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More Realistic, More Better? How Anthropomorphic Images of Virtual Influencers Impact the Purchase Intentions of Consumers

Siyu Pan †, Zhouyao Qin † and Yiwei Zhang *

School of Business, Guangxi University, Nanning 530004, China; pansy@gxu.edu.cn (S.P.); 2229301033@st.gxu.edu.cn (Z.Q.)
* Correspondence: zyw3723@126.com
† These authors contributed equally to this work.

Abstract: A growing number of enterprises are using virtual influencers on livestreaming e-commerce platforms to extend the duration for which live streamers stay online. This article uses the uncanny valley phenomenon to investigate the effects of the level of anthropomorphization of images of virtual influencers on the purchase intention of consumers. We divided the images of virtual influencers into three categories according to their level of anthropomorphization: cartoon images (low), medium-realistic images (medium), and hyper-realistic images (high). We identified a U-shaped relationship between the level of anthropomorphization of images of virtual influencers and consumers' purchase intention. Virtual influencers represented by cartoon images and hyper-realistic images enhanced the purchase intentions of consumers, while streamers with medium-realistic images reduced them. Algorithmic aversion was found to play a mediating role in this relation. In addition, self-efficacy had an inhibitory effect on the inverted U-shaped relationship between the anthropomorphism of the image of the virtual influencer and algorithmic aversion. When the virtual influencer had a medium-realistic image, consumers exhibited the strongest algorithmic aversion, the lowest purchase intention, and the most significant inhibition in self-efficacy. This work provides guidance for designing images of virtual influencers for marketing-related activities on livestreaming e-commerce platforms.

Keywords: virtual influencers; image anthropomorphism; algorithmic aversion; self-efficacy; consumer purchase intention

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1. Introduction

The concept of the metaverse has lately gained considerable traction, while livestream e-commerce has grown significantly in recent years. A growing number of virtual influencers are being used on livestreaming e-commerce platforms; they offer a new look as well as novel business opportunities for the online live broadcasting industry [1,2]. The most significant economic value of virtual influencers can be obtained by extending the duration of their livestreams. Enterprises and merchants mostly choose live streamers for live sales during prime hours every day and on holidays to improve their revenues. However, hiring live streamers during non-prime-time hours increases their cost such that it exceeds the corresponding profit. Introducing virtual influencers enables e-commerce companies to obtain high returns at a low cost. Virtual influencers are cheap and can operate for a long period while remaining highly stable. Unlike with human streamers, there is little risk of virtual influencers causing a scandal that can compromise the brand that they are trying to promote [1,3–5]. This is a significant advantage in the context of livestream e-commerce.

Virtual influencers, also known as AI synthesized streamers, digital human streamers, machine streamers, and virtual streamers, are intelligent machines that can replace (or partially replace) humans in broadcasting or live broadcasting tasks [2,4,6]. The term "virtual influencer" as used in this study refers to the "cloning" of a human streamer's "doppelganger" based on virtual technology. It has the same capability of live broadcasting as a human influencer, and its appearance includes various anthropomorphic features [4]. It is trained through modeling by using speech, lip alignment, expression migration, and deep learning, and it can convey the same information as a human influencer. Anthropomorphization is a crucial feature of AI technology [7–9]. The appearance of virtual influencers is the most important factor impacting a user's visual cues in the metaverse [10–12], and it can directly influence a consumer's interactive experience [9]. Therefore, it is important to examine the extent of anthropomorphization of the images of virtual influencers.

Virtual influencers represented by images featuring different degrees of anthropomorphization are widely used for live broadcasts. For example, whenever a human influencer who is selling products for the retailer Three Squirrels on a livestream goes offline, a virtual influencer represented by a cute, short-haired cartoon image takes over the live broadcast room. It can introduce the characteristics, tastes, and preferential policies of more than 600 items in the store. On "Double Eleven" day in 2023, the Jingdong chain of department stores and several well-known brands introduced virtual influencers depicted by hyper-realistic images to their live rooms to compensate for a lack of human influencers to market their products. Mengniu Dairy created a medium-realistic image of its virtual influencer, milk Si, in its live debut, which attracted nearly three million viewers. A useful question to ask in this context is related to the extent of anthropomorphization of the image of the virtual influencer that can enhance the purchase intentions of consumers. Imagine that a consumer wants to buy certain products through a live broadcast on New Year's Eve. When the consumer enters the broadcast room, they see a virtual influencer, with a natural, smooth voice and movements, introducing the details of the products. Will the consumer be more inclined to purchase the products if the virtual influencer was represented by a cute cartoon image, a hyper-realistic image, or a medium-realistic image? We seek to answer this question in this article.

Researchers have extensively studied the effects of the degree of anthropomorphization of the appearance of physical AI robots on the attitudes of consumers based on the uncanny valley phenomenon [13–16]. With the rise of the metaverse and livestream e-commerce, some researchers have begun investigating the impact of the personal attributes of virtual influencers, such as their sensory language [17], attractiveness [18], authenticity [19], and professionalism [20], as well as their relational attributes, such as social interaction [21] and social presence [22], on consumer attitudes and behaviors. Others have investigated how the anthropomorphized visual cues of virtual influencers interact with identity cues and have examined ways in which they can be aligned with the users' expectations of interactivity [23]. Zhang et al. explored users' perception of virtual influencers along two dimensions: the realism in the appearance of virtual influencers, and the entities controlled by them [24]. Deng et al. compared the effects of the appearance of human and virtual influencers on anxiety among users regarding their own personal appearance [6]. However, few studies have considered the anthropomorphic designs of the appearance of virtual influencers.

Most studies in this area have investigated the positive effects of the appearance of AI robots and virtual influencers. Service robots with a high degree of anthropomorphization enjoy enhanced credibility with consumers [25], who are more willing to use them [15]. The higher the degree of anthropomorphization of the image of the virtual influencer, the stronger the consumers' sense of familiarity with it [26]. Recent research has also shown that a highly anthropomorphic appearance of virtual influencers leads to a higher perception of their trustworthiness and capacity for hyper-social relationships among consumers, and it also positively influences their purchase intentions [27]. Some studies have also noted that the anthropomorphization of images of virtual influencers has a certain inhibitory effect. Researchers have used the uncanny valley phenomenon to show that a high level of cosmetic realism of robots or virtual influencers may be perceived as a threat by consumers and could make them feel uncomfortable [28,29], such that this fuels algorithmic aversion in them [30]. It has also been shown that consumers prefer hospitality robots depicted by cartoon images [17]. Virtual hosts represented by cartoon images can easily trigger positive interactions with the consumer and match the preferences of users of a certain age [11]. Given this, an anthropomorphic appearance is a crucial feature of AI technology [7,8]. This underscores the importance of exploring the influence of virtual influencers, as a product of AI, on consumer attitudes and behaviors based on the anthropomorphism of their appearance.

Few studies have simultaneously examined the beneficial and detrimental effects of the degree of anthropomorphization of the images of virtual influencers by using an analytical framework. In light of this shortcoming, we examine these dual effects based on algorithmic aversion. Consumers with different degrees of self-efficacy are impacted to varying extents by the degree of anthropomorphization of the image of the virtual influencer based on algorithmic aversion. We explore the potential mediating role of algorithmic aversion and the moderating role of self-efficacy in the context of the degree of anthropomorphization of the image of the virtual influencer and algorithmic aversion by constructing a U-shaped model of mediating effects, in order to empirically test the relationship between the degree of anthropomorphism of the image of the virtual influencer and consumers' purchase intention. This study provides new theoretical perspectives and empirical evidence to clarify this relationship, as well as the corresponding mechanism of influence and the relevant boundary conditions. By comparing the effects of cartoon images, medium-realistic images, and hyper-realistic images of virtual influencers, we reveal the complex impact of the degree of image anthropomorphism on consumers' purchase intention. This provides critical practical insights for developers of virtual influencer technology.

