AI-generated models and their impact on consumer trust and perceived risk in online fashion retail

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Abstract

The purpose of this research is to understand how the use of fashion models generated by artificial intelligence (AI) in product imagery affects consumer trust and perceived risk in the online retail setting. As AI technology continues to advance, its implementation and the opportunities it offers have noticeably expanded across marketing practices. AI-generated models are one of the latest phenomena observed in advertising and retailing spheres. Previous literature has widely explored the effects of different types of sources in marketing content, with recent studies focusing on the use of virtual endorsers and AI imagery in advertising. However, as AI-generated models start to become a more common occurrence in online retail spaces, its impact on consumers in this setting remains under researched. Understanding the effects of this phenomenon is particularly important in the online retail context due to its intangible nature, which can lead to higher perceptions of risk and lower level of trust (Teo & Liu, 2007; Handoyo, 2024). As consumers often rely on visual information to reduce perceived risks, particularly when shopping for clothing online (Yu et al., 2012), the use of AI generated models can be expected to negatively impact consumer trust and perception of risk. Recent studies have demonstrated that disclosed AI imagery in ads is associated with a decrease in credibility and trust (Grigsby et al., 2025), while other studies have shown that virtual influencers have the same effect (Hofeditz et al., 2022; Nissen et al., 2023). Such outcomes can be related to a reduction in perceived anthropomorphism, whereby lower perceptions of anthropomorphism in AI imagery are associated with a decrease in consumer trust (Muniz et al., 2024; Luo et al., 2019).

Thus, using a quantitative research approach, the current study aims to address these observed gaps in the literature. This work's research question seeks to understand how the use of AI-generated models impacts consumer trust and perceived risk, specifically in online fashion retail setting. This research question will be answered using five hypotheses:

H1: AI-generated models in online product images negatively impact consumer trust and perceived risk.
H2: The impact of AI-generated models on consumer trust and perceived risk is greater when the use of AI is explicitly disclosed compared to when it is not disclosed.
H3: The conditions (human model vs. AI model vs. AI model with disclosure) predict varying levels of perceived anthropomorphism
H4: Anthropomorphism is associated with consumer trust and perceived risk.

H5: Anthropomorphism mediates the effects of model type on consumer trust and perceived risk.

Using the online survey platform Qualtrics, the study was distributed through panel recruitment agency ResearchConnect and gathered 202 participants. The research rejects both H1 and H2, however, it fully supports H3, H4, and H5. The study reveals that there are no differences in trust and perceived risk between consumers exposed to AI-generated models (with and without disclosure) and human models in product images. However, the study shows that there are differences in perceived anthropomorphism between the different types of models. The study reveals that perceived anthropomorphism mediates the relationship between model type and responses in trust and perceived risk. This means that when some consumers are exposed to AI models in e-commerce product images, a decrease in perceived anthropomorphism negatively impacts their perceptions of trust and risk.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signed,

Milana Melamed

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Ethics Approval

The Auckland University of Technology Ethics Committee approved this research on 09.09.25 (Ethics application: 25/270). Full approval can be found in Appendix A.

Chapter 1: Introduction

In recent years e-commerce has increasingly developed and grown, allowing retailers to reach a much wider audience, generate revenue growth, and maintain relationships with consumers, all while cutting the costs of maintaining physical stores (Taher, 2021). E-commerce also offers various benefits to consumers, allowing them to shop at any time of the day, directly from home, while being able to choose from an extensive range of products and brands worldwide (Kleisiari et al, 2021). As the world becomes more digitalised and technologically advanced, the online retail landscape continues to increasingly transform, allowing retailers to bridge the gap between online and physical shopping spaces to enhance the online shopping experience (Pillarisetty & Mishra, 2022).

This is particularly evident in the widespread implementation of artificial intelligence (AI) powered technologies, which now allow consumers to use retail websites more conveniently and efficiently than before (Pillarisetty & Mishra, 2022). For instance, websites such as Amazon now have AI algorithms to increase customer personalisation by providing consumers product recommendations based on their website activity and preferences (Burnstine, 2025). Other more advanced AI tools have been noted among well-known clothing and shoe brands including Nike with their Nike Fit feature, which helps consumers receive accurate shoe size recommendations by simply scanning their feet (Reshmidilova et al., 2024). Other examples include the use of deep learning algorithms used by ASOS and Gucci, allowing consumers to virtually try on clothes on their websites by uploading their full-body picture (Burnstine, 2025). These AI-powered features in e-commerce, including product recommendations, personalisation, and chatbots, have been widely researched with studies showing their positive effects on consumer trust, satisfaction, and loyalty (Hassan et al., 2025).

However, some innovations remain under-researched and their effects on consumers are not yet known. Among these innovations is the use of AI-generated imagery such as synthetic models in the fashion e-commerce industry. This phenomenon is becoming more widespread with numerous AI technology companies offering these services and brands beginning to adopt them in their marketing and retailing practices. For example, companies such as Lalaland.ai are now able to generate hyper-realistic looking AI models with different body types, sizes, and skin tones, offering fashion brands innovative ways of designing advertisements and presenting products online (Harsanto et al., 2025). Levi's is one of the well-known examples of fashion brands partnering with this company to experiment with synthetic human-like models to advertise and present their products online in an effort to promote more diversity for more inclusive shopping experiences (Maiolo, 2024). Along with Levi's, brands such as Hugo Boss and Zalando have also joined this trend, while H&M has integrated this technology using "AI twins" to generate AI-generated images of real existing models for social media content and advertising imagery with the consent of the featured models (Cochrane, 2025). Similarly, Vogue's print edition in August 2025 presented a Guess advertisement featuring a fully synthetic, AI-generated model for the first time (Rufo, 2025).

Although this technology is still in its early stages of adoption, it is expected to show broader uptake in the near future as reports predict that the AI-generated fashion photography market will generate up to $6.12 billion by 2029 (Research and Markets, 2026). This can be anticipated with the continuous growth of the online fashion retail market and the promising operational benefits this technology can offer for online fashion retailers (Research and Markets, 2026). The use of AI-generated models provides opportunities for creating highly customizable visual content for fashion products and also offers a more time- and cost-effective alternative to employing human models and photographers. For instance, reports show that in the U.S. a single professional photoshoot can cost $10,000 to $30,000 USD for fashion brands, while using AI-generated fashion models can cost $29–$59 per month (Laney, 2025). Such opportunities presented by generative AI are predicted to increase operating profits by approximately $150-275 billion within the next few years for businesses in the apparel, fashion, and luxury industries (Harreis et al., 2023).

Despite the numerous advantages this technology can present to brands and retailers, it also presents potential risks, particularly given the media controversies that have recently emerged regarding its use. For instance, Levi's decision to use AI-generated models faced criticism for failing to promote genuine diversity by replacing real models with AI ones (Maiolo, 2024). Vogue's recent AI-generated ad feature by Guess has also raised concerns among consumers and workers in the fashion industry in regard to AI's place in the industry and its potential threat to progress made in establishing more realistic beauty standards, body positivity, and diversity (Roberts-Islam, 2025; Rufo, 2025). In other recent cases, Australian brand Atoir, featured on popular e-commerce platform The Iconic, has become one of the first brands to receive public criticism for their explicit use of AI-generated models in their product detail pages (Feiam, 2025). Despite the brand's declaration of AI use in the product description section, online users have expressed frustration and distrust towards the displayed products, commenting on how the models create an inaccurate and deceptive representation of the actual fit and appearance of the clothing (Feiam, 2025).

Despite increasing public attention to the use of AI-generated models, there is limited understanding of how consumers actually respond to their use, particularly within online retail environments. Additionally, to date, no known studies have specifically addressed this context yet. This raises important questions about how consumers respond to this emerging trend, especially when AI-generated models become more common in e-commerce. Moreover, with growing global attention on ethical AI use, future regulations may soon require brands to become more transparent about their AI use in marketing practices (ASA, 2025). This means it is necessary to understand how brands may be affected by these future requirements by examining how consumers respond to AI use and the explicit disclosure of it.

