Building Relationships through AI-Influencers: The Role of AI-Influencer-Product Congruence and Interaction

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Abstract

This research paper examines the effectiveness of artificial intelligence (AI) influencers in public relations by investigating the interplay between AI influencer-product congruence and AI influencers' interaction with the public. The study aims to shed light on the role of interaction in influencing product and brand attitudes, as well as positive word-of-mouth (WOM) intentions.

To examine these relationships, a factorial experimental design was employed, involving participants who were exposed to different levels of congruence and interaction with AI influencers. The findings reveal that congruence between AI influencers and endorsed products has a significant impact on product attitude, brand attitude, and positive WOM intentions. Additionally, the study demonstrates that AI influencers' interaction with their audience plays a crucial role in enhancing these outcomes.

The results support the idea that when AI influencers actively engage with their followers, the influence of congruence between the influencer and the endorsed product becomes more pronounced. This highlights the importance of fostering meaningful interactions to enhance brand communication and build stronger connections with the audience. Organizations and practitioners are encouraged to prioritize interactive communication with AI influencers, as it can lead to more positive brand attitudes and increased positive WOM intentions.

Overall, this research provides valuable insights into the efficacy of AI influencers in public relations. It highlights the potential of AI influencers as gatekeepers to benefit product, brand, and positive WOM intentions. Organizations are recommended to collaborate with AI influencers to build relationships with their target audience. However, it is crucial to design AI influencers with interactive capabilities to maximize their persuasiveness and effectiveness.

This study contributes to the field by addressing a gap in research on AI influencers in public relations. It demonstrates the potential value of this new form of communication in improving attitudes towards products, brands, and WOM. By leveraging AI influencers, organizations can enhance relationship-building with the public. It is important to consider the design and interactivity of AI influencers, while also being mindful of ethical considerations and potential challenges associated with their utilization.

In conclusion, this study underscores the importance of interactive communication in harnessing the power of AI influencers for effective public relations. By fostering meaningful interactions and aligning AI influencers with endorsed products, organizations can build positive attitudes, promote positive WOM, and enhance their overall communication strategies.

Introduction

In the rapidly evolving digital landscape, the practice of public relations (PR) is facing new challenges and opportunities. Building a meaningful relationship between organizations and the publics has been viewed as essential for public relations (Kent & Taylor, 1998, 2002; Taylor & Kent, 2014). However, with the emergence of social media and the rise of influencers, the dynamics of these relationships have undergone significant changes. This paper aims to address the industry issue of the evolving role of influencers and, specifically, the introduction of a new influential figure, the artificial intelligence (AI) influencer, in the context of public relations.

With the increasing reliance on social media platforms for communication, organizations have recognized the potential of these platforms to facilitate two-way, interactive communication with their target audiences (W. Liu et al., 2020; Nah & Saxton, 2013; Wang & Yang, 2020). While the rise of social media allows the environment to be crosslinked, the emergence of social media influencers (SMIs) has called into question conventional concepts of media relations, requiring practitioners entrusted with developing strong connections with their publics to interact with these growing array of opinion leaders, influencers, and gatekeepers (Dhanesh & Duthler, 2019; Pang et al., 2016; Walden et al., 2015).

While traditional social media influencers have played a significant role in disseminating messages and promoting products (Breves et al., 2019; D. Y. Kim & Kim, 2021; Schouten et al., 2020), the emergence of AI influencers adds a new dimension to this landscape. AI influencers are digitally created artificial humans that leverage software and algorithms to perform tasks typically associated with human influencers (Dhanesh & Duthler, 2019; Pang et al., 2016; Walden et al., 2015). It is important to note that an AI influencer is different than virtual endorsers, which are defined as “CGI influencers that look human but are not” (Appel et al., 2020, p.83); as virtual endorsers were ran by the human behind the screen. As a matter of fact, according to the findings from Liu (2019)’s study, approximately 30% of user-generated writings on Twitter is already produced by bots impersonating people using AI technology. This recent development has raised questions and concerns regarding their impact and effectiveness in public relations.

AI influencers represent a novel phenomenon, and their adoption and implications in public relations practice are still emerging. Prominent examples of AI influencer usage in public relations practice are limited at this stage, and empirical research exploring these aspects is scarce. Practitioners need to navigate the challenges of engaging with AI-powered personas and evaluate the potential benefits and risks associated with their use. It is crucial to understand the implications of AI influencers on relationship building, message effectiveness, and public perceptions. To address these industry issues and contribute to the field of public relations, this study aims to investigate the role of congruence between AI influencers and endorsed products, as well as the impact of interactive interaction on communication outcomes. By examining the interplay between these factors, we seek to shed light on the effectiveness of AI influencers in building positive public attitudes, promoting behavioral intentions such as positive word-of-mouth, and ultimately enhancing the practice of public relations.

Literature Review

AI-Created Influencers: Distinctive Aspects and Implications

In recent years, the application of AI technology has extended to various domains, including advertising and marketing. A series of recent studies have focused on the bright sides of the use of an AI in these areas. For instance, Kietzmann, Paschen, and Treen (2018) not only discussed how an AI impacts advertising practice and helps consumers, but also presented five AI building blocks (i.e., natural language processing, image recognition, speech recognition, problem-solving, and machine learning) along with helping to create AI influencers. These building blocks contribute to the creation of AI influencers, enabling them to gather data from social media posts, analyze user-generated content, and deliver content that better resonates with their audience.

Natural language processing enables the AI system to evaluate the subtleties of human language in order to infer meaning from social media posts, product reviews, and/or blogs (Kietzmann et al., 2018). *Image recognition* enables the analysis of photos and videos uploaded by users on social media, providing insights into genuine consumer behavior (Kietzmann et al., 2018, p. 264). *Speech recognition* allows AI to interpret spoken words, finding applications in call centers. These technologies empower AI influencers to collect and analyze user-generated content, enhancing their understanding of consumers and potentially surpassing human influencers in this regard.

AI's *problem-solving* ability to decide on the best solution to a problem helps distinguishing insights that were unseen in the contents (Kietzmann et al., 2018). This trait results in the critical discovery of patterns in data, which improves the capacity to anticipate future behavior (Paschen et al., 2020). When there is no one optimal option for the problem, AI employs divergent problem-solving to generate and analyze multiple solutions, often resulting in equally beneficial outcomes (Paschen et al., 2020). AI influencers can leverage this problem-solving ability to navigate interactions with their followers, posts, or messages, thereby optimizing engagement and fostering meaningful conversations (Araujo et al., 2020).