2. Theoretical Foundations and Synthesis of Research

2.1. Image Anthropomorphism

Anthropomorphism is the assignment of human form, characteristics, or behavior to non-human organisms or objects [31,32]. It is a crucial feature of artificial intelligence (AI) technology [7–9]. In light of the growing use of avatars (e.g., virtual influencers) for promoting products and serving consumers, Miao et al. proposed the theory of avatar marketing [4]. They defined avatars as digital entities with an anthropomorphic appearance that are capable of interacting with consumers, and they are controlled by humans or software. Research has shown that the anthropomorphic effect of virtual influencers is more pronounced when they have a human-like appearance, including a recognizable name, gender, race, and age [33]. It has also been shown that all the appearance-related features of virtual influencers, such as their eyes, mouths, and facial expressions [34,35], can be used to achieve anthropomorphic effects through a variety of AI techniques such as face recognition, face modeling, and image synthesis [36]. Image anthropomorphization here refers to lending features of human appearance to non-human digital entities, and its degree reflects the extent to which it resembles a human.

Virtual influencers can be divided into three categories according to the degree of anthropomorphization of their images: cartoon images, medium-realistic images, and hyper-realistic images (as shown in Figure 1). Virtual influencers depicted by cartoon images are based on images of humans [36] but are highly animated, have a plastic appearance, and have the capabilities of drawing and making phantom movements [18]. The cartoon images of virtual influencers can be considered to have a lower degree of anthropomorphism. This type of virtual influencer can attract consumers' attention and enhance their engagement and attachment [9]. On the contrary, hyper-realistic images of virtual influencers have a human-like appearance, with a refined portrayal of the hair, pupils, and other details. This realistic appearance makes it difficult for the consumer to quickly identify them as a virtual influencer rather than a human [11,24]. Such depictions are thus known as "hyper-realistic" digital humans [36]. We assume that hyper-realistic virtual influencers have a high degree of image anthropomorphization and can convey human-like emotional qualities [9] to gain the trust of the consumer [37,38].

(a) (b) (c)

Figure 1. Chart showing the degrees of anthropomorphization of the images of virtual influencers. (**a**) Cartoon image. (**b**) Medium-realistic image. (**c**) Hyper-realistic image.

Although Miao et al. proposed two types of avatars represented by images conforming to the above two levels of anthropomorphism [4], some virtual influencers are depicted by images with a moderate level of anthropomorphism. Virtual influencers with such medium-realistic images are more animated than hyper-realistic virtual influencers [39] and are more human-like than virtual influencers represented by cartoon images [11]. Therefore, they can be regarded as virtual influencers with a medium degree of image anthropomorphism. Although these three types of virtual influencers are widely used in live broadcasting, few studies have examined their varying impacts on consumers' purchase intention. We do so here.

2.2. Algorithmic Aversion

Although the developers of virtual influencers are working to enhance their anthropomorphic perceptual and interactive capabilities, some researchers have shown that consumers tend to have negative attitudes toward anthropomorphized AI products. They are more likely to accept AI products with animated features [16] and a low degree of anthropomorphization [40,41]—a phenomenon known as algorithmic aversion [30]. Algorithmic aversion is an emotion, attitude, or cognition [42], the negativity of which reduces the users' willingness to accept AI products [29]. There are three reasons for it.

First, some studies have used the uncanny valley phenomenon to show that a certain degree of image anthropomorphism weakens consumers' acceptance of virtual influencers, such that they respond negatively to non-human and highly humanized entities [40,43,44]. The uncanny valley phenomenon claims that as AI-generated physical robots and virtual bots become increasingly human-like in appearance, consumers first exhibit positive affinity toward them. However, when they become too human-like, some consumers experience an uncomfortable or uncanny feeling [42] and may be offended by this realism [40,45].

Second, evidence has shown that the development of algorithmic aversion among users with regard to AI is mainly rooted in their fear that AI technology will reduce job opportunities for humans [46]. Algorithmic aversion is the negative feedback that AI may face when it enters the market. The rise of virtual influencers suggests that human influencers will eventually be replaced by them. This represents the consumers' concerns about AI "taking over" and "replacing" human decision-makers, and it can lead to negative feelings, such as anxiety and fear, towards AI [26,46]. The more anxious people are about using technology, the greater is the extent to which they dislike it [47].

Third, speciesism is the practice of treating members of one species as more important than those of another. Some consumers who exhibit algorithmic aversion exhibit this bias against AI [46,48], as they believe that humans are unique and different from other forms of natural life and AI [49]. Once AI is indistinguishable from human intelligence, as evidenced by the high degree of similarity between the appearance and behavior of virtual influencers and human streamers in livestreaming, consumers have no reason to treat virtual influencers differently from human streamers [48]. However, even perfect virtual influencers may still be subject to speciesism bias and, thus, algorithmic aversion [46,48].

We define algorithmic aversion here as consumers' aversion to AI due to anxiety and prejudice caused by a certain degree of image anthropomorphism among virtual influencers. Virtual influencers with highly anthropomorphized images may thus be perceived as a threat [26], and they may make consumers feel uncomfortable [28,29]. It is necessary to incorporate algorithmic aversion into the model of the effects of the degree of anthropomorphism of the images of virtual influencers on consumers' purchase intention.

2.3. Self-Efficacy

Self-efficacy refers to an individual's expectations, beliefs, and self-control with regard to their ability to accomplish specific goals [50]. The concept emphasizes an individual's cognition and perception and is a self-assessment of their confidence and ability to act. Self-efficacy is correlated with individual personality traits and personal competence but is not entirely equivalent to competence [51]. Moreover, a person who believes that they can trigger events is in control of a more active and autonomous course in life [52,53]. This perception of "agency" reflects a sense of control over the environment. Specifically, it is the belief of being able to control the demands of a challenging environment by taking adaptive action [54,55]. People with higher self-efficacy are more likely to embrace AI technologies and exhibit more positive attitudes than algorithmic aversion [56]. The more anthropomorphic a virtual influencer is, the more likely is it to raise consumers' concerns about AI replacing humans [26]. People with different levels of self-efficacy take different adaptive actions, which influences their algorithmic aversion. Therefore, it is important to explore the self-efficacy of consumers as a boundary condition when investigating the relationship between the degree of anthropomorphization of images of virtual influencers and consumers' algorithmic aversion.

3. Research Hypotheses and Modeling

3.1. Effects of Anthropomorphization of Virtual Influencers on Consumers' Purchase Intention

Vision is the most valuable sensory dimension of customer experience in the metaverse [10], and a realistic appearance is thus an important feature of virtual influencers [11] as it can significantly influence the user's perception of them [24]. In a study on facial anthropomorphism and the trustworthiness of social robots, Song et al. found that animated and hyper-realistic faces most significantly increased the users' perception of trustworthiness [57] and their willingness to purchase [24,25,27]. Virtual influencers represented by cartoon images can easily trigger positive psychological interactions among consumers that can bridge the psychological distance between them to enhance their purchase intentions [9]. As the degree of image anthropomorphism increases, consumers' purchase intention shifts from positive to negative. As virtual influencers with medium-realistic images are more human-like than those represented by cartoon images but not as lifelike as those with hyper-realistic images [11], consumers may have negative attitudes of their credibility and sense of professionalism [25]. Moreover, the uncanny valley effect suggests that this "almost, but not quite human" appearance can trigger feelings of discomfort and even disgust in consumers [45]. Therefore, moderately anthropomorphized virtual influencers can reduce consumers' willingness to purchase [15]. When a virtual influencer has a hyper-realistic image such that it is indistinguishable from a human, this significantly increases consumers' perception of its capability and credibility, and this in turn enhances their positive attitudes toward the product [24,25,27]. In addition, consumers can better identify with a highly realistic virtual influencer as this enhances their sense of interpersonal contact [58].

The above analysis implies that the degree of image anthropomorphism of virtual influencers may have both inhibitory and facilitative effects on consumers' purchase intentions. There is a U-shaped relationship between them, whereby image anthropomorphism first inhibits and then facilitates consumers' intention to purchase. Therefore, we propose the following hypothesis:

H1. *There is a U-shaped relationship between the degree of anthropomorphization of the images of virtual influencers and consumers' purchase intention.*

3.2. Effects of Anthropomorphization of Virtual Influencers on Algorithmic Aversion

Because the degree of anthropomorphization of virtual influencers varies according to people's perception [59,60], we use the uncanny valley phenomenon to explain how varying degrees of image anthropomorphization influence consumers' algorithmic aversion. Japanese roboticist Masahiro Mori proposed the uncanny valley phenomenon in 1970. It has since become a widely cited concept in research on robotics, AI, and human–computer interaction [40]. It claims that when observing humanoid objects (e.g., humanoid robots or avatars), people's emotional responses to them may involve a mixture of positive and negative feelings, depending on the degree of similarity between the form of the object and its human appearance [61]. Notably, the relationship between the potency of the emotional response and the degree of image anthropomorphism is non-linear.