1.1. Research Question

Given that the adoption of AI-generated model imagery is becoming more apparent in online fashion retail, it is then important to understand the implications of its use on consumers within that context. Trust plays a crucial role in online retail (Toufaily et al., 2013), and since consumers heavily rely on visual cues to assess products in that setting (Boardman & McCormick, 2019), AI-generated models can be expected to affect consumer trust and perceived risk. The current proposed research then aims to address this gap by examining the following research question:

RQ: How does the use of AI-generated models impact consumer trust and perceived risk in online fashion retail?

1.2. Methodology

This dissertation uses a quantitative research method, driven by a set of hypotheses. To identify whether there are differences in trust, perceived risk, and other variables between consumers exposed to human models and AI-generated models, the study uses an experimental research design. A quantitative research approach will allow the study to gain objective insights from a population sample, enabling it to draw more generalisable conclusions (Steckler et al., 1992). An experimental research design enables the study to measure participant responses and make comparisons by manipulating different conditions (Jackson & Cox, 2013). The study uses Qualtrics, an online survey platform, to create the survey and recruits participants through ResearchConnect, an online panel recruitment agency. Three conditions were created for the study's experiment, in which participants were exposed to one of three model types. These models were featured in a product image on a mock e-commerce site as a part of the experiment's visual stimuli. The three conditions included: (1) human model condition, (2) AI-generated model with no disclosure condition, and (3) AI-generated model with disclosure condition. Lastly, for the data collection and analysis process, the study used univariate regression analysis, analysis of variance, and mediation via Hayes Process model 4.

1.3. Organisation of Dissertation

This dissertation is organised into this introduction and four other chapters which include:

1) Literature review
2) Research methodology
3) Results
4) Discussion

Chapter two's literature review focuses on defining and explaining key concepts, such as trust and perceived risk. This includes a discussion of their importance and influence, specifically within the online retail environment. The chapter then discusses the influence of human models in online product presentation, demonstrating how they can be used as a visual cue to aid the decision making process of consumers, particularly when shopping for fashion products online. Moreover, the chapter draws on past research which explores the use of AI imagery in advertising content and its impact on consumers and marketing outcomes. This enables the current study to become informed of similar potential outcomes. This is followed by a discussion of anthropomorphism and how perceived anthropomorphism can influence the way consumers view and respond to AI imagery in advertising content. The chapter draws on two theoretical concepts, including the persuasion knowledge model and source credibility theory, to support the reasoning of the proposed hypotheses. Lastly, the chapter summarises insights covered in the literature review to guide the development of the study's hypotheses.

Chapter three next explores the study's methodology, with a discussion of the founding ontology, epistemology, and research paradigm that guide the chosen quantitative research approach. This section further discusses the procedure, method, and participants, as well as the visual stimuli used in the study's experiment. Lastly, the chapter examines the scales used in the data collection, including a comprehensive table of the measures and the reliability tests conducted on SPSS.

Chapter four discusses the main study findings that were analysed in SPSS. This includes a series of analyses of variance to test H1, H2, and H3, as well as a simple linear regression to test H4, and a mediation analysis conducted using Hayes' Process model 4 to test H5.

Chapter five presents a discussion of the study's main findings, which draws on relevant findings from past research. This chapter also explores the academic and theoretical contributions that this dissertation presents, with insightful implications for the continued use of AI in online retail imagery. Lastly, the chapter discusses the study's limitations and suggests directions for future research.

Chapter 2: Literature Review

2.1 Introduction

Online shopping can involve various forms of risk and can require a great degree of trust from consumers. This is particularly true in the case of fashion products, which often demand greater consideration and accuracy in attributes such as size and fit. This means that without physically inspecting products, consumers purchasing fashion products may face a higher likelihood of post-purchase dissatisfaction, which may help explain higher return rates observed for online clothing purchases compared to other product categories (Richter, 2025).

As the use of AI imagery grows in the fashion industry with brands such as Levi's, Hugo Boss, and H&M integrating AI-generated models in their marketing content (Cochrane, 2025), it presents promising opportunities for online retailers while also introducing potential further risks for online shoppers. As observed in a recent case involving an Australian brand, the use of AI-generated models in product imagery can evoke distrust and uncertainty in e-commerce shoppers (Feiam, 2025). While the brand disclosed their use of AI for the featured models in the description, the move has still gained criticism from online consumers who perceived it as a deceptive and inaccurate portrayal of products (Feiam, 2025). Although there is currently no known research exploring this phenomenon in the online retail setting, these reactions can give some insight into the potential issues AI-generated models may involve. It also highlights the role that product imagery may play in shaping trust and perceived risk in this context.

In order to gain a better understanding of how AI-generated models may impact consumer responses in the online fashion retail setting, the current chapter will review a wide range of empirical literature. This includes literature focusing on the significance of consumer trust in online retail, the risks associated with online fashion retail, and the importance of visual product presentation within that setting. Next, the chapter will review previous research on consumer responses to AI imagery in the advertising field to understand how it may similarly impact consumers in the online retailing sphere. Additionally, this literature review will investigate factors that influence the effectiveness of AI-generated imagery, such as the declaration of AI use and perceived anthropomorphism. Based on these understandings, relevant theories such as source credibility theory and the persuasion knowledge model will also be explored to further support the development of the hypotheses that will be tested in the current study.

2.2. Consumer Trust in Online Retail

Consumer trust is a complex and context-dependent concept, which usually refers to the willingness to rely on another party based on positive expectations (Jiang et al., 2024). Building and maintaining consumer trust in online stores has been shown to be essential for encouraging loyalty and lowering risk perceptions (Quintus et al., 2024). Additionally, research on the links between consumer trust and purchase attitudes has consistently shown that consumer trust has a significant effect on attitudes towards retailers and can influence purchase attitudes (Jarvenpaa et al., 2000; Teo & Liu, 2007; Lăzăroiu et al., 2020). For instance, Teo and Liu (2007) show that in online shopping settings consumer trust is associated with positive attitude towards retailers, a relationship that is positively associated with willingness to purchase. Furthermore, the study demonstrated a significant relationship between trust and perceived risk, whereby consumer trust mitigates perceived risk, which consequently promotes willingness to purchase (Teo & Liu, 2007). Similarly, a study by Handoyo (2024) underscores the importance of consumer trust by demonstrating that in online retail, consumer trust and perceived risk have a significant effect on purchasing decisions, whereby risk has a negative moderating effect on trust. This effect remains consistent regardless of the consumer's income level and country (Handoyo, 2024).

Studies have consistently demonstrated that consumer trust plays a much more critical role in online shopping settings compared to brick-and-mortar stores (Toufaily et al., 2013). This is often associated with the higher level of risk that consumers are exposed to when shopping online. This includes factors such as the lack of physical interaction with the seller and products, the requirement to pay before receiving the goods, the possibility of receiving an incorrect or unsatisfactory item, potential difficulties with receiving customer support, and growing concerns over cybersecurity (Toufaily et al., 2013). In online stores, consumers must rely on a more limited amount of information regarding the products. In physical stores, consumers have direct access to products, allowing them to examine products in a visual and tactile way. In this regard, the online shopping experience does not provide consumers with the same sensory interaction with products, which can increase uncertainty and reluctance towards making online purchases (Kleisiari et al, 2021). This means that in online settings detailed and accurate product presentation are a highly valuable cue for consumer judgements about the offered goods and for building trust, while enabling them to mitigate product-related risk when shopping online (Sutinen et al., 2022). Thus, due to its close links to consumer trust, it is critical to understand the factors that influence perceived risk in online shopping contexts.

2.3. Perceived Risk in Online Fashion Retail

Perceived risk has been defined in several ways across consumer behaviour literature. According to Schierz et al. (2010), it is the consumer's expectation of potential losses, in which a greater expectation of loss would correspond to a higher degree of perceived risk. Laroche et al. (2005) define perceived risk as the negative perception of unpredictable and variable outcomes that are associated with purchased products. Similarly, Ko et al. (2004) explain perceived risk as the consumer's perception of uncertain and potentially adverse consequences when purchasing a product or service. Based on these conceptualisations, the current study will define and measure perceived risk as the level of uncertainty and perception of negative consequences that are associated with purchasing a product.