Machine learning, a final AI building block from Kietzmann et al. (2018), enables AI to improve their performance without relying on pre-programmed rules. Advanced or "deep" machine learning is a crucial component of today's AI systems, thanks to algorithms created by AI researchers that can extract new information from massive amounts of data (Paschen et al., 2020). Deep machine learning boosts the accuracy of recurrent task solutions and improves the system's capacity to tackle more issues more effectively (Paschen et al., 2020). This capability empowers AI influencers to learn from their interactions with followers, continuously improving the quality and relevance of their conversations.

While AI influencer marketing presents promising opportunities, it is important to consider the challenges and concerns associated with this emerging practice. Wu and Wen (2021) examined how AI-created advertisements influenced consumer appreciation and found that while consumers' perceived objectivity of the advertisement increased machine heuristic and consumer appreciation of AI-created advertisement, the more a consumer has feelings of discomfort or eeriness, the less appreciation the consumer has for AI-created advertisements. Mogaji, Olaleye, and Ukpabi (2020) cautioned against application of AI in, particularly, emotionally appealing advertisements due to limitations in data accuracy and the exclusion of traditional media channels.

Research regarding the use of AI influencers and their effects has become highlighted in recent years. In AI influencers as brand endorsers specifically, Thomas and Fowler (2021) investigated how AI influencers as new endorsers effect brand attitudes and purchase intentions. They particularly applied AI influencers in transgression contexts and found when an AI influencer is involved in a transgression, the endorsed brand was negatively impacted just like human influencers. Likewise, interest in research using AI influencers is increasing, and it is expected that the research will gradually proceed actively.

The unique attributes and implications of AI influencers differentiate them from traditional influencer marketing practices. Therefore, this study aims to explore the distinctiveness of AI influencers in the context of public relations and investigate their impact on relationship-building efforts.

Influencer Marketing and AI Influencers: Differentiating Factors

To understand the effects of AI influencer endorsements on public perception and intentions, it is crucial to contextualize AI influencer marketing within the broader framework of influencer marketing. Influencer marketing traces its roots to the concept of native advertising, which refers to digital content that seamlessly integrates with the surrounding content flow, enhancing the user experience (Asquith & Fraser, 2020).

Similar to native advertising, influencer marketing leverages individuals with the ability to influence target audiences to promote brands or products (Brown & Hayes, 2008). The Interactive Advertising Bureau (IAB) defines Influencer marketing as “a tactic by which a brand/agency/publisher works with individuals, aka influencers, to drive brand messages to meet strategic goals" (IAB, 2018, p.5). Influencers are individuals who are seen to have the capacity to generate interaction, drive discourse, and/or sell products/services to the desired target audience (IAB, 2018).

The popularity and impact of influencers have grown significantly on social media platforms such as YouTube (Dekavalla, 2020), and Instagram (O'Meara, 2019; van Driel & Dumitrica, 2021). Influencers encompass a range of individuals, including celebrities, bloggers, YouTubers, and domain specialists (Dekavalla, 2020; E. Kim et al., 2014; Lou & Yuan, 2019). However, the emergence of AI influencers introduces a new dimension to influencer marketing. AI influencers are digitally created artificial personas that utilize AI technology to interact with and influence their audiences. This distinction raises the question of how AI influencers differ from traditional social media influencers and what specific insights they offer in the context of public relations.

Perceived Congruence

Congruence has been defined as the degree to which two objects are similar (Dhanesh & Duthler, 2019; O'Meara, 2019). In the context of influencer marketing, perceived congruence focuses on the fit between the influencer and the endorsed product (Kamins & Gupta, 1994; Till & Busler, 2000). According to the congruity theory, individuals prefer features that are cognitively compatible with each other, and congruent information is recalled and favored over incongruent information (Osgood & Tannenbaum, 1955). Congruence, in particular, can create a stronger associative link, resulting in increased memory spreading activation and attitude accessibility (Till & Busler, 2000; Zdravkovic & Till, 2012). Congruence is often used in advertising or celebrity endorsements to evaluate the fit between the celebrity and endorsed product (Kamins & Gupta, 1994; Till & Busler, 2000). Previous studies have shown that the success of endorsed advertising is inextricably linked to the degree to which the endorser's image, personality, or skill matches the promoted product (e.g., De Cicco et al., 2021; Kamins & Gupta, 1994).

These links are also supported by the match-up hypothesis (Kahle & Homer, 1985; Kamins & Gupta, 1994; Till & Busler, 2000), which states that when an endorser and an advertised product have a high fit, a promotional effort is more compelling (Kamins, 1990). That is, congruence between celebrity and product is an important factor when deciding the efficacy of celebrity endorsement (Xu (Rinka) & Pratt, 2018) and affecting customers' behavioral aspects (Poon & Prendergast, 2006). Conversely, endorsers who promote products that do not fall inside their area of expertise are regarded as less credible (Dwivedi & Johnson, 2013; Lee & Koo, 2015).

In the context of AI influencers, perceived congruence between the AI influencer and the endorsed product plays a crucial role in shaping public attitudes and behavioral intentions. Followers of AI influencers often have shared interests in specific areas (Zhang et al., 2020), , making them more receptive to products that align with the AI influencer's expertise or characteristics (Casaló et al., 2020). Influencer-based marketing strategies are more effective when the influencer and the products that the influencer supports are a good match (D. Y. Kim & Kim, 2021). In this light, perceived congruence between AI influencers' sharing characteristics/expertise and the endorsed product could positively affect the product attitude and brand attitude. Extending this research stream, this study claims that a higher level of congruence between an AI influencer and the endorsed product results in positive outcomes for the brand. Therefore, the following hypothesis was proposed:

H1: Perceived congruence between an AI influencer and an endorsed product positively influences (a) product attitudes, (b) brand attitudes, and (c) positive word-of-mouth intentions. Higher perceived congruence will lead to more favorable attitudes and intentions compared to lower perceived congruence.

AI Influencer Interaction

Using a congruence between an AI influencer and product in an advertisement does not ensure that it will be successful in terms of positively influencing the public's attitudes towards the product and brand, and WOM intention. Another important factor that influences peoples' perceptions and attitudes in influencer advertising is interaction (e.g., Ashley & Tuten, 2015; Chung & Cho, 2017). Within the literature, interactivity is generally divided into three types (Rafaeli & Ariel, 2007): (1) *a perception-related variable* (i.e., focused on individuals' experiences); (2) *a medium characteristic* (i.e., focused on technology aspects and activity) and (3) *a process-related variable* (i.e., focused on information transfer to one another.

In the context of AI influencers, interaction refers to the level of engagement and communication between the AI influencer and their audience. AI influencers who actively interact with their followers and foster engagement play a crucial role as information brokers between brands and the public (Meng & Wei, 2015). Perceived interactivity with a social media post is positively associated with the attitude towards the brand (Daems et al., 2019). Thereby, it is important to note that incorporating interaction has a greater impact on the individuals' persuasiveness.