We leverage conceptual and supporting research to apply the uncanny valley phenomenon to virtual reality. Virtual influencers represented by cartoon images deflate consumers' perceptions of their ability because of the low realism in their appearance, thus increasing consumers' algorithmic aversion and inhibiting their willingness to accept them [24]. As the level of anthropomorphization of the virtual influencer's image increases, it manifests itself as "almost, but not quite, human", i.e., a state of medium realism. At this stage, consumers' emotional responses quickly shift from positive to negative and include feelings of weirdness, discomfort, and even disgust that cause them to assume to an aversive attitude toward AI [29,62]. On the contrary, when the image of the virtual influencer exceeds this "medium" level and becomes so realistic that it is perceived as a human being, this significantly improves consumers' perception of the virtual influencer [24] and their trust in it [25], which in turn promotes their positive opinion of AI and lowers their algorithmic aversion [23]. The above analysis implies that the anthropomorphic features of the images of virtual influencers first enhance and then reduce algorithmic aversion among consumers, i.e., there is an inverted U-shaped relationship between them. Therefore, we propose the following hypothesis:

H2. *There is an inverted U-shaped relationship between the degree of anthropomorphization of the image of the virtual influencer and the algorithmic aversion of the consumer.*

A large number of studies on prediction [42], medical diagnosis [63,64], and chatbots [65] have shown that algorithmic aversion reflects various types of biases harbored by consumers toward algorithm-based AI products [66]. These biases can lead them to adopt distrustful, unaccepting, resistant, and even rejecting behaviors [46]. In short, algorithmic aversion directly reduces the users' willingness to accept and purchase AI products. We thus propose the following hypothesis:

H3. *Algorithmic aversion has a significant negative effect on consumers' purchase intention.*

Based on the above, we argue that algorithmic aversion may play a mediating role in the effect of the degree of anthropomorphization of the image of virtual influencers on consumers' purchase intention. Specifically, virtual influencers with cartoon images elicit positive and empathetic emotional responses from consumers [9], resulting in a low algorithmic aversion and, thus, a high purchase intention. Human-like virtual influencers can make consumers feel uncomfortable and weird to some extent [28,29], and the resulting algorithmic aversion can directly reduce their purchase intention. However, as the degree of image anthropomorphization increases to the extent that the appearance of the virtual influencer becomes indistinguishable from that of a human [40,45], consumers' affective responses gradually become positive, which in turn significantly reduces their algorithmic aversion and improves their purchase intention [28]. Therefore, we propose the following hypothesis:

H4. *Algorithmic aversion mediates the U-shaped relationship between the degree of anthropomorphization of the image of the virtual influencer and consumers' purchase intention.*

3.3. The Moderating Role of Self-Efficacy

According to research on human–computer interaction, individuals have different self-efficacious responses to the degree of image anthropomorphism in AI. Self-efficacy is known to influence decision-making behavior [67]. A high self-efficacy can stimulate positive behaviors among individuals, while a low self-efficacy tends to lead to negative behaviors [50]. Self-efficacy reflects an individual's belief that they can manage the demands of a challenging environment by taking adaptive measures [52]. Individuals with low self-efficacy doubt their ability to cope with risks and withstand threats.

By contrast, individuals with high self-efficacy are likely to adopt positive behaviors in response to threats and face challenges head on [50]. In the context of the anthropomorphization of virtual influencers, the uncanny valley phenomenon suggests that virtual influencers with a medium-realistic image are likely to trigger consumers' concerns about AI replacing human decision-makers [26], implying a high perceived threat. Compared with consumers with low self-efficacy, those with high self-efficacy have more confidence in their ability to control external risks and thus have a diminished perception of the threat posed by virtual influencers. On the contrary, virtual influencers represented by cartoon images affect the users' ability to perceive virtual influencers as human-like [24], while those with hyper-realistic images significantly enhance consumers' trust in them [25]. Hence, they are less likely to trigger consumers' fears and are perceived by them as posing a low and stable level of threat. Therefore, the effect of the degree of image anthropomorphism on algorithmic aversion is unlikely to yield a significant difference for consumers with either high or low self-efficacy. We thus propose the following hypothesis:

H5. *Self-efficacy inhibits the inverted U-shaped relationship between the image anthropomorphization of virtual influencers and the algorithmic aversion of consumers. Specifically, when the image of the virtual influencer is anthropomorphized to a medium degree, the higher the self-efficacy of the consumer is, the more pronounced is the inhibitory effect on their algorithmic aversion. When the image of the virtual influencer is anthropomorphized to a low or a high degree, there is no significant difference in the resulting inhibitory effect in terms of algorithmic aversion between consumers with varying self-efficacy.*

The proposed model is shown in Figure 2.

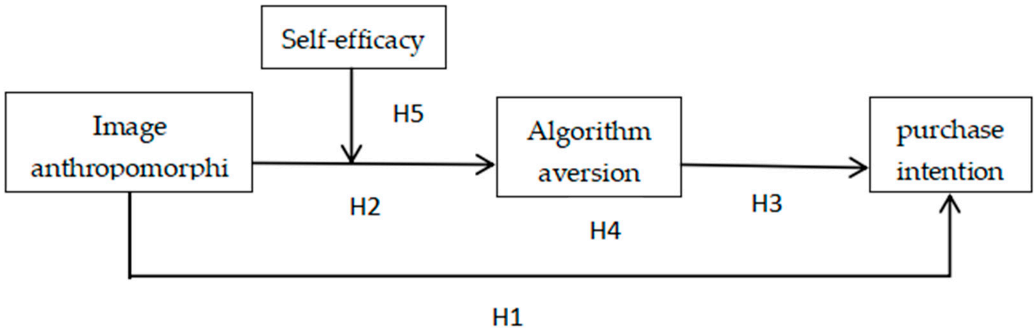


Figure 2. Proposed model.

4. Research Design

4.1. Questionnaire Design and Variable Measurement

The data for this study were collected through questionnaires, each of which was divided into three parts. The first part provided an introduction to the purposes of the study and the role of virtual influencers in livestream e-commerce. A chart showing the three categories of virtual influencers according to the degree of image anthropomorphism was also provided to ensure that the respondents understood the research background of the questionnaire.

To ensure the validity of the questionnaire, the second part included a screening question asking the respondents whether they had ever watched virtual influencers in livestream e-commerce. If they responded "Yes", they were directed to answer further questions. If they chose "no", they ended the question and quit the experiment. Then the respondents noted which category the virtual influencers belonged to according to their degree of anthropomorphism. The eligible respondents then answered questions based on their latest experience of virtual influencers in livestream e-commerce. The items used to measure the latent variables, such as image anthropomorphization [32,68], algorithmic aversion [69], and purchase intention [70], were adapted and modified based on a previous study in conjunction with the context of livestream shopping. Following this, the respondents were asked to measure their self-efficacy by using the 10-item GSES scale of measurement [52]. All items were measured on a seven-point Likert scale, with "1" meaning "completely disagree" and "7" meaning "completely agree". Detailed information on the measurement items is provided in Table 1.

Table 1. Scale of measurement for each variable.

	1. Image anthropomorphism (ANT)
ANT1	The image of this virtual influencer is realistic.
ANT2	From the image, this virtual influencer appears to be alive.
ANT3	From the image, this virtual influencer appears life like.
ANT4	From the image, this virtual influencer appears natural.
	2. Algorithmic aversion (ALG)
ALG1	I find this virtual influencer intimidating to look at.
ALG2	I find the appearance of this virtual influencer intimidating.
ALG3	I don't know why, but the appearance of this virtual influencer scares me.
ALG4	I'm worried that virtual influencers might take someone's job.
ALG5	The latest developments in this virtual influencer are challenging me as a human being.
	3. Purchase intention (PUI)
PUI1	I would consider purchasing a product recommended by this virtual influencer online.
PUI2	If given the opportunity, I predict I will consider purchasing the products recommended by this virtual influencer soon.
PUI3	If given the opportunity, I plan to place an order with this virtual influencer.
PUI4	I will most likely purchase products from this virtual influencer soon.