In consumer behaviour theory, risk perception plays an important role during the consumer decision-making process. Consumers often rely on their perception of risk when making a decision in assessing and weighing the potential benefits and the costs of purchasing a product (Taylor, 1974). This perception can vary depending on the type of product and shopping context, such as whether the purchase is made online or through other channels (Laforet, 2008). In the online fashion retail setting, perceived risk is particularly high, as the setting involves high-involvement products that require more certainty and accuracy in their assessment. This contributes towards a more complex decision-making process for consumers (Sutinen et al., 2022). However, with a lack of opportunities for sensory interaction with products, such as physically trying on items, consumers are often faced with risks of receiving the wrong size, improper fit, and unsatisfactory garment quality (Sutinen et al., 2022).

This particular type of risk aligns with the definition of product risk. Product risk refers to potential loss associated with a product's failure to meet consumer expectations in relation to its quality or performance. Product risk is often the result of the inability to accurately examine or evaluate the product prior to purchase (Ariffin et al., 2018; Yu et al., 2012). Product risk has been shown to have a significant effect on consumer purchase intentions, particularly if the product is highly priced or lacks sufficient information (Ariffin et al., 2018). In attempt to reduce these product-related risks involving apparel products, consumers often participate in more exhaustive information seeking behaviours, often heavily relying on visual information to compensate for their lack of tactile product experience (Yu et al., 2012). This suggests that in online fashion retail it is particularly important to provide sufficient and accurate visual product information to reduce risks associated with the intangible nature of the online shopping experience and to encourage consumer trust.

2.4. The Use of Human Models in Online Product Presentation

Currently, there is a limited amount of research focusing on the influence of human models in product imagery within the online retail context. However, some studies have found that visual product presentation that includes human models can be an effective tool for reducing perceived risk in online fashion retail settings. For instance, Boardman and Mccormick (2019) find that visual product presentation that features human models wearing the advertised clothing can provide more effective visual product cues compared to the use of mannequins and flat product displays. Human models allow consumers to better visualise the fit of clothing, which can help to reduce perceptions of risk when purchasing online (Boardman & Mccormick, 2019). Additionally, images that include human models can capture higher levels of attention, evoke emotional responses, and appear more appealing to consumers online (Boardman & Mccormick, 2019). Model traits such as levels of attractiveness can further influence how consumers process product information, whereby more attractive models promote higher levels of information processing (Yoo & Kim, 2012).

Human models can facilitate a "surrogate experience" for consumers who share similar physical characteristics by helping them to visualise themselves wearing the same apparel product (Zhang et al., 2024). This effect is particularly evident when featured models represent more realistic and diverse body sizes. This can provide consumers with more relatable visual cues that support a more accurate evaluation of fit and sizing (Zhang et al., 2024). In turn this can reduce the perceived risk of poor fit in online apparel shopping and increase purchase intentions and brand authenticity (Zhang et al., 2024). Similar findings emerge in a study by Plotkina and Saurel (2020), who examine the influence of human models on consumer responses in online fashion retail with a focus on body inclusivity, ethnic diversity, and posing style. Female consumers demonstrate a greater willingness to purchase fashion products when they are presented by models who display more natural poses and represent diverse ethnicities and body sizes (Plotkina & Saurel, 2020). This is evidence for a preference for more realistic representation, which enables consumers to more closely identify with models whose appearance is more congruent with their own actual self-image rather than an idealised one (Plotkina & Saurel, 2020). These findings together suggest that the type of model used in product presentation can play an important role in influencing consumer purchasing decisions.

Overall, these studies highlight that human models can act as a significant visual cue for guiding consumer decision making and reducing perceived risks when purchasing fashion products online. This raises the question of whether AI-generated models are capable of offering the same level of product information and connection with consumers. Given that AI-generated models do not possess a real human body, it may not be able to similarly represent and portray unique variations in physical appearance and serve as a reliable point of reference for consumers when evaluating fashion products online. In this context, consumers can be expected to respond differently to product imagery that features these type of models compared to real human models.

2.5. AI-Generated Content and Disclosure in Advertising

While academic literature directly addressing AI-generated product presentation in the e-commerce context appears to be limited, a few studies have begun exploring the effects of AI-generated imagery in advertising, which can provide some useful insights for the current study. A recent study by Hartmann et al. (2025) shows that images made using generative AI for visual advertising content are able to outperform human-made images in quality, realism, and aesthetics. Their findings show that ads featuring AI-generated images resulted in more impressions and a higher click-through rate, while also receiving more positive consumer ad attitudes and behavioural intentions compared to human-made images (Hartmann et al., 2025). Although these findings suggest a preference for AI generated images, the study did not test whether the same findings can be achieved if AI use in advertising content is explicitly declared. Thus, it is not certain whether consumer lack of awareness plays a role in influencing these results.

This noted limitation has been further examined in other recent studies on the effects of AI disclosure in visual advertising content, which demonstrate contrasting outcomes. For instance, a study by To et al. (2025) found that that email ads for luxury brands with disclosure of AI received more negative consumer evaluations, were rated lower on perceived authenticity and effort, and generated significantly lower click-through rates compared to non-disclosed ads. Although the study found that these differences were significant only in the context of luxury brands and not for mainstream brands, it demonstrates that consumers' awareness of AI use in marketing imagery can play an important role in influencing consumer responses and that it can also be context dependent.

In related work, Grigsby et al. (2025) examined the effects of AI disclosure and use of different types of AI imagery in service advertisements on consumer attitudes and trust. When using AI imagery of a business (e.g. inside of a restaurant), the study found that ads with AI disclosure resulted in more negative consumer attitudes towards the ad compared to those without AI disclosure, an effect that was mediated by consumer trust (Grigsby et al., 2025). Additionally, the study found that AI disclosure resulted in lower trust and more negative ad attitudes towards ads that focused on imagery of a service professional (e.g. a dentist) compared to ads focused on service imagery (e.g. a dentist office; Grigsby et al., 2025). When comparing ads that featured either an AI-generated service professional or a real service professional (with an AI-generated background), consumer trust was significantly higher for the real service professional when AI disclosure was included (Grigsby et al., 2025). This further supports the idea that responses towards AI imagery can be context dependent, whereby consumers' awareness of its use can negatively impact marketing efforts, especially if it features people who represent the service or product.

These studies show that consumers can perceive individuals featured in advertising imagery as a source of trust, which can be particularly affected if their appearance is revealed to be fake or non-human. This effect has been similarly observed in research focused on virtual social media influencers. Like AI-generated models, virtual influencers are generated with AI and can be hyper-realistic in their appearance, while others can be anime-like or non-human-like (Kim & Wang, 2024). Similarly to human social media influencers, virtual influencers can be used as a marketing tool for endorsing brands and products, with famous examples like Lil Miquela, who previously partnered with brands Prada and Samsung (Kim & Wang, 2024). Although consumers were shown to find it difficult to distinguish virtual influencers from real human influencers (Franke et al., 2023), several studies show that consumers perceive virtual influencers as less credible and trustworthy compared to human social media influencers (Hofeditz et al., 2022; Nissen et al., 2023). Muniz et al. (2024) reveal that when the use of virtual influencers is disclosed, influencer credibility and brand trust is reduced. This further demonstrates that disclosure of AI in marketing imagery can negatively impact consumer responses not only towards the ad but also towards the brand, supporting findings from the earlier discussed studies.

Although academic literature on AI-generated imagery remains scarce, existing studies are able to draw on some emerging patterns in consumer responses that may carry important implications for online retail. Awareness of AI-generated imagery can be especially relevant in that context, as visual product information is known to play an important role in reducing perceived risk, particularly when shopping online for apparel products (Yu et al., 2012). Due to this, consumers are likely to process visual product information differently to the way they would in response to advertisements. For instance, within online retail environments, consumers may place greater reliance on product imagery as a key source of information guiding their purchase decisions, while in advertising, exposure to the product may be more passive and less decision oriented. In that case, consumers can be expected to be more sensitive to visual information and react more adversely to imagery that uses and declares AI compared to either undisclosed AI-generated imagery or real imagery. Thus, this highlights a gap in existing research regarding the use of AI as a visual cue in the online retail setting, while also addressing the importance of examining the effects of disclosure in this context.