Compared to the traditional media context, it is more important that influencers boost interaction in the social media context as their interaction with their followers can shape their perceptions. A large number of existing studies in the broader literature have supported that interaction has a positive effect on the individuals' attitudes and behavior (Wang & Li, 2016). Chen et al, found that individuals acquired a higher trust in the vendor and a better comprehension of its products as a result of increased interactivity (2005). The findings from Jun & Yi (2020), suggest that influencer interaction is connected to influencer authenticity and emotional attachment in a positive way. Furthermore, they found the effect of interaction on emotional attachment is mediated by influencer authenticity, which has a direct impact on brand trust. Likewise, high interaction with online followers can positively impact an individual's attitude such as attitudes towards the product and brand. This study, thereby, expects that AI influencers' interactions play a role as moderator. In particular, AI influencers can interact with their publics by aiming at fostering engagement promptly and effectively. Considering the importance of interaction in the context of AI influencers, it is hypothesized:

H2. The level of interaction with an AI influencer positively influences (a)product attitudes, (b) brand attitudes, and (c) positive word-of-mouth intentions. Higher levels of perceived interaction will lead to more favorable attitudes and intentions compared to lower levels of perceived interaction.

Mediating Role of Product Attitudes and Brand Attitudes

Previous research has highlighted the influence of product attitudes on brand attitudes. Product attitudes reflect individuals' evaluations and perceptions of a specific product (Ajzen & Fishbein, 1980), and these attitudes can shape broader brand perceptions. When individuals develop positive attitudes towards a particular product, they are more likely to extend these positive evaluations to the overall brand (Keller, 1993).

Furthermore, brand attitudes encompass a broader set of evaluations, encompassing not only the product but also other brand-related dimensions, such as brand reputation, brand image, and brand personality (Keller, 1993). Brand attitudes are influenced by consumers' overall perceptions of the brand, which are shaped by their experiences with the product, advertising messages, and other brand-related touchpoints (Aaker, 1991).

Previous study has found that perceived interaction between an influencer and followers can strengthen the effects of influencer-product congruence on public responses (Ju & Lou, 2022). When people perceive high engagement and interaction, they may view the influencer endorsement as more authentic and impactful (Agnihotri et al., 2023; Jin et al., 2021; Um, 2022). This is especially true when the influencer-follower relationship is perceived as exchange-oriented, leading to higher credibility of the influencer and more favorable brand attitudes toward the influencer-endorsed ad (Ju & Lou, 2022). This enhances the positive effects of perceiving congruence between the influencer and product. However, when the relationship is perceived as communal-oriented, the congruence between the influencer and product does not significantly affect participants' responses (Ju & Lou, 2022). Based on this prior work, it is expected that:

H3. Where perceived interaction between an AI influencer and its public is high, high-perceived AI influencer-product congruence will have a greater effect on (a) product attitude, (b) brand attitude, and (c) positive WOM than low-perceived AI influencer-product congruence. The effect will not be apparent when perceived interaction between an AI influencer and its public is low.

[Insert Figure 1. Conceptual Model]

In the context of AI influencer marketing, it is logical to posit that consumers' attitudes towards the endorsed product will impact their overall brand attitudes. When consumers perceive congruence between the AI influencer and the product, and develop positive attitudes towards the product, these positive evaluations can extend to shape their brand attitudes. Consumers may associate the favorable product experience and the AI influencer's endorsement with positive brand attributes, resulting in more positive brand attitudes (De Cicco et al., 2021; Kamins & Gupta, 1994).

Existing literature has supported that when people have a favorable attitude toward an entity, the likelihood of behavioral intention increases (e.g., Ajzen & Fishbein, 1980; Eagly & Chaiken, 1993). In realm of public relations research, studies have shown the direction between attitudes and behavioral intentions; that is, positive attitudes (e.g., attitude towards the company) increase behavioral intentions such as engaging positive WOM and expressing an interest in working for a particular company (Boukes & LaMarre, 2021). While it is reasonable to assume that positive attitudes escalate behavioral intention, the relations among the different types of attitudes were not apparent. Therefore, this study attempts to find out the relations between the product attitude and brand attitude. The following research question is explored as well:

RQ: Does the product attitude and brand attitude mediate the relations between congruence and positive WOM intention? If so, is there a clear direction that generates more positive WOM intention than another?

Method

Pretest

In order to ensure whether the relationship between an AI influencer's expertise and the endorsed product is high – vs. low-congruent for the main study, a pretest was conducted. Forty participants were recruited through the SONA system at a large mid-western university and these participants completed the online questionnaire developed with Qualtrics. Participants were given extra course credits as compensation.

[Insert Figure 2. Mock-up AI Influencer's Profile]

First, participants were instructed to read the information in which participants were asked to imagine themselves on Instagram and while they were browsing, they run across an AI influencer ‘AI Tech Insider’ on their feed. The AI influencer ‘AI Tech Inside’ is a fake account that was purposely created for this study (Figure 2). Then, the participant read more information about ‘AI Tech Inside’ (i.e., "AI Tech Insider" has 2,378,054 (2.3 M) followers and is renowned for reviewing cutting-edge technology to increase the knowledge base of its followers). Lastly, in each set, participants were provided a definition of an AI influencer.

After reading the information, participants were instructed to view the AI influencer’s profile page which displays the preview of the six previous posts with a short description of the AI influencer’s expertise (i.e., posts of innovative technology by an AI). To encourage the participants to read the posts, participants were required to view the post for at least 40 seconds and the timer was shown on the screen. After looking at the profile and posts, participants evaluated a set of four Instagram posts representing the AI influencer endorsing four technology products (a keyboard, an electric kettle, an electric vehicle, and a drone) which were selected based on the researcher’s own knowledge of well-known influencers in technology. The posts were presented with names, brands, short descriptions, and pictures of the products. Next, participants were instructed to indicate the perceived congruence of the AI influencer with the technology products on a seven-point Likert scale (1 = strongly incongruent, 7 = strongly congruent).

By comparing the mean of each product, the electric vehicle was perceived to have the highest congruence with the AI influencer’s expertise (M= 5.08), while the electric kettle was perceived to have the lowest congruence (M=2.7). Thus, the mock-up displaying the electric vehicle and the electric kettle was used for the main experiment.

Participants

A total of 196 participants were recruited using the Amazon Mechanical Turk (MTurk) worker pool for this experiment. There was no exclusion for participation and these participants were paid $0.50. The participants agreed to participate in this study by completing an informed consent form.

Out of all participants, the most frequently used social media was reported as Instagram (n = 177, 90.3%), Facebook (n = 169, 86.2%), Twitter (n = 129, 65.8%), WhatsApp (n = 109, 55.6%), and TikTok (n = 54, 27.6%). The 67.4% (n=132) of the participants used social media 5-6 times a week. Participants were an average age of 33.3 years (SD = 10.3; range = 19-60 years). In terms of ethnicity, the participants consisted of white (83.2%), Asian or Pacific Islander (11.2%), Black or African American (7.1%), Hispanic or Latino (4.1%), Native American or Native Indian (1%).