Table 1. *Cont.*

	4. Self-efficacy (SES)
SES1	If I do my best, I can always solve the problem.
SES2	Even if people are against me, I still have a way to get what I want.
SES3	Sticking to my ideals and reaching my goals is easy for me.
SES4	I am confident that I can effectively cope with anything that comes my way.
SES5	With my talents, I can handle the unexpected.
SES6	I can solve most problems if I put in the necessary effort.
SES7	I can face difficulties calmly because I can rely on my ability to deal with them.
SES8	When faced with a problem, I can usually find several solutions.
SES9	When there is trouble, I can usually think of some ways to cope with it.
SES10	I can cope with whatever happens to me.

The third part of the questionnaire collected information on the demographics of the respondents, including their gender, age, education, income, and occupation. To exclude interference by irrelevant variables, it also measured the subjects' perceptions of the novelty of virtual influencers (1 = very non-novel; 7 = very novel) and familiarity (1 = very unfamiliar; 7 = very familiar).

4.2. Pre-Testing

We mainly recruited young people for our survey as they have rich experience in online shopping and are more open to accepting novelty than older people in general. This choice also helped eliminate the impact of the novelty of virtual influencers on the respondents' choices.

We initially collected 90 questionnaires for pre-testing. We used them to check whether the design of the questionnaire was reasonable, and whether the questions were precise and clear in meaning. Of the 90 respondents, 67 chose "yes" in response to the screening question, and 54 correctly answered the subsequent screening questions. The pre-test questionnaire thus had a validity of 60%.

Our analysis of the data showed that the values of Cronbach's alpha of the four variables in the pre-test questionnaire—namely, the degree of image anthropomorphism, algorithmic aversion, purchase intention, and self-efficacy—were 0.885, 0.966, 0.932, and 0.943, respectively. As they were all higher than 0.8, the initial scales of the questionnaire were considered to be reliable and internally consistent. The KMO value of each variable was greater than 0.7, and its Bartlett value was lower than 0.001. The cumulative ratio of variance explained by the factors was greater than 70%, which indicated that the questionnaire had sound structural validity. There was also a correlation between the variables, and all the items could be used in the final questionnaire.

4.3. Data Collection and Sampling

China provides a suitable context to test the hypotheses of this study as it is a developing country with widespread use of the Internet and AI technologies as well as the consumption of AI products [70]. Moreover, a growing number of Chinese consumers is interacting with virtual influencers [71]. The respondents of the questionnaire were Chinese consumers who had had experience with virtual influencers. We distributed our questionnaire online through the survey platform Questionstar. As few consumers have experienced virtual influencers in a livestream business environment, we used the snowball sampling procedure to collect the data. Once the eligible respondents had completed the questionnaire, we invited them to share the link to our survey with other consumers who had had similar experiences. We thus collected a total of 585 questionnaires and excluded ones in which the respondents had answered "No" to the screening questions, provided contradictory answers, or offered consistent or regular answers. We finally obtained 470 valid questionnaires, which accounted for 80.34% of the total.

We applied one-way ANOVA to the collected questionnaires (N = 470) to confirm the successful manipulation of the degree of anthropomorphization of the virtual influencer's image ($F(2, 467) = 596.336$). Of the virtual influencers shown to the respondents, 190 were represented by cartoon images ($M_{cartoon}$ = 2.7711, SD = 1.119), 124 were represented by medium-realistic images ($M_{medium\text{-}realistic}$ = 4.3972, SD = 1.042), and 156 were depicted by hyper-realistic images ($M_{hyper\text{-}realistic}$ = 6.2452, SD = 0.473). The order of the degree of anthropomorphization of images of the virtual influencers was cartoon images < medium-realistic images < hyper-realistic images.

Detailed descriptive statistics on the samples are shown in Table 2. The demographic characteristics of the respondents were as follows: A total of 37.2% were male (62.8% were female), and their ages were concentrated in the range of 20–29 years, accounting for 89.6% of all respondents. The average monthly income of 51.5% of the respondents ranged from CNY 1 to 3000 (the living expenses of university students were included in the "average monthly income"). A total of 48.1% of the respondents had complete undergraduate education, while 47.4% were postgraduate students. Students constituted 56.2% of all respondents. According to the "China Live E-Commerce Industry Operation Big Data Analysis and Trend Research Report 2022–2023" [72] and the "China Virtual Streamer Industry Research Report 2023" by iiMedia Consulting [73], and the "Global Gen Z Consumption Insight Report 2024" by Fastdata [74], there is a higher ratio of female users of livestream e-commerce than male users, and most of them are aged 22–30 years. We can conclude that the sample data collected in this study were representative, and they could be used to explore the relationship between virtual influencers and consumers' purchase intention in the context of livestream e-commerce.

Table 2. Descriptive statistics.

Statistical Characteristics	Categories	Frequency	Percentage
Gender	Male	175	37.20%
	Female	295	62.80%
Age (years)	≤19	14	3%
	20–29	421	89.60%
	30–39	26	5.50%
	40–49	5	1.10%
	≥50	4	0.90%
Monthly income (CNY)	≤3000	242	51.50%
	3001–6000	98	20.90%
	6001–9000	68	14.50%
	≥9001	62	13.20%
Education	≤Middle school degree	21	4.50%
	Bachelor's degree	226	48.10%
	≥Master's	223	47.40%
Career	students	264	56.20%
	Government/Enterprise worker	58	12.30%
	Business/Corporate staff	83	17.70%
	Self-employed/Freelance	36	7.70%
	Retiree	0	0
	Other	29	6.20%

5. Empirical Results and Analysis

5.1. Analysis of Reliability and Validity

We used Cronbach's alpha and validation factor analysis to test the reliability and validity of the scales, respectively. As shown in Table 3, the values of Cronbach's alpha of image anthropomorphism, algorithmic aversion, purchase intention, and self-efficacy were 0.961, 0.921, 0.925, and 0.939, respectively. As they were all greater than 0.8, the questionnaire was considered to be reliable and highly internally consistent.

Table 3. Reliability analysis.

Variables	Measured Item	Corrected Item–Total Score Correlation (CITI)	Cronbach's Coefficient After Item Deletion	Cronbach's α
Image anthropomorphism	ANT1	0.907	0.947	0.961
	ANT2	0.898	0.949	
	ANT3	0.916	0.944	
	ANT4	0.889	0.952	
Algorithmic aversion	ALG1	0.803	0.901	0.921
	ALG2	0.795	0.902	
	ALG3	0.785	0.904	
	ALG4	0.797	0.902	
	ALG5	0.791	0.903	
Purchase intention	PUI1	0.773	0.920	0.925
	PUI2	0.863	0.890	
	PUI3	0.850	0.894	
	PUI4	0.818	0.905	
Self-efficacy	SES1	0.668	0.935	0.939
	SES2	0.702	0.933	
	SES3	0.686	0.935	
	SES4	0.803	0.928	
	SES5	0.824	0.927	
	SES6	0.757	0.931	
	SES7	0.824	0.927	
	SES8	0.745	0.931	
	SES9	0.769	0.930	
	SES10	0.727	0.932	

Table 4 shows that the statistic of Bartlett's test of sphericity was 9280.034 at a significance level of 0.000 < 0.05. The original hypothesis should be rejected at a significance of α = 0.05, and the matrix of the correlation coefficients was considered to be significantly different from the unit matrix. Moreover, the KMO value was 0.92 > 0.8, because of which the items of the questionnaire were considered to be suitable for factor analysis.

Table 4. Results of the KMO and Bartlett's test.

KMO and Bartlett's Test		
KMO, number of suitability measures for sampling		0.920
Bartlett's test of sphericity	Approximate cardinality	9280.034
	Degrees of freedom	253
	Significance	0

To avoid homoscedasticity, we used a neutral context when designing the questionnaire. We blurred the roles of the items to eliminate the influence of the respondents' qualifications on their answers. As the data in this study were self-reports by respondents who had had experience of virtual influencers, we used Harman's one-way test of homoscedasticity and extracted the factors by using principal component analysis. The results are shown in Table 5. The unrotated first factor explained only 34.12% of the overall variance. This indicates that there was no homogeneous variance in the data used here.