2.6. Anthropomorphism and AI

Anthropomorphism can be defined as the tendency to attribute human-like characteristics, emotions, behaviours, or abilities to non-human entities, such as animals, objects, technologies, or artificial agents (Salles et al., 2020). This cognitive phenomenon is understood to be caused by two motivational factors, one of which is driven by the human tendency to search for meaning, make sense of the world, and interpret ambiguity (Epley et al., 2008). The second factor is due to the fundamental human need for social connection, whereby the act of anthropomorphising objects can enable individuals to form emotional bonds with non-human beings and objects (Epley et al., 2008).

Past research has supported these views by showing that higher levels of perceived humanness can promote greater trust with greater perceived competence and lower perceived ambiguity (Muniz et al., 2024). This suggests that non-human entities that are more anthropomorphic in their appearance and behaviour can evoke a greater sense of perceived connection, trust, and usefulness. Similarly, research in consumer behaviour has also shown that anthropomorphism can be a significant factor in influencing consumer responses. Xu (2014) demonstrates that the inclusion of images in consumer reviews, as opposed to their absence, promoted a more humanlike experience for consumers, which in turn increased the reviewers' perceived credibility and trust.

In the context of AI, research has shown that factors that facilitate anthropomorphism include social behaviour, adaptability, perceived similarity to the user, personality, independence, appearance, and capacity for interaction (Li & Suh, 2021). As technology progresses, these attributes are becoming increasingly more anthropomorphic, with some studies demonstrating that AI-enabled technologies can even be mistaken for real humans (Wuenderlich & Paluch, 2017). AI technologies that are designed with more anthropomorphic qualities can promote social connection and elicit more favourable consumer responses (Araujo, 2018; Willemse & Van Erp, 2019), as well as encourage positive emotional attachment and increase purchase intentions (Kim et al., 2022). In this line of research, more anthropomorphic AI tends to be evaluated as more credible and trustworthy, which promotes more positive consumer attitudes (Airenti, 2015; Chen & Park, 2021; Hu et al., 2021).

While AI can achieve highly humanlike behaviours and appearances, research shows that perceptions of anthropomorphism, as well as its positive effects, can diminish when consumers become aware that the entity is AI. For instance, a study by Luo et al. (2019) has found that although the AI-powered chatbots in the study were able to achieve the same level of effectiveness as human workers, disclosing the AI identity of the chatbot resulted in reduced perceived humanness and conversation length with customers. This finding was shown to be the result of lower perceptions of knowledge and empathy of the disclosed AI chatbot (Luo et al., 2019). Another study by Muniz et al. (2024) similarly finds that when an AI influencer's identity was disclosed, consumers reported lower perceived anthropomorphism, which is associated with reduced influencer credibility and brand trust. This suggests that anthropomorphism is not only enabled by visual or behavioural resemblance but is also reliant on consumers' cognitive understanding of the entity's true nature. Consequently, revealing that an agent is AI may weaken perceived anthropomorphism and, in turn, reduce emotional connection through trust, or perceived competence and reliability through credibility.

Other studies have shown that the negative effects of disclosure of AI can also be mitigated by the degree to which AI is perceived to be humanlike by individuals. For instance, AI-generated ads that include AI disclosure result in greater negative attitudes towards the ad and lower ad credibility compared to AI ads that are disclosed as human-made (Baek et al., 2024).

However, the study noted that when accounting for consumers' perceptions of anthropomorphism, the difference in responses between the two conditions was significantly smaller when the AI-disclosed ad was perceived as more human-like rather than AI-like (Baek et al., 2024). This suggests that the subjective perception of anthropomorphism can also play a role in influencing consumer responses to AI imagery, even when they are cognitively aware of its AI source.

Thus, based on the discussed research, it is evident that anthropomorphism can play a significant role in influencing consumer trust, attitudes, and behaviours. These findings can have relevant implications in the online fashion retail context, particularly with the growing adoption of AI-generated models. Given that product modelling can be an influential visual cue for consumers in online shopping settings (Boardman & Mccormick, 2019), perceived anthropomorphism of the models and its consequential effect on consumer responses can be similarly expected to vary depending on whether the model is AI-generated or human. As AI-generated models can appear as realistic and humanlike as real models, consumers may perceive them as equally anthropomorphic. By being able to represent a realistic human body, from which evaluations about the product can be reliably made, this may then increase consumer trust and reduce perceived risks relating to the product and purchasing from the store. However, if the identity of the AI-generated model is disclosed, consumers may struggle to connect or relate to the model in a similar way, by increasing their awareness of their unhuman identity. That can reduce their perceived anthropomorphism of the model and consequently negatively impact trust and perceived risk.

2.7. Persuasion Knowledge Model

The Persuasion Knowledge Model explores how consumers can use their knowledge of persuasion tactics to interpret, evaluate, and respond to marketing attempts (Friestad & Wright, 1994). In this view, consumers are not necessarily passive recipients of persuasion attempts as over time they actively adapt and learn about how marketers try to influence them through experience, social interactions, and media exposure (Friestad & Wright, 1994). Gaining this awareness allows consumers to manage persuasion attempts through three types of knowledge including persuasion knowledge (understanding of tactics), agent knowledge (beliefs about the marketer), and topic knowledge (understanding of the product or related issue; Friestad & Wright, 1994). When consumers are able to recognise a message as a persuasion tactic, it can then change the meaning of it, giving them more control over the influence and triggering scepticism or resistance towards the persuasion attempt (Friestad & Wright, 1994).

In the context of the current study, the use of AI-generated models can be considered a marketing tactic. Fashion brands can use AI-generated models to communicate brand values such as promotion of diversity, innovativeness, or creativity to persuade consumers and offer a point of differentiation from other fashion brands. In explicitly declaring the use of AI in online product images, consumers are exposed to a potential persuasion attempt, and their awareness or knowledge of it may consequently evoke scepticism and negatively impact their trust towards the brand or product.

While the Persuasion Knowledge Model offers a useful framework for understanding why the declaration of AI use may impact consumer trust, it does not fully help to determine whether these potential effects are driven by the disclosure as a marketing tactic or simply by the presence of AI-generated content. Thus, the following theory is also considered in further supporting the understanding of the potential effects that may be observed while specifically focusing on the AI-generated models as a potential source influencing consumer trust.

2.8. Source Credibility Theory

Source Credibility Theory explains that the perceived credibility or believability of a message can depend on the credibility of the message's source and is often perceived through three dimensions which include trustworthiness, competence, and goodwill (Umeogu, 2012). In the context of AI, there are two dimensions that are generally agreed on in academic literature which include trustworthiness and expertise (Khan & Mishra, 2024). Trustworthiness in relation to AI involves qualities such as honesty, transparency, and being disinclined to deceive, while expertise relates to AI's experience, competency, knowledge, and skills (Khan & Mishra, 2024). As the current study solely focuses on AI-generated models that are limited to providing visual product information, evaluating their credibility based on their level of trustworthiness may then be more appropriate.

Since product images have the ability to provide product information, the featured individuals in these images act as a potential source of credibility in an online shopping setting. In this sense, a real human model in product imagery may be a more truthful source as they are able to visually represent a higher level of realism, which consumers are more able to rely on to judge how a clothing item may actually look. Thus, product presentation with human models should offer consumers more reliable and transparent visual information that can reduce perception of risk toward the product presented in the image, compared to AI-generated models. The use of AI-generated models in product imagery, especially if declared, may create a further impression that the product in the image is also not truly representative of the real product. Consumers may question whether the product has actually been manufactured already or if it is a prototype or a concept design that has also been completely generated by AI, similarly to the model. This may ultimately create uncertainty regarding the legitimacy, quality, or overall appearance of the product. This can be particularly concerning as recent research shows that AI-designed clothing tends to be perceived more negatively by consumers compared to human-designed clothing (Lee & Kim, 2024). Thus, it can be argued that the perceived credibility and trustworthiness that AI-generated models as sources present in a product image may influence consumer trust and perceived risk.

2.9. Hypothesis Development

Based on the literature review, it is evident that consumer trust is critical in the online retail setting due to risks associated with online shopping (Toufaily et al., 2013). The inability to have direct physical interaction with products poses a particularly significant risk which means that consumers must rely on available product information such as visual cues to build their trust (Sutinen et al., 2022). In the online fashion retail context, human models have been shown to be a particularly helpful tool in reducing perceived risk by aiding the visualisation of products in online retail settings (Boardman & Mccormick, 2019). Thus, as AI-generated models can represent a less realistic representation of the product compared to human models, they can be anticipated to be associated with greater perceived risk and lower consumer trust. Source Credibility Theory offers support for this expected effect by explaining that human models, compared to AI-generated models, may be perceived as more reliable and trustworthy visual communicators in relation to the product. Therefore, the following hypothesis is proposed:

Hypothesis 1: AI-generated models in online product images negatively impact consumer trust and perceived risk.