Design and Procedure

This study examines whether the AI influencer–endorsed product congruence and an AI influencer's interaction affect the attitude (i.e., product and brand attitude) and behavioral intention (i.e., WOM). A 2 AI influencer–endorsed product congruence (high vs. low) x 2 AI influencer interaction (high vs. low) between-subjects factorial design was used to test hypotheses.

[Insert Figure 3. Sample Post Stimuli (High congruence & High Interaction)]

The data was collected by Qualtrics and distributed by MTurk as per its privacy agreement. Once participants clicked the external link (i.e., Qualtrics), on the first page, they were guided to fill out the informed consent form. On the next page, participants were asked to answer questions on their social media usage patterns, including preferred social media platforms and weekly frequency (times per week) use. There were no participants who specified as having no experience with social media.

On the next page, participants read the instructions in which participants were asked to imagine themselves on Instagram and while they are browsing, they run across an AI influencer 'AI Tech Inside' on their feed. Then, the same background information about the AI influencer 'AI Tech Inside' which was given in the pretest was shown on the screen. Afterwards, to expose the AI influencer's established expertise, the profile page displaying the preview of the latest posts was shown. On the following page, one of the four stimuli was given to the participants at random (Figure 3 and 4).

[Insert Figure 4. Sample Post Stimuli (Low congruence & Low Interaction)]

The conditions consisted of four AI Tech Insider's posts resembling the typical posts shared by tech influencers. For the high congruence case, the post consisted of the picture of the electric car combined with a description. For the low congruence case, the post consisted of the picture of the electric kettle combined with a description as well. For the high interaction case, in the comments section, the AI influencer's interaction with its public were present. For the low interaction case, the AI influencer's interaction with its public were absent. Then, participants answered perceived congruence between the AI influencer and the product, perceived interaction between the AI influencer and its followers, product attitude, brand attitude, behavioral intention, a series of confounding checks, and disclosing demographics including gender, age, and ethnicity.

Measures

Manipulation Checks

Perceived congruence. To check the manipulation of perceived congruence in the AI influencer's post, the extent to which participants perceived congruence between the AI influencer and the endorsed product was measured. The questions were included: "How relevant is this AI influencer to the product?" "How congruent is the AI influencer with the product? "Overall, how congruent is the AI influencer with the product?" (Menon & Kahn, 2003) ($\alpha = .95$). Scales were rated on a seven-point Likert Scale (1 = *Strongly disagree*, 7 = *Strongly agree*).

Interaction. Manipulation of interaction was checked by adapting the interaction scale from Ki and Kim (2019). The questions involved were: "I feel that the AI influencer 'AI Tech Insider' would talk back to me if I send a private message," "I feel that the AI influencer 'AI Tech Insider' would talk back to me if I post a comment," "I feel that the AI influencer 'AI Tech Insider' would respond to me quickly and efficiently if I send a private message," "I feel that the AI influencer 'AI Tech Insider' would respond to me quickly and efficiently if I post a comment" and "I feel that the AI influencer 'AI Tech Insider' would allow me to communicate directly with him/her" ($\alpha = .77$). A seven-point Likert Scale (1 = *Strongly disagree*, 7 = *Strongly agree*) was used.

Dependent Variables

Attitude towards the product. Attitude towards the product were measured by modifying the product attitude scale from Silvera and Austad (2004). The questions included were: "My impression of (the product name) is desirable," "My impression of (the product name) is pleasant" and "My impression of (the product name) is good" ($\alpha = .81$). Scales were rated on a seven-point Likert Scale (1 = *Strongly disagree*, 7 = *Strongly agree*).

Attitude towards the brand. The scales to measure attitude towards the brand were adapted from Spears and Singh (2004). The questions included were: "My impression of the brand is good," "My impression of the brand is pleasant," "My impression of the brand is likable" and "My impression of the brand is favorable" (α = .88). Scales were rated on a seven-point Likert Scale (1 = *Strongly disagree*, 7 = *Strongly agree*).

Behavioral intention. Behavioral intentions to word-of-mouth were measured by modifying the WOM intention from the previous research (Overton, Kim, Zhang, & Huang, 2021; Zeithaml, Berry, & Parasuraman,1996). The questions included were: "I will say positive things about the brand endorsed by the AI influencer *AI Tech Insider,*" "I will recommend the brand endorsed by the AI influencer *AI Tech Insider* to others," and "I will refer people I know to the brand endorsed by the AI influencer *AI Tech Insider*" (α = .77).

Confounding checks

Perceived message credibility. The perceived message credibility of the AI influencer's post was measured by asking the participants how credible they perceived the AI influencer's post to be. This measurement was considered to be necessary since each individual might have different perceptions concerning the AI influencer's post regardless of the information presented in the post to them. The questions used five bipolar adjectives Likert-type scale by asking participants to rate along a continuum whether the message was 1. unbelievable or believable, 2. inaccurate or accurate, 3. not trustworthy or trustworthy, 4. biased or not biased, and 5. incomplete or complete (Roberts, 2010). In the analysis, the perceived message credibility was controlled as covariate (α = .72).

Perceived content creator. The perceived content creator was measured by asking "who do you think the content creator is for the post that you saw?" (Human vs. AI). Participants who perceived the content creator as human (n=22) were excluded in the final analysis.

Results

Manipulation Checks

A series of independent sample *t*-tests revealed a significance of the effects of influencer–product congruence and interaction manipulations. The results showed a significant effect of influencer–product congruence. The congruence was higher for participants in the high congruence condition than for those in the low congruence condition ($M_{\text{high congruence}} = 6.03$, $SD = 0.65$ vs $M_{\text{low congruence}} = 2.75$, $SD = 1.21$; $t\,(179) = -22.38$, $p < 0.001$). The interaction manipulation was found to be successful. The mean score for the high interaction condition was significantly higher ($M_{\text{high interaction}} = 5.66$, $SD = 0.92$) than that for the low interaction condition ($M_{\text{low interaction}} = 4.1$, $SD = 1.12$; $t\,(179) = -10.221$, $p < 0.05$).

[Insert Table 1. Descriptive statistics for dependent variables]

Tests of Hypotheses

The perceived message credibility toward the AI influencer's post was included as a covariate. The perceived content creator did not have a significant effect on the focal dependent variables and thereby were excluded.