Further, we tested the validity of the four latent variables by using confirmatory factor analysis (CFA) to examine their convergence and discriminant validity and compared the indices of fit with those of several other models. The factor loadings of all the measured entries were higher than 0.6. Their p-values reached the level of significance of 0.05, as shown in Table 6, which suggests that all four factors had good convergent validity.

Table 5. Common method bias test.

Component	Initial Eigenvalue			Extracted Load Sum of Squares			Rotated Load Sum of Squares		
	Total	Percentage of Variance	Cumulative %	Total	Percentage of Variance	Cumulative %	Total	Percentage of Variance	Cumulative %
1	7.848	34.120	34.12	7.848	34.12	34.120	6.486	28.198	28.198
2	4.733	20.580	54.701	4.733	20.58	54.701	3.864	16.800	44.999
3	3.409	14.823	69.524	3.409	14.823	69.524	3.614	15.713	60.712
4	1.176	5.112	74.635	1.176	5.112	74.635	3.202	13.923	74.635
5	0.844	3.670	78.305						
6	0.674	2.928	81.233						
7	0.447	1.943	83.176						
8	0.411	1.789	84.965						
9	0.384	1.671	86.637						
10	0.339	1.473	88.110						
11	0.304	1.322	89.432						
12	0.297	1.290	90.722						
13	0.291	1.266	91.987						
14	0.260	1.130	93.117						
15	0.232	1.009	94.127						
16	0.216	0.941	95.067						
17	0.204	0.889	95.956						
18	0.201	0.873	96.830						
19	0.177	0.771	97.601						
20	0.159	0.691	98.291						
21	0.152	0.660	98.951						
22	0.127	0.553	99.503						
23	0.114	0.497	100						

Table 6. Values of factor loading.

Latent Variable	Measurement Item	Estimate	S.E.	C.R.	*p*
Image anthropomorphism	ANT1	0.932	3.026	0.228	***
	ANT2	0.922			
	ANT3	0.942			
	ANT4	0.912			
Algorithm aversion	PUI1	0.813	1.842	0.175	***
	PUI2	0.910			
	PUI3	0.894			
	PUI4	0.862			
Purchase intention	ALG5	0.830	1.784	0.165	***
	ALG4	0.843			
	ALG3	0.823			
	ALG2	0.838			
	ALG1	0.845			
Self-efficacy	SES10	0.756	1.124	0.118	***
	SES9	0.801			
	SES8	0.779			
	SES7	0.862			
	SES6	0.791			
	SES5	0.853			
	SES4	0.828			
	SES3	0.711			
	SES2	0.713			
	SES1	0.680			

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

The results of the discriminant validity test are shown in Table 7. It is evident that each fitting index of the four-factor model reached a high standard and was significantly better than those of the alternative models. We also calculated the average variance extracted (AVE) to assess discriminant validity. The square roots of the AVE for image anthropomorphization, algorithmic aversion, purchase intention, and self-efficacy on the diagonal were 0.869, 0.689, 0.661, and 0.572, respectively. These values are higher than the correlation coefficients of the data in the same column or peer group. This suggests that the main variables had satisfactory discriminative validity (see Table 8). In summary, the data used in this paper were highly reliable and valid, providing a sound foundation for subsequent research.

Table 7. Test of discriminant validity.

Factor Model [1]	c^2	df	c^2/df	RMSEA	IFI	TLI	CFI	Comparative Model Testing		
								Model Comparison	Δc^2	Δdf
Four-factor model	708.989	224	3.165	0.0405	0.947	0.94	0.947			
Three-factor Model	2589.343	227	11.407	0.2105	0.744	0.714	0.743	2 vs. 1	1880.354 ***	3
Two-factor Model	3524.254	229	15.39	0.1374	0.643	0.604	0.642	3 vs. 1	2815.265 ***	5
One-factor model	6004.627	230	26.107	0.2656	0.374	0.309	0.372	4 vs. 1	5295.638 ***	6

Note: *** $p < 0.001$. [1] Four-factor model: ANT, ALG, PUI, SES. Three-factor model: ANT + ALG, PUI, SES. Two-factor model: ANT + ALG + PUI, SES. One-factor model: ANT + ALG + PUI + SES. "ANT" represents "image anthropomorphization", "ALG" represents "algorithmic aversion", "PUI" represents "purchase intention", "SES" represents "self-efficacy", and "+" represents a combination of two factors.

Table 8. Means, standard deviations, and correlation coefficients of the main variables.

Main Variables	Mean Value	Standard Deviation	Image Anthropomorphism	Algorithmic Aversion	Self-Efficacy	Purchase Intention
Image anthropomorphism	4.353	1.752	0.869			
Algorithmic aversion	3.428	1.394	0.127 **	0.689		
Self-efficacy	4.944	1.103	0.01	−0.289 **	0.572	
Purchase intention	4.906	1.519	0.019 *	−0.660 **	0.176 **	0.661
Image anthropomorphism Squared term	3.062	2.943	−0.259 **	−0.627 **	0.002	0.482 **

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$, all two-tailed tests. The squared term for image anthropomorphism is the result of its decentering. The AVE square-root values are shown in bold on the diagonal.

5.2. Descriptive Statistical Analysis

Table 8 reports the mean, standard deviation, and correlation coefficient of the main variables. Preliminary evidence showed that image anthropomorphism was positively correlated with consumers' purchase intention (r = 0.019, $p < 0.05$), while its squared term was significantly positively correlated with purchase intention (r = 0.482, $p < 0.01$). Moreover, image anthropomorphization was significantly and positively correlated with algorithmic aversion (r = 0.127, $p < 0.01$), while its squared term was significantly negatively correlated with algorithmic aversion (r = −0.627, $p < 0.01$). In addition, algorithmic aversion was significantly negatively correlated with consumers' purchase intention (r = −0.660, $p < 0.01$). Overall, the results of the partial correlation analysis were generally consistent with our expectations.

5.3. Hypothesis Testing

We used stratified regression for hypothesis testing. We added the term representing the anthropomorphized image of the virtual influencer to the regression equation after centering the primary term. As shown in Table 9, Model 5 was first used to test the effects of the individual characteristics of the variables on consumers' purchase intention. Based on this, the primary term for image anthropomorphization was added to Model 6, and the results of regression showed that it had an insignificant effect on consumers' purchase intention (β = −0.075, $p > 0.05$). Model 7 included the quadratic term for image anthropomorphization. The results of regression showed that the primary term for image anthropomorphization was still insignificant (β = 0.04, $p > 0.05$). By contrast, the quadratic term for image anthropomorphization had a significant positive effect on consumers' purchase intention (β = 0.257, $p < 0.01$), with a value of ΔR^2 of 0.227, and was significant at the 0.01 level. Therefore, Hypothesis 1 was accepted as valid; that is, there is a positive U-shaped relationship between the degree of anthropomorphization of the image of the virtual influencer and consumers' purchase intention. In addition, Model 8 contained the variable for algorithmic aversion based on Model 5. The results of regression showed that algorithmic aversion had a significant negative effect on consumers' purchase intention (β = −0.72, $p < 0.001$), with an ΔR^2 of 0.425, and was significant at the 0.001 level. Therefore, Hypothesis 3 was valid; that is, algorithmic aversion has a significant negative effect on consumers' purchase intention.

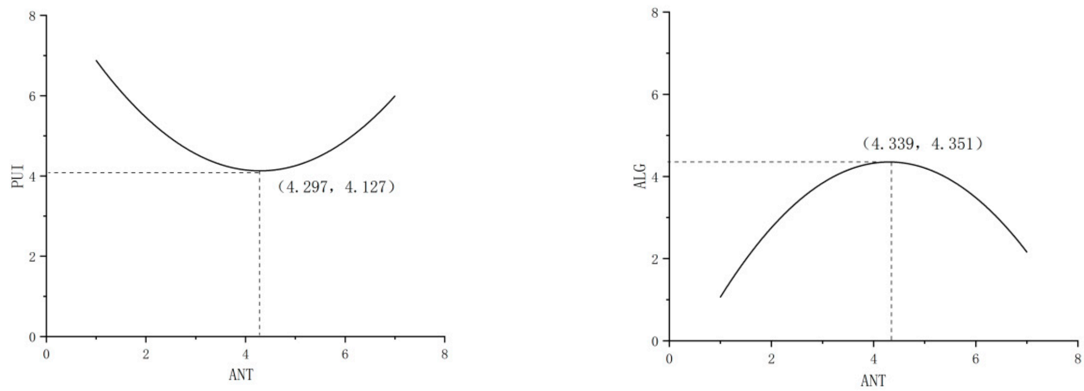
Table 9. Results of regression analysis.