Disclosure of AI use in advertising and influencer marketing can produce more negative consumer reposes, such as lower perceived authenticity, credibility and consumer trust, compared to non-disclosed use of AI (To et al., 2025; Grigsby et al., 2025; Muniz et al., 2024). Due to consumers' high reliance on visual product presentation in online fashion retail

(Yu et al., 2012), it can be expected that disclosing the use of AI-generated models may lead to similar negative effects on consumer trust and perceived risk. This effect can be explained through the Persuasion Knowledge Model, in which knowledge of AI use as a marketing tactic through its disclosure can help consumers recognise it as a persuasion attempt, triggering potential consumer scepticism and leading to more negative consumer responses. Together, these insights support development of the following hypothesis:

Hypothesis 2: The impact of AI-generated models on consumer trust and perceived risk is greater when the use of AI is explicitly disclosed compared to when it is not disclosed.

Anthropomorphism has also been shown to be a significant factor capable of influencing consumer responses. For instance, increased perceived anthropomorphism has been previously associated with greater trust and lower perceived ambiguity (Xu, 2014). Studies exploring responses towards AI-enabled technology have also demonstrated that without the disclosure of their AI identity, consumers can fail to distinguish AI from humans (Wuenderlich & Paluch, 2017; Luo et al., 2019). Furthermore, AI disclosure has been shown to reduce perceptions of anthropomorphism, which was associated with a decrease in trust and credibility (Muniz et al., 2024; Luo et al., 2019). This suggests that perceived anthropomorphism can vary depending on what consumers think they see. This can then consequently impact consumer trust and the perceived competence of the agent.

As AI-generated models are created to mimic the appearance of real human models, understanding how their perceived anthropomorphism can impact consumers in online product imagery can be highly relevant. Given that AI-generated imagery is becoming increasingly realistic and human-like, similar findings can be expected for AI-generated models, whereby AI models would be viewed as being as anthropomorphic as actual human models, while disclosed AI models would be perceived as less anthropomorphic. These differences in perceived anthropomorphism are then predicted to be associated with varying responses in trust and perceived risk. Thus, the following hypotheses are proposed:

Hypothesis 3: The conditions (human model vs. AI model vs. AI model with disclosure) predict varying levels of perceived anthropomorphism.

Hypothesis 4: Anthropomorphism is associated with consumer trust and perceived risk.

Lastly, research by Baek et al. (2024) has demonstrated that while disclosure of AI sources in ads can negatively impact consumer responses, the level of anthropomorphism that consumers perceive in the AI source can reduce the effect of its disclosure. That is, if consumers perceive an AI source as highly anthropomorphic, the effects of the source's AI disclosure will not be as significant compared to those who perceive it as less anthropomorphic. This suggests that perception of anthropomorphism may have a mediating role in influencing how consumers respond to AI disclosure in marketing content. Thus, the following hypothesis is proposed:

Hypothesis 5: Anthropomorphism mediates the effects of model type on consumer trust and perceived risk.

Chapter 3: Research Methodology

3.1. Ethical Considerations

Ethics approval for this research was received from Auckland University of Technology's Ethical Committee on 09.09.25 (Ethics application: 25/270 see Appendix A) before data collection commenced. This approved application included all necessary materials such as the information sheet and survey content (see Appendix B). The information sheet ensured that the participants were fully informed about study's details, potential risks, and their participant rights. At the beginning of the survey, participants were then asked whether they agreed to participate, followed by instructions for their participation. The final part of the survey experiment asked participants for general demographic details such as gender and age, however, no identifying data such as names, contact details, or addresses was collected to allow participant anonymity and confidentiality. Due to this, the study qualified for minimal risk assessment.

3.2. Research Questions

The primary goal of this research is to examine whether the use of AI in e-commerce product pictures, specifically the use of AI-generated models in fashion product presentation, affects consumer behaviour and attitudes towards the product and brand. As well-known fashion brands and e-retailers begin to implement such AI imagery in online retailing spaces, it is imperative to understand how it impacts consumers, as an under researched emerging phenomenon. Thus, the current study aims to answer the following research question:

RQ: How does the use of AI-generated models impact consumer trust and perceived risk in online fashion retail?

To answer this research question, the current study uses a quantitative research method with an experimental research design which includes three conditions: human model condition, AI-generated model condition without disclosure, and AI-generated model condition with disclosure. This methodology and research design is discussed in more detail in the following sections of this chapter.

3.3. Methodology

The methodology of this study is underpinned by a realist ontology, which provides a consistent philosophical foundation for examining the research question and achieving its aims. In research, ontology seeks to understand the essence of existence and what comprises reality to inform the researcher's fundamental assumptions about the studied subject (Levers, 2013). This can be understood through the realist or relativist ontological positions (Gray, 2022). The relativist ontology holds that reality is subjective and plural with its existence being restricted to the individual's mind, while the realist ontology argues that reality is singular and objective, existing separately from human perception (Pretorius, 2024).

These two ontologies further support two opposing epistemological positions, objectivism and subjectivism, to explain how knowledge is defined and acquired (Levers, 2013). Objectivism, based on realist ontology, argues that knowledge is objective and is only discoverable through unbiased observation, which means that what can be known exists outside of the observer's mind and therefore cannot be influenced by it (Pretorius, 2024). In contrast, subjectivism argues that knowledge is value-laden and can be affected by contextual factors such as the gender or cultural background of the observer, which informs their subjective experience of reality (Levers, 2013).

The current study more closely identifies with the realist position as it reflects the assumption that there is a broader consumer reality in which the effects of phenomena, such as AI imagery, present themselves in a somewhat universal reality rather than being confined to unique individual interpretations. Although the measured variables in the study, such as consumer trust and perceptions of risk, may be considered as inherently subjective experiences, the aim of the current study adopts a more objectivist orientation. This is because the study is not focused on capturing individual differences in how trust or risk are personally experienced, but rather on identifying generalisable patterns to gain a more objective understanding of the impact that AI imagery has on consumers more broadly.

Based on these ontological and epistemological positions, the study adopts a positivist paradigm to guide the research design. This paradigm is grounded in the belief that reality is governed by stable cause-effect laws which similarly apply to social phenomena as they do in the natural world (Rehman & Alharthi, 2016). It emphasises that truth can be established through observation, verification and replication of findings, which enables reliable prediction of phenomena (Tuli, 2010; Davies & Fisher, 2018). Thus, positivist research employs quantitative research methods which rely on deductive reasoning, often through experimentation, using hypotheses based on what is usually already known or indicated in theory, to test and establish causal relationships between variables (Davies & Fisher, 2018).

This position aims to minimize individual bias, while maximizing validity, objectivity, and generalisability to gain the most approximate understanding of reality (Berryman, 2019; Rehman & Alharthi, 2016). However, it is argued that applying the same causal laws observed in the natural world to social phenomena and reducing it to quantitative data may produce an oversimplified understanding of human experience (Rehman & Alharthi, 2016). In contrast, paradigms such as interpretivism take a more relativist and subjectivist approach in which qualitative methods with inductive reasoning are employed to develop theories, rather than test them, by exploring, describing, and understanding individual experiences to gain deeper insight into social phenomena (Davies & Fisher, 2018).

The current study more closely supports a positivist approach to research as it aims to predict and test a causal relationship, based on relevant data from past similar research, to verify and expand this knowledge to other contexts. Furthermore, existing studies have demonstrated this approach's effectiveness in examining similar variables that are researched in the current study. Such studies include those by Grigsby et al. (2025) which examine the effects of AI advertising imagery versus human advertising imagery, as well as disclosed versus undisclosed AI imagery, on variables such as consumer trust and credibility. Within a slightly different context, Hofeditz et al. (2022) and Nissen et al. (2023) examine the effects of virtual influencers versus human influencers on consumer trust, while Muniz et al. (2024) focused on the effects of disclosure of virtual influencers on brand trust.

