longevity	Engagement Rate	Following Size	Sentiment	Skepticism
Longevity	Pearson's r	—				
	p-value	—				
Engagement Rate	Pearson's r	-0.235	—			
	p-value	0.008	—			
Following Size	Pearson's r	0.262	-0.414	—		
	p-value	0.003	< .001	—		
Sentiment	Pearson's r	0.444	0.034	-0.147	—	
	p-value	< .001	0.701	0.098	—	
Skepticism	Pearson's r	-0.388	0.040	0.049	-0.682	—
	p-value	< .001	0.655	0.581	< .001	—

HIs-Only Sample

Correlation Matrix

		Longevity	Engagement Rate	Following Size	Sentiment	Skepticism
Longevity	Pearson's r	—				
	p-value	—				
Engagement Rate	Pearson's r	-0.311	—			
	p-value	0.012	—			
Following Size	Pearson's r	0.484	-0.514	—		
	p-value	< .001	< .001	—		
Sentiment	Pearson's r	-0.206	0.172	-0.255	—	
	p-value	0.100	0.171	0.040	—	
Skepticism	Pearson's r	0.217	0.120	0.189	-0.112	—
	p-value	0.083	0.339	0.133	0.374	—

VIs-Only Sample

Correlation Matrix

		Longevity	Engagement Rate	Following Size	Sentiment	Skepticism
Longevity	Pearson's r	—				
	p-value	—				
Engagement Rate	Pearson's r	-0.161	—			
	p-value	0.211	—			
Following Size	Pearson's r	0.161	-0.313	—		
	p-value	0.212	0.013	—		
Sentiment	Pearson's r	0.099	0.106	-0.211	—	
	p-value	0.445	0.414	0.099	—	
Skepticism	Pearson's r	-0.049	-0.023	0.099	-0.603	—
	p-value	0.708	0.858	0.445	< .001	—

Appendix C: Comment Ratings

Example of Final Comment Ratings for VI @xx_uca_xx

Post	Username	Researcher 1 Sentiment	Researcher 2 Sentiment	Average Sentiment	Researcher 1 Skepticism	Researcher 2 Skepticism	Amended Skepticism	Original Comment	Translation
Post 1	kokoadog	4	3	3.5	0	0	0	黒のイメージあんまり無かったので新鮮で大人っぽいくて素敵です！	There wasn't much black image, so it's fresh and mature!
Post 2	mina36mii	4	4	4	0	0	0	どっちもすき🥰✨	Whichever you like ✨
Post 3	kokoadog	5	5	5	0	0	0	もー全てがキレイ過ぎて。いつも目の保養をありがとうございます✨	Everything is too beautiful. Thank you very much for your eyelid ✨
Post 4	kokoadog	5	4	4.5	0	0	0	うかさんはどんな事があっても自分を捨てず、輝いてるのが素敵です！！	It's nice that Kaka shines, no matter what happens! !!
	minemixx	5	5	5	0	0	0	😭❤️	😭❤️
Post 5	dauren.kazymbek	4	3	3.5	1	1	1	Like a doll)	Like a doll)
	okamemaro	4	4	4	0	0	0	❤️	❤️
	dfmychan22	4	3	3.5	0	0	0	うかちゃんがくにかさんのクッキー持ってる🤭💕あゆみさんのプロップスタイリングで3人の神コラボも見たいです🎀月曜どうでしょうへのゲスト出演もお待ちしております（笑）	Ukachangakunika's cookies have are 🤭💕 in Prop styling of Ayumi 3 people of God collaboration is also want to see 🎀 We look forward also guest appearances on Monday what about (laughs)
	strawberry6yuri	4	4	4	0	0	0	KUNIKAさんのクッキー😭💓💓💓可愛くてucaちゃんに似合ってます👼🏻✨	KUNIKA's cookie 😭💓💓💓 Cute and suits uca-chan 👼🏻✨
	kokoadog	4	4	4	0	0	0	めちゃくちゃ可愛いです！	It is insanely cute!
	avamamaia	5	4	4.5	0	0	0	So cute 😍	So cute 😍
Post 6	mohammed.2925	5	5	5	0	0	0	@xx_uca_xx I want marry you💍	@xx_uca_xx I want marry you💍
	victorkahnwald	5	5	5	0	0	0	Beautiful 😍🇧🇷	Beautiful 😍🇧🇷
	kokoadog	4	4	4	0	0	0	チョコ作って食べてもらいたいですね(笑)	I want you to make chocolate and eat it (laughs)
Post 7	3107.md	4	4	4	0	0	0	🎁	🎁
	luccas_br_	5	5	5	0	0	0	Meu deus q perfeitaaa 💖💗	My god q perfectaa 💖💗
	kokoadog	4	4	4	0	0	0	いつもと違って、カッコいい！素敵です✨	Cool, unlike usual! It's nice ✨
Post 8	avamamaia	5	5	5	0	0	0	So beautiful ❤️	So beautiful ❤️
	pocoapocotokyo	4	4	4	0	0	0	タグ付けありがとうございました。repostしても大丈夫ですか？	Thank you for tagging. Is it okay to repost?
	___tzm	5	4	4.5	0	0	0	一回のいいね❤じゃ足りないです🥺💖	One like ❤ is not enough 💖
	__04s.__	5	5	5	0	0	0	あけおめことよろ💖かわいすぎ💖	Happy New Year 💖 Too Cute 💖
	kokoadog	5	5	5	0	0	0	新年から最高に可愛いです！今年も沢山投稿お待ちしてます✨	It is cute best from the New Year! Also look forward to many post this year ✨
	kiradayooo	5	5	5	0	0	0	今年もよろしくお願いします🐁💜	Thank you again this year 🐁💜
Post 9	tyoke.k.mint	5	5	5	0	0	0	🎄☃️Merry X'mas🤶💫☃️🎄	🎄☃️Merry X'mas🤶💫☃️🎄
	kokoadog	5	5	5	0	0	0	ぬくぬく最高💗暖炉素敵。うかさんキレイ！	Warm and warm 💗 Fireplace nice. Kasan is beautiful!
	rm_ksn_kiki	5	5	5	0	0	0	うかちゃん大天使😭🎀	Ikachan archangel 😭🎀
Post 10	kokoadog	5	5	5	0	0	0	Merry Christmas。引きこもり万歳🙌	Merry Christmas. Withdrawal hurry🙌
	co.co2187	5	5	5	0	0	0	🎀きょうちゃん🎀おめめ可愛い❤️🎈🌈	🎀 Kyo-chan 🎀 Adorable cute ❤ 🎈 🌈