For the statistical analysis, the study used SPSS 25. The study tested H1, H2, and H3 using a series of two-way ANOVAs to examine the effects of the interaction between AI influencer–product congruence and AI influencer interaction (Table 2). The results for H1 showed the main effects of influencer–product congruence on product attitude, $F(1,169) = 72.08$, $p < .000$, $\eta 2 = .30$, brand attitude, $F(1,169) = 94.90$, $p < .000$, $\eta 2 = .36$, and WOM, $F(1,169) =$

19.48, p <.000, η2 = .10, were significant. The effects of influencer–product congruence occurred in the predicted direction. The product attitude among participants who were exposed to the high congruence condition was significantly higher than those observed in participants exposed to the low congruence condition ($M_{\text{high congruence}}$ = 5.42, SD = 0.89 vs. $M_{\text{low congruence}}$ = 4.03, SD = 1.43). Participants in the high congruence condition rated more positive brand attitude than those who were in the low congruence condition ($M_{\text{high congruence}}$ = 5.43, SD = 0.96 vs. $M_{\text{low congruence}}$ = 4.03, SD = 1.28). In addition, the high congruence condition generated greater WOM than the low congruence condition ($M_{\text{high congruence}}$ = 5.73, SD = 0.97 vs. $M_{\text{low congruence}}$ = 5.13, SD = 1.09). Therefore, H1a, H1b, and H1c were supported. The descriptive statistics are shown in Table 1.

[Insert Table 2. Two-way ANOVA Summary Table for Product Attitude, Brand Attitude, and WOM]

H2 predicted that the high AI interaction generates greater product attitude, brand attitude, and WOM compared to the low AI interaction condition. The results showed that the main effects of AI interaction on product attitude F(1,169) = 72.08, p <.000, η2 = .12, brand attitude, F(1,169) = 37.17, p <.000, η2 = .19, and WOM, F(1,169) = 6.05, p <.01, η2 = .04, were significant. Participants in the high interaction condition gave more positive product attitude ratings than those who were in the low interaction condition ($M_{\text{high interaction}}$ = 5.06, SD = 1.48 vs. $M_{\text{low interaction}}$ = 4.34, SD = 1.20). The high interaction condition also generated more positive brand attitudes than the low interaction condition ($M_{\text{high interaction}}$ = 5.08, SD = 1.60 vs. $M_{\text{low interaction}}$ = 4.33, SD = .89). The WOM in participants who were exposed to the high interaction condition was greater than that observed in participants exposed to the low interaction condition (M_{high}

$_{\text{interaction}}$ = 5.50, *SD* = 1.23 vs. $M_{\text{low interaction}}$ = 5.33, *SD* = .90). Thus, H2(a), H2(b), and H2(c) were supported.

[Insert Figure 5 Interaction of congruence and interaction on brand attitude]

H3 predicted an interaction between AI influencer–product congruence and AI influencer interaction. The effect of the two-way interactions on product attitude was not significant ($F(1,169) = 2.95$, $p = .088$, $\eta 2 = .02$). The high perceived AI influencer-product congruence generated a greater effect on product attitude than the low congruence group regardless of the degree (i.e., low vs. high) of AI interaction condition. Therefore, H3(a) was not supported.

[Insert Figure 6 Interaction of congruence and interaction on WOM]

Further analysis discovered that the interaction effects of congruence and interaction on brand attitude and WOM. The ANOVA predicting the brand attitude suggested that there is an interaction effect of congruence and interaction, F (1,169) = 38.93, p <.000, $\eta 2$ = .10. The simple main effect revealed that under the high interaction condition, the high congruence condition ($M_{\text{high congruence}}$ = 6.23, *SD* = .67; F (1,169) = 95.14, p<.001, $\eta 2$ = .36) generated greater brand attitude compared to the low congruence condition ($M_{\text{low congruence}}$ = 4.13, *SD* = 1.52). Therefore, H3(b) was supported. Additionally, the simple main effect showed that under the low interaction condition, the high congruence condition generated greater brand attitude compared to the low congruence condition ($M_{\text{high congruence}}$ = 4.74, *SD* = .54 vs. $M_{\text{low congruence}}$ = 3.94, *SD* = .99; F(1, 169) = 15.29, p < 0.001, $\eta 2$ = .08) (Figure 5 and Table 3). Even though there was a significant difference under both low and high interaction conditions, the F value showed that the higher interaction condition has a greater F value than the lower interaction condition.

The ANOVA predicting the WOM suggested that there is an interaction effect of congruence and interaction, F (1,169) = 6.18, p <.05, $\eta 2$ = .04. The simple main effect revealed that under high interaction condition, the high congruence condition ($M_{\text{high congruence}} = 6.04$, $SD = .74$; $F(1,169) = 95.14$, $p<.001$, $\eta 2 = .36$) generated greater brand attitude compared to the low congruence condition ($M_{\text{low congruence}} = 5.06$, $SD = 1.38$). There was no difference between the high congruence condition ($M_{\text{high congruence}} = 5.46$, $SD = 1.07$) and low congruence condition ($M_{\text{low congruence}} = 5.20$, $SD = .68$) under the low interaction condition (Figure 6 and Table 3). Therefore, H3(c) was supported.

[Insert Table 3. Simple Main Effects Summary Table for Brand Attitude and WOM]

Explanatory Analysis

A serial mediation analysis using PROCESS macro (Model 6, n = 5,000 bootstrap samples; Hayes, 2017) was executed between congruence on positive WOM intention with mediation of product attitude and brand attitude (see Figure 7 and Table 4). There was a serial mediation effect of product attitude and brand attitude between congruence on positive WOM intention. Even though there was no direct effect of congruence on positive WOM intention, there was an indirect effect mediated via product attitude and brand attitude (indirect effect: 0.0610, 95% CI = [0.0098, 0.1241]). In addition, there was an indirect effect mediated via brand attitude between congruence and positive WOM intention (indirect effect: 0.0277, 95% CI = [0.0045, 0.2567]).

Discussion

This study provides crucial insights into the efficacy of AI influencers in the field of public relations. The findings contribute to the growing body of evidence that highlights the positive impact of perceived congruence between AI influencers' expertise and the endorsed product on product attitude, brand attitude, and positive word-of-mouth (WOM) intentions. These findings are consistent with previous studies on SMIs and native advertising, emphasizing the importance of influencer-product congruence in message persuasiveness (Choi & Rifon, 2012; De Cicco et al., 2021; McCormick, 2016). By further exploring the context of AI influencers, this study expands our understanding of the relationship between influencer-product congruence and consumer attitudes and behaviors.