Based on the observed similarities in their findings, such as the general consumer distrust towards non-human sources, these studies are able to exemplify how human experiences, such as trust, can be reliably and objectively measured using a positivist approach in research. Additionally, this common finding within these studies, which the current study would build upon, further supports the realist stance that a universal consumer reality exists. This suggests that an objective truth about consumer responses towards AI can be predicted and tested in the current study through a positivist approach, using quantitative research methods and an experimental design, similarly to the discussed studies.

From these foundational ontologies, epistemologies, and research paradigms, two main research approaches emerge which include quantitative and qualitative research methods. The quantitative approach enables researchers to deductively measure data and analyse a cause-and-effect relationship between variables, allowing them to draw conclusions about a population through logical and statistical observations from a sample (Ahmad et al., 2019). Quantitative research focuses on outcome verification and objective, population-oriented measurement which can give quantitative studies greater reliability and generalisability (Steckler et al., 1992).

In contrast, the qualitative approach aims to gain an understanding of subjective meanings and interpretations of certain situations and experiences, as well as language and communication processes of particular groups of people (Fossey et al., 2002). Unlike the quantitative approach, which focuses on testing specific hypotheses, the qualitative approach explores broader research questions and builds theoretical understandings through the interpretation of patterns and connections (Fossey et al., 2002). This allows qualitative studies to explore more in-depth understanding of social phenomena through data collection methods, such as in-depth interviews and focus groups (Tuli, 2010). These methods allow researchers to become immersed in discussions with participants which delve deeper into human complexities and unique cultural meanings (Tuli, 2010). However, such qualitative methods can also be more time consuming and costly, while also resulting in smaller sample sizes. Quantitative methods, such as experiments, allow researchers to collect data from larger samples (Tuli, 2010). Additionally, experimental research designs are widely employed in the social sciences, as they allow researchers to manipulate and have full control over treatments while also facilitating the random assignment of participants to groups, thereby facilitating an accurate measurement of outcome variables (Jackson & Cox, 2013).

For the current study, a quantitative research design with an experiment would then allow the researcher to compare multiple groups of participants in different conditions in a controlled manner. This would enable discovery of any potential differences in responses and analysis of a potential relationship between the independent variable (model type) and the dependent variables such as consumer trust and perceived risk.

3.4. Method and Procedure

The independent variable in this experimental design is 3 conditions that vary in model type (human model vs. AI-generated model with no disclosure vs. AI-generated model with disclosure). The key dependent variables are consumer trust (towards the brand and product) and perceived risk. Thus, the research uses a 1-factor between-subjects design. It should be noted that this experimental design did not include a human model condition in which disclosure is used, the effects of disclosure were only explored in relation to the AI-generated models. This decision can be justified by the current continued dominant use of human models in online fashion retail. At this point in time, consumers can still be expected to believe that human fashion models portrayed in e-commerce imagery are in fact human by default, unless it is stated otherwise. Based on this context, the use of a disclosure for the human model condition in the current study is assumed to be redundant.

The experiment was conducted through an anonymous online survey which was created via Qualtrics, an online questionnaire platform. The link to the survey was then distributed through ResearchConnect, an online panel recruitment agency, through which the participants were recruited for the study. To participate in the study, participants were required to meet some criteria, such as being over the age of 18 and having some experience in online shopping. Having met these requirements on the recruitment platform, participants were then directed to the survey link which presented the participant information sheet and a section asking for their agreement for participation. Upon their agreement to participate, participants were presented with instructions for the survey and were asked to evaluate a product detail page from a mock e-commerce site.

Following these instructions, participants were then randomly assigned to one of three conditions exposing them to a picture of the mock website that was either featuring (1) human models, (2) AI models with no declaration, or (3) AI models with declaration. After viewing the randomly assigned picture, participants were then asked to answer the survey questions which were presented in two parts. In part one, participants answered questions about the presented product, brand, website, and featured models. In part two, participants were asked to answer a few demographic questions (see Appendix B).

3.5. Participants

As this is an online experiment with 1 factor (model type) between-subjects design with three conditions, it was expected that at least 210 participants would be needed (minimum 70 participants per condition) with an anticipated small effect size (.2). A smaller effect of 0.2 is common in marketing research (Eisend, 2015), thus appropriate for the current study. This sample size is based on a close estimate of a G-Power analysis for 3 groups, which recommends 246 participants or 82 per group (Brysbaert, 2019). However, due to the limited funding resources available, the study resulted in a slightly smaller sample size.

Table 1
Gender Categories of Participants

Gender	Counts	% of Total
Female	93	46%
Male	107	53%
Non-binary/third gender	1	0.5%
Prefer not to say	1	0.5%
Total	202	100%

After the data was collected, the study's sample consisted of a total of 202 participants, of which 107 were male (53%), 93 were female (46%), one was non-binary/third gender (0.5%) and one preferred not to say (0.5%) (see Table 1). The participants' ages ranged from 18 to 78 years old, with the average age being 37.5 years old (*SD* = 11.53) and the largest age groups were represented by participants aged 30-34 and 40-44 (see Table 2). Additionally, most of the participants indicated that they shop online for clothing either "sometimes" (38.6%) or "often" (39.1%) (see Table 3).

Table 2
Age Groups of Participants

Age Group	Counts	% of Total
18-24	26	12.9%
25-29	26	12.9%
30-34	44	21.8%
35-39	27	13.4%
40-44	34	16.8%
45-49	15	7.4%
50-54	8	4.0%
54-59	13	6.4%
60-64	1	0.5%
65+	7	3.5%
Total	201	99.5%

Table 3
Frequency of Online Clothing Shopping Habits

Response	Counts	% of Total
Very Rarely	8	4%
Rarely	14	6.9%
Sometimes	78	38.6%
Often	79	39.1%
Very Often	23	11.4%
Total	202	100%

3.5. Stimuli

For the experiment's visual stimuli, a picture of a mock website was created using Canva to resemble a realistic website for the fictional brand 'Main Character'. The website was designed to appear as realistic as possible and was inspired by websites of popular clothing brands and retailers. This aimed to reinforce a natural online shopping environment, thereby enhancing ecological validity and minimizing the influence of potential bias towards the website's design on the study's findings. A fictional brand was also chosen to avoid brand-related bias and help maintain the study's internal validity.

The human model condition included photographs that were taken of a male and female model (see Figure 1) who were asked to wear a basic black or white T-shirt as the featured product on the website page. For the AI model conditions, the photographs of the real human models were used to generate an AI version of them using OpenAI's Sora image generation tool. The prompt simply instructed to recreate the same image in a subtlety enhanced way. The same AI-generated images were then used for both the AI model without disclosure condition (see Figure 2) and AI model with disclosure condition (see Figure 3). For the disclosure, a moderately sized label was added on the photo of each AI-generated model with a further disclaimer included in the product description.