Variables	Algorithmic Aversion				Purchase Intention				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Constant term	4.224 ***	4.019 ***	4.814 ***	8.281 ***	4.445 ***	4.918 ***	3.737 ***	7.487 ***	6.869 ***
1. Control variables									
sex	−0.06	−0.049	0.019	−0.02	0.05	0.042	−0.016	0.007	−0.004
age	−0.137	−0.092	−0.187	−0.094	0.408 *	0.376 *	0.457 **	0.31 **	0.339 **
Average monthly income	0.054	0.048	0.006	−0.029	−0.06	−0.055	−0.019	−0.021	−0.015
Academic qualifications	0.093	0.13	0.099	0.077	−0.157	−0.183	−0.157	−0.09	−0.094
Occupation	−0.065	−0.061	−0.041	−0.019	−0.007	−0.01	−0.026	−0.054	−0.053
Novelty	−0.119 *	−0.119 *	−0.069	−0.059	0.053	0.053	0.011	−0.032	−0.033
Familiarity	−0.017	−0.025	−0.002	0.03	−0.023	−0.017	−0.036	−0.035	−0.038
2. Independent variables									
ANT		0.105 *	−0.029	−0.02		−0.075	0.04		0.022
ANT^2			−0.299 ***	−0.301 ***			0.257 ***		0.067 **
SES				−0.744 ***					
3. Interaction terms									
ANT × SES				0.06 *					
ANT^2 × SES				0.108 ***					
4. Intermediary variable									
ALG								−0.72 ***	−0.634 ***
Adjusted R^2	0.011	0.026	0.398	0.535	0.007	0.012	0.242	0.438	0.457
ΔR^2	0.026	0.017	0.367	0.137	0.022	0.007	0.227	0.425	0.435
ΔF	1.75	8.148 **	285.45 ***	46.205 ***	1.471	3.451	140.766 ***	354.796 ***	122.519 ***

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$, all two-tailed tests. The coefficients of regression in the table are unstandardized: "ANT" stands for "image anthropomorphism", "ANT^2" represents "quadratic term for image anthropomorphization", "SES" represents "self-efficacy", and "ALG" represents "algorithmic aversion".

Furthermore, Model 1 first tested the effects of the individual characteristic variables on consumers' algorithmic aversion. The primary term for image anthropomorphization was added to Model 1 to form Model 2, and the results of regression showed that its effect on algorithmic aversion was significant only at the 0.05 level (β = −0.105, $p < 0.05$). The secondary term for image anthropomorphization was added to Model 2 to form Model 3, and the results of regression showed that the primary term for image anthropomorphization was insignificant in this case (β = −0.029, $p > 0.05$). By contrast, the secondary term for image anthropomorphization significantly negatively influenced algorithmic aversion (β = −0.299, $p < 0.01$), with a value of ΔR^2 of 0.367, and was significant at the 0.01 level. This result supports Hypothesis 2: The relationship between the degree of anthropomorphization of the image of the virtual influencer and algorithmic aversion is an inverted U-shaped curve.

We then plotted the curvilinear relationships in Hypotheses 1 and 2 by using vertices in Origin 2022. As shown in Figure 3a, consumers' purchase intention first reached its minimal value as image anthropomorphization increased, but it then increased with the continued enhancement in image anthropomorphization. When the value of image anthropomorphization was 4.297, that of consumers' purchase intention reached its minimal value of 4.127. Similarly, Figure 3b shows that algorithmic aversion first reached its maximum value with an increase in image anthropomorphism and then decreased when image anthropomorphism continuously increased. When the value of image anthropomorphism was 4.339, that of algorithmic aversion was 4.351. Figure 3 thus further supports Hypotheses 1 and 2. This shows that there is a U-shaped relationship between image anthropomorphism and consumers' purchase intention, and algorithmic aversion has a U-shaped relationship of inhibition, followed by activation, followed by restriction, respectively. Moreover, when consumers' purchase intention and the algorithmic aversion were at their minimal values, the value of image anthropomorphization was closest to that of the medium-realistic image ($M_{cartoon}$ = 2.7711, SD = 1.119; $M_{medium\text{-}realistic}$ = 4.3972, SD = 1.042; $M_{hyper\text{-}realistic}$ = 6.2452, SD = 0.473), with a difference of only 0.042. We can conclude that the anthropomorphization of the image of the virtual influencer is not identical to its image. When the image of the virtual influencer was in the medium-realistic category, consumers exhibited the highest algorithmic aversion and the lowest purchase intention. Table 10 reports the non-linear equations relating image anthropomorphism with consumers' purchase intention and algorithmic aversion, with F-values of 151.76784 and 71.34533, respectively. Both of them were significant at the 0.01 level, which once again verifies Hypotheses 1 and 2.



(**a**) (**b**)

Figure 3. Graphs of relationships. (**a**) Curvilinear relationship between image anthropomorphization and purchase intention. (**b**) Curvilinear relationship between image anthropomorphization and algorithmic aversion.

Table 10. Non-linear equations.

Independent Variable	ANT	
Dependent Variable	**PUI**	**ALG**
Equation	$\mathbf{y = A + B \times x + C \times x^2}$	
A	8.80236 ± 0.34482	−1.23097 ± 0.28149
B	−2.17912 ± 0.18243	2.59445 ± 0.14892
C	0.25393 ± 0.02164	−0.30142 ± 0.01767
R^2	0.23404	0.39393
Adjusted R^2	0.23076	0.39133
F	151.76784 ***	71.34533 ***

Note: *** $p < 0.001$, all two-tailed tests. "ANT" represents "image anthropomorphism", "PUI" represents "purchase intention", and "ALG" represents "algorithmic aversion".

We subsequently tested Hypothesis 4. Given that the path from image anthropomorphism to consumers' algorithmic aversion and purchase intention involved non-linear interactions, the traditional Baron and Kenny's test of the effect of mediation [75] might have distorted the relationship between the variables. We thus needed to calculate the instantaneous mediation θ to test the mediation effect. Stolzenberg claimed [76] that when there is a non-linear relationship in the path of action of the independent variable (X) on the dependent variable (Y) through a mediator variable (M), the indirect rate of change in Y due to a change in M as a result of a change in X is denoted by θ:

$$\theta = \frac{\partial M(X)}{\partial X}\frac{\partial Y(X,M)}{\partial M} \tag{1}$$

Hayes and Preacher refer to the indirect rate of change θ as the instantaneous indirect effect [77]. It is calculated by assigning a value to X with respect to Y, and then using the bootstrap method to test the instantaneous mediated effect corresponding to X. We used the MEDCURVE macro plug-in in SPSS 26.0 to obtain 5000 bootstrap samples to test the instantaneous mediating effect of algorithmic aversion between image anthropomorphism and purchase intention when image anthropomorphism had a mean and standard deviation of ± 1, and the results are shown in Table 11.

Table 11. Results of tests of the instantaneous mediation effect.

Intermediary Variable	Independent Variable Taking Values	Bootstrap Sampling Count	95% Confidence Interval		Transient Mediation Effect
			Lower Bound	Upper Bound	
ALG	2.6014	5000	−0.8260	−0.5124	−0.6579
	4.3532	5000	−0.0069	0.0474	0.0191
	6.1050	5000	0.5390	0.8739	0.6962

As shown in Table 11, the confidence intervals were smaller than zero when the value of image anthropomorphism was $\overline{x} - \sigma$ (2.6014), indicating that algorithmic aversion had a significant and negative transient mediating effect between image anthropomorphism and purchase intention. When image anthropomorphism was increased from $\overline{x} - \sigma$ (2.6014) to $\overline{x}$ (4.3532), θ rose from −0.6579 to 0.0191, and the confidence interval appeared to be "across zero", indicating that the positive instantaneous mediating effect of algorithmic aversion had changed "from nothing to something". When image anthropomorphization was as high as $\overline{x} + \sigma$ (6.1050), θ rose from 0.0191 to 0.6962, with confidence intervals greater than zero. This suggests that algorithmic aversion had a significant and positive instantaneous mediating effect between image anthropomorphization and purchase intention. Thus, Hypothesis 4 was verified.