In addition, as expected, based on the effects of interactivity (Chung & Cho, 2017; Wang & Li, 2016), this study found that AI influencers' interactions with the followers are positively associated with both of product and brand attitudes, and WOM. This indicates that the more AI influencers interact with their publics, the more the publics will perceive the message as more persuasive, leading to have a positive attitude towards the product, the brand, and WOM intention. The interactivity between AI influencers and their publics enhances the persuasiveness of their messages, which can be attributed to the problem-solving ability of AI technology (Paschen et al., 2020) and the machine learning capabilities that improve interactions over time (Kietzmann et al., 2018). The unique contribution of AI influencers lies in their capacity to learn from and improve interactions, a trait not commonly found in research on SMIs, gatekeepers, or spokespersons in public relations. This suggests that incorporating interactivity in AI influencer campaigns can effectively enhance message persuasiveness and consumer engagement.

The significant interaction between AI influencer-product congruence and AI influencers' interactions on brand attitude and WOM has important implications for both practice and theory.

From a practical perspective, the findings highlight the critical role of interaction in maximizing the impact of AI influencers in brand communication. When AI influencers engage actively with their audience, the influence of congruence between the influencer and the endorsed product becomes more pronounced. This emphasizes the importance of interactivity as a means of exchanging information (Rafaeli & Ariel, 2007). This implies that organizations and public relations practitioners should prioritize fostering meaningful interactions between AI influencers and their followers. By encouraging two-way communication, responding to comments and messages, and actively engaging in discussions, AI influencers can establish stronger connections with their audience, leading to more positive brand attitudes and increased positive WOM intentions. This emphasizes the need for organizations to design AI influencers with interactive capabilities (e.g., tailoring to the publics' comments continuously) and allocate resources for managing and facilitating their interactions effectively.

Furthermore, the lack of a significant effect on product attitude in the interaction between AI influencer-product congruence and AI influencers' interactions suggests that other factors, such as personal involvement with the product, may play a role in shaping individuals' evaluations. This implies that the impact of AI influencers may vary depending on the level of personal relevance or attachment that individuals have towards the endorsed product (Van den Broeck et al., 2018). Practitioners should consider the unique characteristics and context of the product being promoted and tailor their strategies accordingly. This could involve identifying specific target segments with higher levels of product involvement or utilizing additional marketing tactics to complement the influence of AI influencers on product attitude.

The unique nature of AI influencers presents both opportunities and challenges for public relations practitioners. Organizations can benefit from collaborating with AI influencers as gatekeepers to build relationships with their publics. The findings provide practitioners with useful insights into the factors that impact relationship formation in the emerging setting of AI influencers. This study recommends that organizations should consider collaborating with AI influencers to build a relationship with the publics. According to relationship management theory in public relations, communication is a tool that helps organizations to develop strong and beneficial relationships between organizations and their publics (Ledingham, 2009; Ledingham & Bruning, 2000). As shown by the results from the study, this new form of communication has a great potential value as it improves attitudes toward the product and brand, and WOM.

Successfully implementing an AI influencer as an opinion leader or gatekeeper can improve the dialogue between the organization and its public. It is important to note that when employing AI influencers, the practitioner should consider designing the AI influencers to enable the function of interactivity to ensure the maximize the effects of persuasiveness. AI influencers can engage with their followers and the broader public in meaningful ways. Through interactive platforms and personalized content, they can foster engagement, respond to inquiries, and provide valuable recommendations. This can enhance the overall public experience and build stronger connections between organizations and their target audiences. Additionally, AI influencers can collect and analyze vast amounts of data from their interactions, enabling organizations to gain valuable insights into consumer behaviors, preferences, and sentiment. This data can inform public relations strategies, shape messaging, and guide decision-making processes.

However, it is important to acknowledge that utilizing an AI influencer can raise several issues. For instance, recent AI research has discussed how the spread of unverified information (i.e., misinformation) has resulted in the use of social bots (Broniatowski et al., 2018; Shao et al., 2018). In addition, Paschen, Pitt, and Kietzmann (2020) were concerned about compatibility with the data. Besides, privacy concerns (Campbell et al., 2020) may not be avoided. Hence, the scholars should keep in mind these concerns when integrating the AI technology into research. Moreover, the PR practitioners should consider the ethical issues when collaborating with an AI influencer.

Although this study offers meaningful implications, it is limited by some factors. First, while this study checked the possible confounding variables such as message credibility and content creators (i.e., human vs. AI) among all the stimulus, it is possible that other confounding factors may play a role in the outcomes such as the trust/distrust of the AI influencers. People may blindly trust or distrust of the AI influencers, thus, people may recklessly like/dislike the AI influencers' contents or messages (e.g., automation bias). Thus, future studies should consider examining the role of trust/distrust of an AI influencer and its impact on possible outcomes. Second, there is a question of how parasocial relations between AI influencers and their publics impact on the present outcomes. Since the present study used the fake AI influencer account, how existing relationship between the influencer and the follower was unable to take into account. An inherent limitation of this study is the chosen directionality of the relationships between product attitude, brand attitude, and WOM. While we focused on product attitude as a predictor of brand attitude and WOM, alternative models considering brand attitude as a predictor could provide valuable insights and should be explored in future studies. Last but not least, the study used student samples for the pre-test and MTurk samples for the main study, which means sample bias is unavoidable, so the future study explores if the findings from the study still hold true with other samples.

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Table 1.

Descriptive statistics for dependent variables.

Variables	Congruence	Interaction	*M*	*SD*	*N*
Product Attitude	High	High	6.01	.651	38
		Low	4.92	.74	44
		Total	5.42	.88	82
	Low	High	4.28	1.52	46
		Low	3.78	1.29	46
		Total	4.03	1.43	92
	Total	High	5.06	1.48	84
		Low	4.34	1.20	90
Brand Attitude	High	High	6.23	.67	38
		Low	4.74	.54	44
		Total	5.43	.96	82
	Low	High	4.13	1.52	46
		Low	3.94	.99	46
		Total	4.03	1.28	92
	Total	High	5.08	1.60	84
		Low	4.33	.89	90
Word-of-mouth (WOM)	High	High	6.04	.74	38
		Low	5.46	1.07	44
		Total	5.73	.97	82
	Low	High	5.06	1.38	46
		Low	5.20	.68	46
		Total	5.13	1.09	92
	Total	High	5.50	1.23	84
		Low	5.33	.90	90

Table 2.

Two-way ANOVA Summary Table for Product Attitude, Brand Attitude, and WOM.

Variables	Source	*df*	*MS*	*F*	*p*	*Partial η2*
Product Attitude (N = 174, R^2 = .38, Adj. R^2 = .37)	Congruence	1	87.60	72.08	***	.30
	Interaction	1	33.41	27.50	***	.12
	Congruence ×Interaction	1	3.59	2.95	.088	.02
	Error	169	1.22			
Brand Attitude (N = 174, R^2 = .48, Adj. R^2 = .46)	Congruence	1	90.57	94.88	***	.36
	Interaction	1	37.17	38.93	***	.19
	Congruence ×Interaction	1	17.81	18.66	***	.10

	Error	169	.96			
WOM (N = 174, R^2 = .29, Adj. R^2 = .27)	Congruence	1	16.38	19.48	***	.10
	Interaction	1	6.05	7.20	**	.04
	Congruence ×Interaction	1	5.20	6.18	*	.04
	Error	169	.84			

***p<.001, **p<.01, *p<.05.

Table 3.