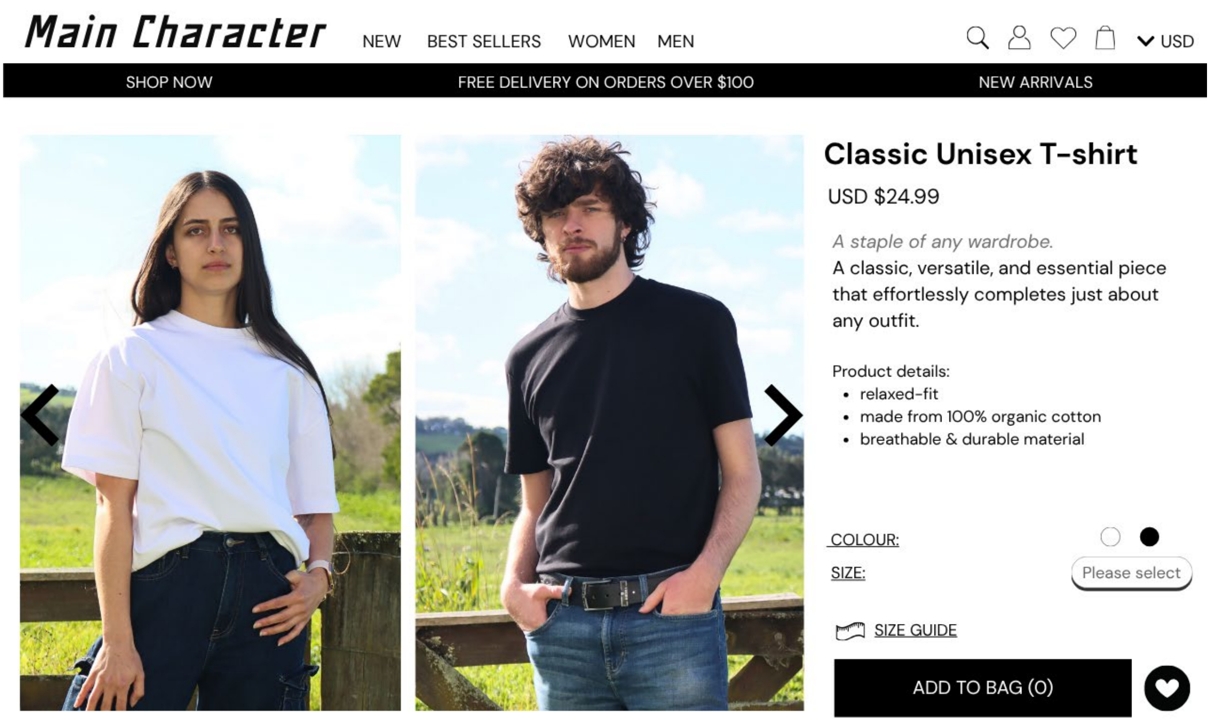

Figure 1. Human condition stimuli

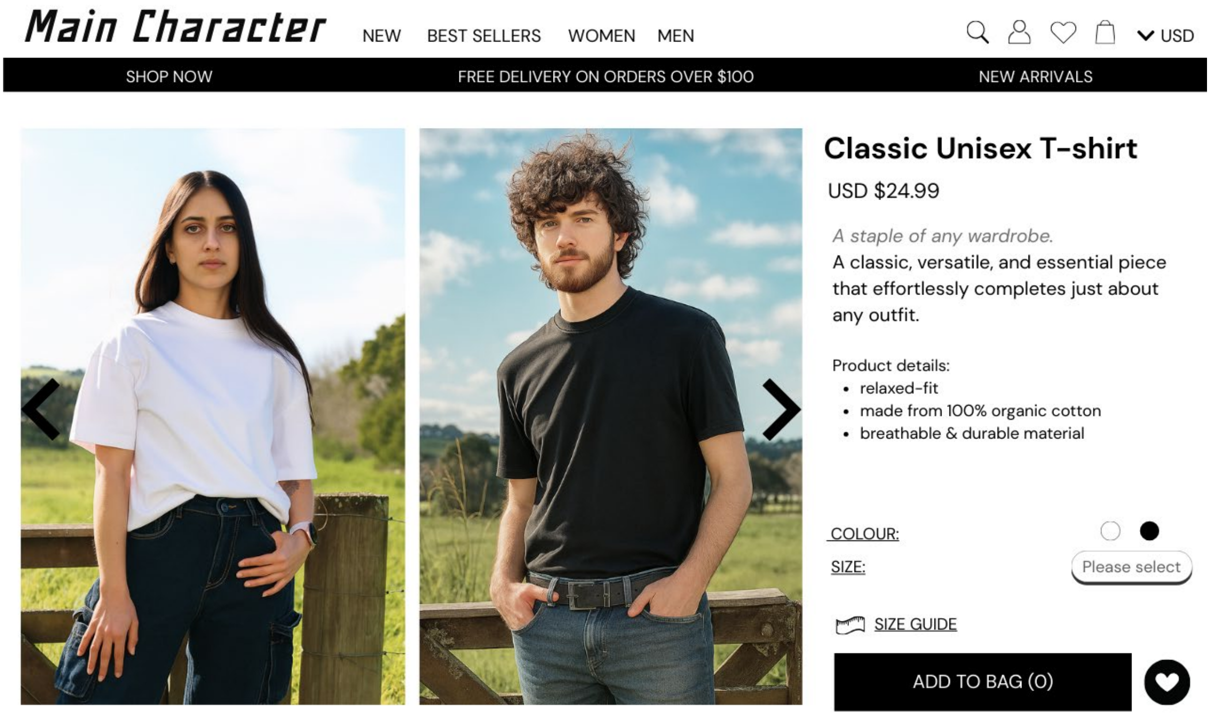

Figure 2. AI model no disclosure condition stimuli

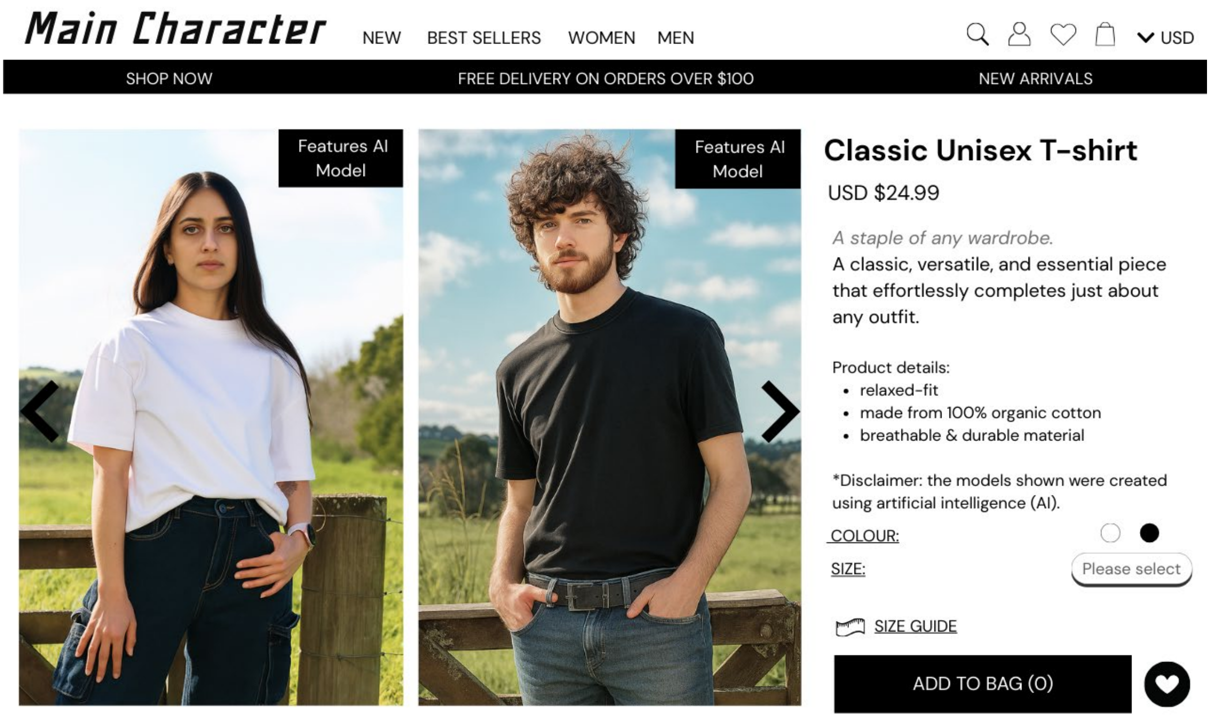

Figure 3. AI model with disclosure condition stimuli

3.6. Measures

In part one of the survey, participants were asked to evaluate the models, brand, product, and online store, measuring their attitudes, trust, perceived risk, and source credibility. Participants rated the models based on source credibility subscales using a 7-point semantic differential scale by Ohanian (1990). These subscales, as shown in Table 4, included trustworthiness which was measured via five items (i.e., undependable/dependable), and attractiveness which was also measured via five items (i.e., unattractive/attractive).

Attitude towards the model (see Table 2) was measured using a 7-point semantic differential scale adapted from Silvera and Austad (2004) via four items (i.e., uninteresting/interesting). Attitude towards the product was measured with five items (i.e., unappealing/appealing) on a 7-point semantic differential scale from Spears and Singh (2004). Attitude towards the store brand was measured using a 7-point Likert-scale (1= Strongly disagree, 7= Strongly agree) by Van Ittersum et al. (2013) with three items (i.e., "I like the store brand"). Attitude towards the product listing (ad) was adapted from Lawrence et al. (2013) using a 7-point Likert-scale with four items (i.e., "I trust what this product listing has to say"). Trust in the online store was measured using a 7-point Likert-scale with three items (i.e., "I trust this online store") adapted from Weisstein et al. (2013).