To test Hypothesis 5, we simultaneously input self-efficacy, as well as the primary and secondary terms for image anthropomorphization and their interactions with self-efficacy, to the regression model to analyze the regression of algorithmic aversion. Table 9 shows that the primary term for image anthropomorphization was still insignificant with respect to algorithmic aversion in Model 4 (β = −0.02, $p > 0.05$). By contrast, the secondary term for image anthropomorphization significantly negatively affected algorithmic aversion (β = −0.301, $p < 0.001$). In addition, self-efficacy and the interaction terms between the primary and secondary terms of image anthropomorphism and self-efficacy all had a significant effect on algorithmic aversion, with regression coefficients of −0.744 ($p < 0.001$), 0.06 ($p < 0.05$), and 0.108 ($p < 0.001$), respectively. According to Aiken and West [78], if only the coefficient of the term "independent variable × moderating variable" is significant when testing the moderating effect of the quadratic curve, the moderating variable changes only the slope of the curve but not its shape (e.g., its curvature). If only the coefficient of the term "the square of the independent variable × the moderator variable" is significant, then the moderator variable changes only the shape of the curve without changing its overall inclination. If both coefficients are significant, then both the inclination and the shape of the curve change. These results indicate that the coefficients of both interaction terms were significant and positive, while ΔR^2 was 0.137 and was significant at the 0.001 level. Thus, part of Hypothesis 5 was initially supported: Self-efficacy plays a moderating role in the inverted U-shaped relationship between the degree of anthropomorphization of the image of the virtual influencer and algorithmic aversion.

To further test the moderating role of self-efficacy in the inverted U-shaped relationship between image anthropomorphism and algorithmic aversion, we used the PROCESS macro plug-in in SPSS26.0 to obtain 5000 bootstrap samples by using Model 1, with the covariates serving as individual characteristic variables. We tested the moderating effects of the independent variable of the decentering of the primary term for image anthropomorphism and its squared term. The results are shown in Tables 12 and 13.

Table 12. Results of the test of moderated effects (ANT × SES).

Variable	Algorithmic Aversion			95% Confidence Interval	
	B	Standard Error	t	Lower Bound	Upper Bound
ANT	0.107 **	0.0354	3.0241	0.0375	0.1765
SES	−0.3569 ***	0.0573	−6.227	−0.4696	−0.2443
ANT × SES	−0.0187	0.0300	−0.6225	−0.0777	0.0403
Adjusted R^2			0.0007		
F			0.3875		

Note: *** $p < 0.001$; ** $p < 0.01$.

Table 13. Results of the test of moderated effects (ANT^2 × SES).

Variable	Algorithmic Aversion			95% Confidence Interval	
	B	Standard Error	t	Lower Bound	Upper Bound
ANT	−0.2980 ***	0.0151	−19.7392	−0.3277	−0.2684
SES	−0.7048 ***	0.0622	−11.338	−0.8269	−0.5826
ANT^2 × SES	0.0926 ***	0.0125	7.4194	0.0681	0.1171
Adjusted R^2			0.0552		
F			55.0469 ***		

Note: *** $p < 0.001$.

Table 12 shows that the interaction between the primary term for image anthropomorphization and self-efficacy had no significant effect on algorithmic aversion (β = 0.03, $p > 0.05$). The confidence interval contained zero, which indicates that self-efficacy had no moderating role in the linear relationship between the primary term for image anthropomorphization and algorithmic aversion. Table 13 shows that the interaction between the secondary term for image anthropomorphization and self-efficacy had a significant positive effect on algorithmic aversion (β = 0.0926, $p < 0.001$). Self-efficacy thus positively moderated the relationship between the secondary term for image anthropomorphization and algorithmic aversion, whereby an increase in self-efficacy by one unit enhanced the effect of image anthropomorphization on algorithmic aversion by 0.0926 units. In addition, the adjusted R^2 was 0.0552 and was significant at the 0.001 level. The moderating effect was thus significant. Hypothesis 5 is hence verified, i.e., self-efficacy moderates the relationship between the degree of anthropomorphization of the image of the virtual influencer and algorithmic aversion.

We estimated the significance of the slope of the regression line for self-efficacy under a mean and standard deviation of ±1 in all three cases. Table 14 shows that self-efficacy had a significant negative effect on algorithmic aversion in the fitted quadratic term in the three cases of M − 1SD, M, and M + 1SD, with effects of −0.4001 ($p < 0.001$), −0.2980 ($p < 0.001$), and −0.1959 ($p < 0.001$), respectively. This suggests that regardless of whether self-efficacy was high or low, its moderating effect was significant. As self-efficacy increased from 3.8409 to 6.0467, the magnitude of its effect increased from −0.4001 to −0.1959, indicating that the higher the self-efficacy, the flatter the inverted U-shaped relationship between image anthropomorphism and algorithmic aversion. Thus, Hypothesis 5 is partially supported.

Table 14. Results of simple slope test of M ± 1SD.

Indicator	Value	Magnitude of Effect	Standard Error	t	95% Confidence Interval	
					Lower Bound	Upper Bound
Low self-efficacy	3.8409	−0.4001 ***	0.0206	−19.4163	−0.4406	−0.3596
Medium self-efficacy	4.9438	−0.2980 ***	0.0151	−19.7391	−0.3277	−0.2684
High self-efficacy	6.0467	−0.1959 ***	0.0202	−9.6757	−0.2357	−0.1561

Note: *** $p < 0.001$.

We also combined the methods proposed by Aiken and Dawson to plot the effects of interactions between the variables, as shown in Figure 4. In case of image anthropomorphism of a medium degree, i.e., medium-realistic virtual influencers, its inhibitory effect on the algorithmic aversion of consumers with a high self-efficacy was more prominent than those in cases of virtual influencers with cartoon images and hyper-realistic images. That is, when the image anthropomorphism was low and high, there was no significant difference in the moderating effect on the algorithmic aversion of consumers with varying self-efficacy levels. This further supports Hypothesis 5.

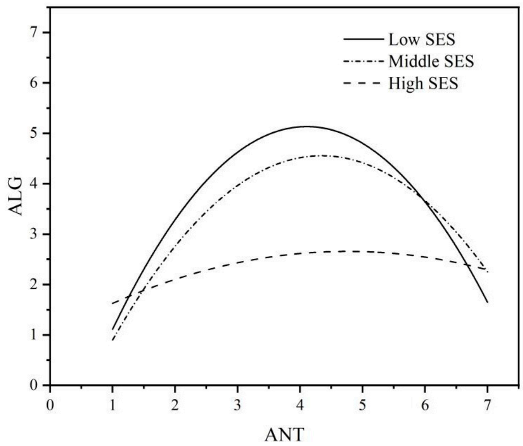


Figure 4. Moderating role of self-efficacy in the relationship between the degree of image anthropomorphism and algorithmic aversion.

5.4. Results

The results of stratified regression show that the image-fitting quadratic term had a significant positive effect on consumers' purchase intention (β = 0.257, $p < 0.01$). ΔR^2 was 0.227 and significant at the 0.01 level; Hypothesis 1 is thus valid. Algorithmic aversion had a significant effect (β = −0.72, $p < 0.001$) on purchase intention; ΔR^2 was 0.425 and significant at the 0.001 level; Hypothesis 3 is thus valid. The quadratic term for image anthropomorphization in the model of regression of algorithmic aversion had a significant negative effect on algorithmic aversion (β = −0.299, $p < 0.01$); ΔR^2 was 0.367 and significant at the 0.01 level. Therefore, Hypothesis 2 is initially supported. We also calculated the instantaneous mediating effect θ. The confidence intervals were all lower than zero when image anthropomorphization had a value of $\overline{x} - \sigma$, indicating that the negative instantaneous mediating effect of algorithmic aversion between image anthropomorphization and purchase intention was significant. When image anthropomorphization increased from $\overline{x} - \sigma$ to $\overline{x}$, θ rose from −0.6579 to 0.0191, and the confidence interval appeared to be "across zero", indicating that the positive and transient mediating effect of algorithmic aversion had changed "from nothing to something". When image anthropomorphization was $\overline{x} + \sigma$, θ rose from 0.0191 to 0.6962, with confidence intervals greater than zero indicating that the positive and transient mediating effect of algorithmic aversion between image anthropomorphization and purchase intention was significant. Therefore, Hypothesis 4 is valid.