Simple Main Effects Summary Table for Brand Attitude and WOM.

						CI95%	
				SE	*p*	lower	upper
Brand Attitude	High Interaction	High congruence	Low congruence	.214	***	1.666	2.512
	Low Interaction	High congruence	Low congruence	.206	***	.399	1.212
WOM	High Interaction	High congruence	Low congruence	.201	***	.565	1.359
	Low Interaction	High congruence	Low congruence	.193	*n.s.*	-.113	.650

***p<.001

Table 4.

Indirect effects of product attitude and brand attitude.

Indirect Effects	Coefficients		Bootstrapping 95% CI	
	Estimate	SE	Lower	Upper
Total Indirect Effects	.1410	.0317	.0833	.2065
Congruence –> Product Attitude –> WOM	.0523	.0315	-.0083	.1188
Congruence –> Brand Attitude –> WOM	.0277	.0134	.0045	.0567
Congruence –> Product Attitude –> Brand Attitude –> WOM	.0610	.0293	.0098	.1241

Figure 1.

Conceptual Model

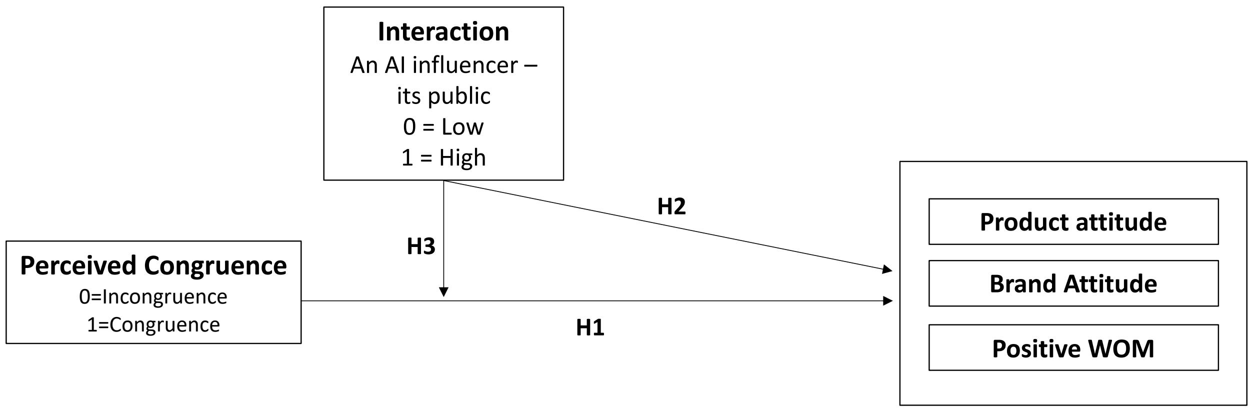


Figure 2.

Mock-up AI Influencer's Profile

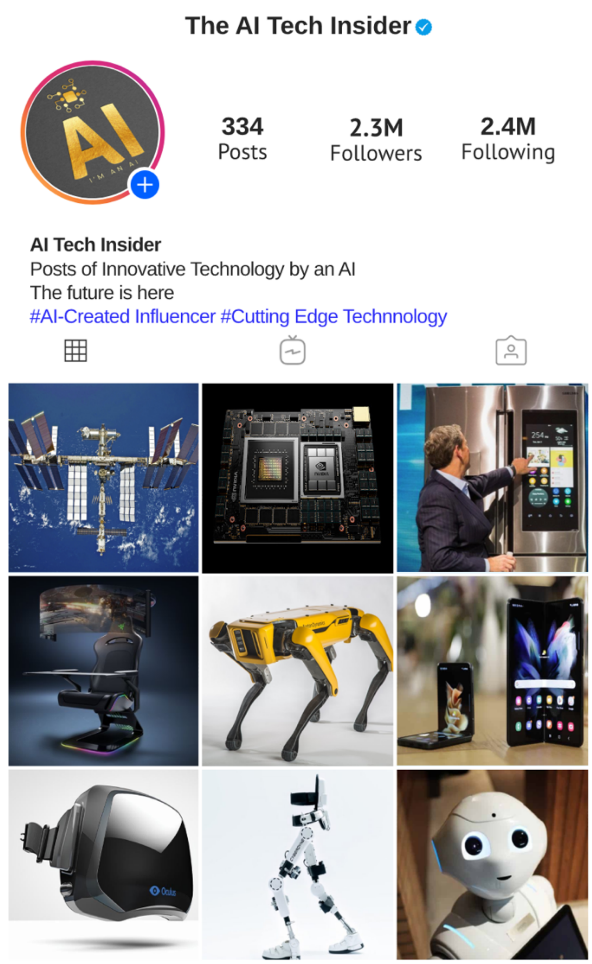


Figure 3.

Sample Post Stimuli (High congruence & High Interaction)