When self-efficacy, as well as the primary and secondary terms for image anthropomorphization and their interaction with self-efficacy, were simultaneously input into the regression model for algorithmic aversion, all of them had a significant impact on algorithmic aversion, with regression coefficients of -0.744 ($p < 0.001$), 0.06 ($p < 0.05$), and 0.108 ($p < 0.001$), respectively. This suggests that self-efficacy changed the skewness and shape of the curvilinear relationship between the degree of anthropomorphization of the virtual influencer's image and algorithmic aversion. A moderating effect existed, and Hypothesis 5 is thus preliminarily supported. We also conducted a test of the moderating effects (Model 1, $N = 5000$ samples) by using the PROCESS macro-plugin in SPSS 26.0. The aim was to assess the moderating effect of the independent variables of the primary term for decentering image anthropomorphization and the secondary term for image anthropomorphization. The results showed that the interaction between the primary term for image anthropomorphization and self-efficacy had no significant effect on algorithmic aversion ($\beta = 0.03$, $p > 0.05$). The confidence interval contained zero, implying that self-efficacy had no moderating effect in the linear relationship between the primary term for image anthropomorphization and algorithmic aversion. Moreover, the interaction between the secondary term for image anthropomorphization and self-efficacy had a significant positive effect on algorithmic aversion ($\beta = 0.0926$, $p < 0.001$). Self-efficacy thus moderated the relationship between the secondary term for image anthropomorphization and algorithmic aversion in a positive manner. The adjusted R^2 was 0.0552 and was significant at the 0.001 level. Thus, there was a significant moderating effect. Hypothesis 5 is thus supported, with self-efficacy moderating the curvilinear, rather than linear, relationship between image anthropomorphization and algorithmic aversion. Further, a simple slope analysis showed that self-efficacy led to a significant negative effect of the quadratic term for image anthropomorphization on algorithmic aversion in all three cases. M − 1SD, M, and M + 1SD had effects of -0.4001 ($p < 0.001$), -0.2980 ($p < 0.001$), and -0.1959 ($p < 0.001$), respectively, indicating that the moderating effect was significant irrespective of whether self-efficacy was high or low. As self-efficacy increased from 3.8409 to 6.0467, the effect size increased from -0.4001 to -0.1959, indicating that the higher the self-efficacy was, the flatter the inverted U-shaped relationship was between image anthropomorphism and algorithmic aversion. Therefore, Hypothesis 5 is valid.

6. Discussion and Insights

6.1. Theoretical Significance

First, this study contributes to the literature on livestream e-commerce and virtual influencers by investigating the impact of anthropomorphization of images of the latter on consumers' purchase intention. Past research has explored how features such as the interactivity and professionalism of virtual influencers affect consumers' emotions and purchase intentions [17,18]. Studies have investigated physical robots, which are also products of AI [57]. The results of research on the appearance of AI robots or virtual influencers are polarizing. Some studies have confirmed that an anthropomorphic appearance can positively influence trustworthiness and enhance consumers' willingness to use AI [15,25,57]. However, other studies have confirmed its inhibitory effect. Research based on the uncanny valley phenomenon has shown that high levels of cosmetic realism in virtual influencers may also be perceived as a threat by consumers [28,29], leading to algorithmic aversion [30]. However, no study to date has simultaneously explored the inhibitory and facilitative effects of the degree of anthropomorphism of virtual influencers' images on consumers' purchase intentions. We identified a U-shaped relationship between them and explored the possible mediating and moderating roles of algorithmic aversion and consumers' self-efficacy in this relationship.

Second, most research on why consumers develop negative attitudes toward AI has focused on two issues: the mechanical nature of algorithms, and the threat to consumer identity [26,46]. However, studies have not examined the role of algorithmic aversion in livestream e-commerce. We introduced algorithmic aversion to a new research setting, expanded its application, and provided its connotations in the context of online broadcasts. By exploring the mediating role of algorithmic aversion between the degree of anthropomorphism of the image of the virtual influencer and consumers' purchase intention, we revealed that anthropomorphic features of the virtual influencer promote and then inhibit consumers' algorithmic aversion, which in turn influences their purchase intention. We also considered the uncanny valley phenomenon, fears of AI, speciesism, and past work to clarify how the degree of anthropomorphization of images of virtual influencers affects the algorithmic aversion of consumers.

Finally, we identified a boundary condition based on the effect of the degree of anthropomorphization of images of virtual influencers on consumers' purchase intention. Past studies have demonstrated that people with higher self-efficacy are more likely to accept AI technologies [56]. However, how self-efficacy influences the relationship between AI technology and algorithmic aversion has not been examined. We undertook this task in this paper. We also classified the degree of image anthropomorphism of virtual influencers into cartoon images, medium-realistic images, and hyper-realistic images. We confirmed that moderate-realistic image yielded the lowest purchase intention and the highest algorithmic aversion among consumers.

6.2. Practical Implications

Given the critical role of virtual influencers with medium-realistic images in inhibiting consumers' purchase intention, we suggest that designers use cartoon or hyper-realistic images in conjunction with the characteristics of the brand being marketed. The image must align with the tone of the brand, attributes of the product, and target audience. Further, the facial expressions of virtual influencers can affect consumer engagement [79]. Designers should guide changes in their expressions based on pop-up emotions to enhance the perception of interactivity among consumers.

In addition, virtual broadcasts should be based on the characteristics of the goods being marketed, such as the "one thing, one scene" matching demonstration. By setting up different kinds of scenes in advance, the virtual influencer can improve the live broadcast such that consumers have a more realistic experience that is likely to enhance their purchase intention. Moreover, in light of the important role of algorithmic aversion, we propose that the designer add the prompt "The streamer is a virtual influencer" to the livestream. This can reduce consumers' psychological defensiveness and enhance their curiosity regarding AI technology.

The most significant economic value of virtual influencers for brands/merchants is in enhancing the weight of the live room, making up for the leakage of the conversion of human streamers in non-prime time and reducing costs. Moreover, we found that cartoon images or hyper-realistic images of virtual influencers can enhance consumers' purchase intention. Brands that have just entered the market and require greater exposure but have a low marketing budget should use such virtual influencers for livestream sales in non-prime-time hours. Moreover, they should choose virtual influencers whose images match the style of their brand. The brand can also set about producing goods in advance and use an animation video with a virtual influencer for selling goods, so consumers can more intuitively understand the product characteristics.

6.3. Limitations and Future Research Directions

As a preliminary study, our research here has some shortcomings. First, owing to the uneven development of livestream e-commerce across the globe, this study is based on the current status of the practice in China. We thus did not consider differences in the characteristics of consumers and their consumption habits in different cultural contexts. Future research should consider a larger number of samples and an expanded scope to explore the influence of cultural differences on the behavior of virtual influencers and consumers in livestream e-commerce. Second, the adjusted R^2 in stratified regression was only 45.7%, indicating that there were many undiscovered dimensions of the effect of virtual influencers on consumers' purchase intention. The anthropomorphic features of virtual influencers include their expression, language, and action in addition to their image. Zhang et al. [80] considered the effects of the images and facial expressions of virtual influencers on consumers' purchase intention. Third, we found that algorithmic aversion partially mediated the U-shaped relationship between the degree of anthropomorphization of images of virtual influencers and consumers' purchase intention. However, there may be different mediating variables in this process. Future research should explore the mediating role of social presence and telepresence in the above relationship. Fourth, we chose different levels of self-efficacy, based on differences between consumers, as a moderating variable. Future research should consider the influence of external factors such as the types of scenario, platform, and product.

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