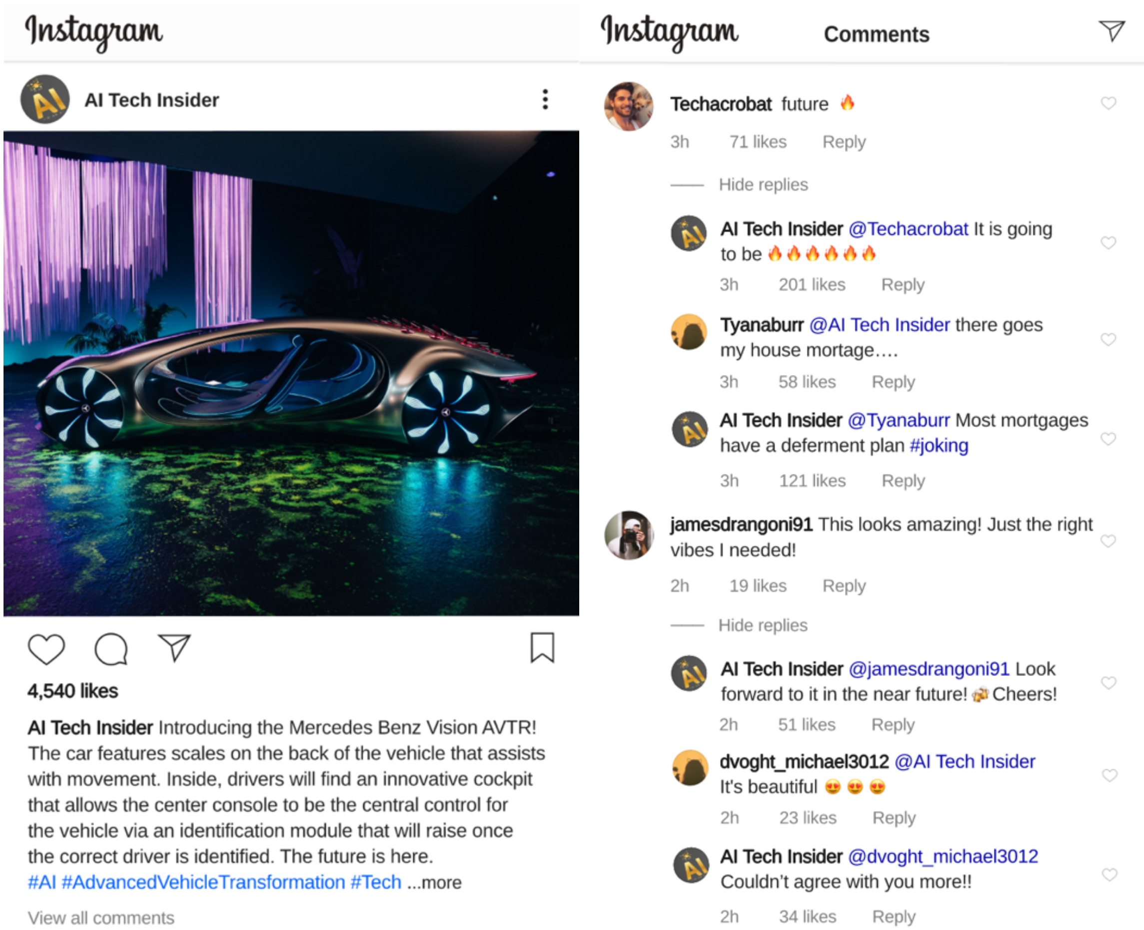


Figure 4.

Sample Post Stimuli (Low congruence & Low Interaction)

Figure 5.

Interaction of congruence and interaction on brand attitude.

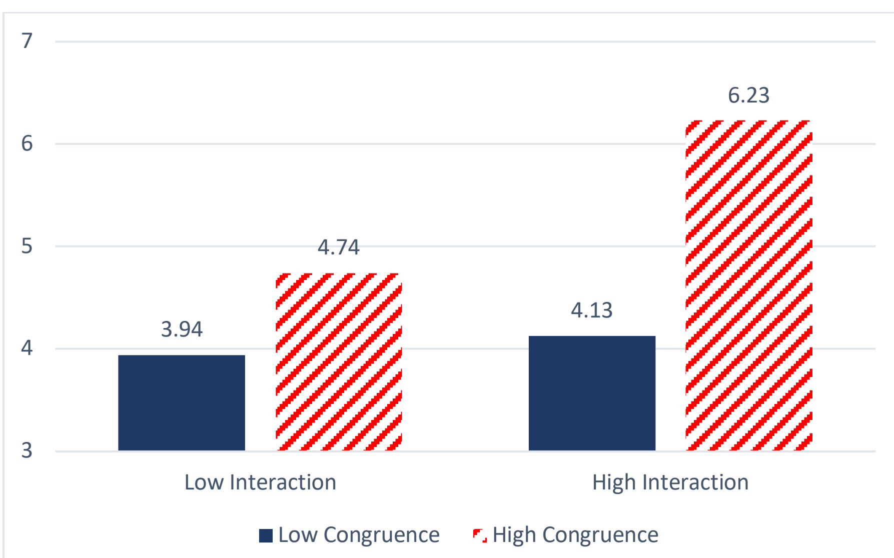


Figure 6.

Interaction of congruence and interaction on WOM.

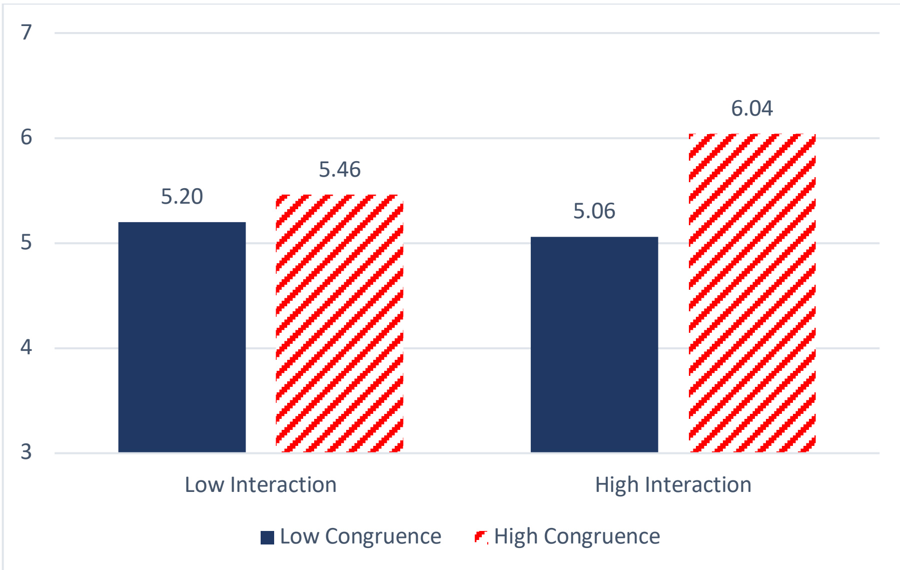
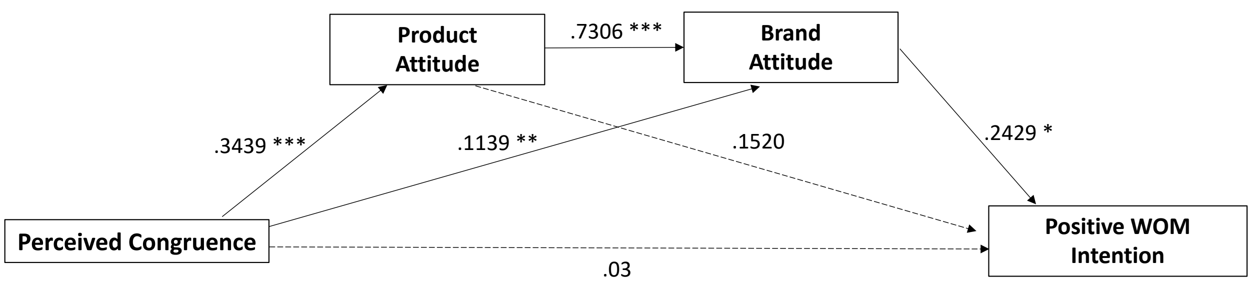


Figure 7.

The serial mediation effect between congruence and positive WOM intention.



*** $p < .001$, ** $p < .01$, * $p < .05$