Purchase intentions were measured with four items. Two items were used from Thomas and Fowler (2021) and asked participants to indicate the likelihood of purchasing the featured product using a using a 7-point semantic differential scale (i.e., likely/unlikely, would definitely/definitely would not). The other two items used a 7-point Likert-scale from Bergkvist and Langner (2017) and included statements such as: "I will recommend the product to others", and "I will consider buying the advertised product". Product risk was measured using a 7-point Likert-scale with three items (i.e., "I will get what I ordered through this website") adapted from Ariff et al. (2014). Perceived risk is measured using a 7-point Likert-scale with four items (i.e., "I believe that the risk of purchasing online from this website is very high") adapted from Teo and Liu (2007).

Perceived anthropomorphism was measured using a 7-point semantic differential scale adapted from Nowak and Rauh (2005) with three items (i.e., does not look human/looks very human, does not look realistic/looks very realistic, looks very AI-like/does not look like AI). Similarly, a manipulation check was included at the end asking the participants to indicate whether they believed the models were AI-generated using a 5-point Likert scale (1=Definitely not, 5=Definitely yes).

In part two of the survey, participants were asked to provide some basic demographic information such as their gender and age. Lastly, the participants were asked how often they shop online with a 5-point Likert-scale (1= Never, 5=Very often).

To evaluate the consistency of the measurement scales, Cronbach's α test was conducted. The test showed high reliability for all the scales: attractiveness (α = .94), trustworthiness (α = .96), source credibility (α = .95), attitude towards the model (α = .95), attitude towards the product (α = .96), purchase intentions 1 (α = .97), purchase intentions 2 (α = .90), attitude towards the store brand (α = .94), trust towards the ad (α = .95), trust in the online store (α = .97), product risk (α = .74), perceived risk (α = .95), and anthropomorphism (α = .79). These dimension scales and the complete list of corresponding items used in the study can be found in Table 4.

Table 4
Measurement Scales

Dimensions	Items	Cronbach's alpha	Source
Source credibility	Trustworthiness 1. Undependable/dependable 2. Dishonest/honest 3. Unreliable/reliable 4. Insincere/sincere 5. Untrustworthy/trustworthy Attractiveness 1. Unattractive/attractive 2. Not classy/classy 3. Ugly/beautiful 4. Inelegant/elegant 5. Not sexy/sexy	Trustworthiness (α = .96) Attractiveness (α = .94) Total Source Credibility (α = .95)	Ohanian (1990)
Attitude towards the model	1. Uninteresting/interesting 2. Unpleasant/pleasant 3. Unlikeable/likeable 4. Bad/good	(α = .95)	Silvera and Austad (2004)
Attitude towards the product	1. Unappealing/appealing 2. Bad/good, 3. Unpleasant/pleasant 4. Not useful/useful 5. Unlikeable/likable	(α = .96)	Spears and Singh (2004)

Attitude towards the store brand	1. I like the store brand 2. I believe the quality of the store brand is high 3. I feel confident about the quality of the store brand	(α = .94)	Van Ittersum et al. (2013)
Attitude towards the product listing (ad) - trustworthiness	1. I trust what the product listing has to say 2. The product listing is trustworthy 3. The claims made in this product listing are credible 4. The product listing felt authentic	(α = .95)	Lawrence et al. (2013)
Trust in the online store	1. I trust this online store 2. I think this online store is reliable 3. I think this online store is credible	(α = .97)	Weisstein et al. (2013)
Purchase intentions	1. Likely/unlikely, 2. Would definitely/definitely would not	(α = .97)	Thomas and Fowler (2021)
	1. I will recommend the product to others 2. I will consider buying the advertised product	(α = .90) Total Purchase Intentions (α = .96)	Bergkvist and Langner (2017)
Product risk	1. I will get what I ordered through this website* 2. I will not receive malfunctioning products from this website* 3. It is easy to judge the quality of the product over this website* *Reverse coded items	(α = .74)	Ariff et al. (2014)
Percieved risk	1. I believe that the risk of purchasing online from this website is very high 2. There is a high probability of losing a great deal by purchasing online from this website 3. There is great uncertainty associated with purchasing online from this website 4. Overall, I would label the option of purchasing online	(α = .95)	Teo and Liu (2007)

	from this website as something negative		
Perceived anthropomorphism	1. Does not look human/looks very human 2. Does not look realistic/looks very realistic 3. Does not look like AI / looks very AI-like* *Reverse coded items	(α = .79)	Nowak and Rauh (2005)

Chapter 4: Research Findings

4.1. Introduction

Analyses of the study are guided by the following key hypotheses:

H1: AI-generated models in online product images negatively impact consumer trust and perceived risk.
H2: The impact of AI-generated models on consumer trust and perceived risk is greater when the use of AI is explicitly disclosed compared to when it is not disclosed.
H3: The conditions (human model vs. AI model vs. AI model with disclosure) predict varying levels of perceived anthropomorphism
H4: Anthropomorphism is associated with consumer trust and perceived risk.
H5: Anthropomorphism mediates the effects of model type on consumer trust and perceived risk.

To address each hypothesis, statistical tests including analyses of variance, regression, and mediation are carried out. The results are reported in this chapter, in the sections below.

4.2. Manipulation Check

Before testing the hypotheses, an analysis of variance was conducted to determine whether the participants respond differently to the manipulation check depending on their condition. In the manipulation check, participants were asked to indicate the degree to which they believed the models were AI-generated. This was measured on a 5-point Likert scale from "1 = Definitely not" to "5 = Definitely yes".

The results revealed a significant effect of the condition (model type) on the manipulation check (F (2, 199) = 28.42, p >.001), indicating that the manipulation was effective. The AI models with disclosure condition (M = 3.7) had the highest average score, which was significantly different to the AI model without disclosure condition (M = 2.73, p < .001) and the human model condition (M = 2.4, p <.001). This indicates that participants in the AI models with disclosure condition were more able to correctly identify the models as AI. However, although the score for this condition was the highest, it is low for a score out of 5, which may indicate that some respondents did not fully engage in assessing the image and may not have noticed the AI disclosure label. Additionally, there was no significant difference between the human model condition and the AI model with no disclosure condition (p = .20), indicating that without disclosure, participants were not able to differentiate between the human and AI models.

4.3. Results

4.3.1. ANOVA and Regression Results

To test hypotheses 1 and 2, a series of analyses of variance tests were conducted with condition (human model vs. AI model vs. AI model with disclosure) as the independent variable and dependent variables relating to consumer trust and perceived risk.

An ANOVA with model condition as the independent variable resulted in a nonsignificant model for source credibility (F (2,199) =.70, p = .49). Pairwise comparisons with Bonferroni adjustment showed the difference in means between the human model condition (M = 4.90) and AI model with disclosure condition (M= 4.83) is not significant and nondirectional. Similar results were also observed in responses for attitude (trustworthiness) towards product listing (F (2, 199) = 1.8, p= .16), trust in the online store (F (2, 199) = 2.3, p = .10), product risk (F (2, 199) = 2.0, p= .14), and perceived risk (F (2, 199) = 1.3, p= .28). Additionally, no significant differences were found for other variables relating to purchase intentions and consumer attitudes.

Overall, the findings indicate that the manipulation across the three experimental conditions did not significantly influence responses, suggesting that exposure to AI models does not affect consumer trust or perceived risk. Therefore, hypotheses 1 and 2 are rejected due to the absence of support in findings.

To test proposed hypothesis 3, an analysis of variance was conducted with condition as the independent variable and anthropomorphism as the dependent variable. Results showed that model condition has a significant effect on the degree of anthropomorphism observed (F (2,199) = 8.6, p < .001). Pairwise comparisons show that the human model condition (M = 5.98) was reported as being significantly more anthropomorphic than the AI model with disclosure condition (M = 5.14, p < .001). Similarly, the AI model without disclosure condition (M = 5.72) was also rated as significantly more anthropomorphic than the AI model with disclosure condition (M = 5.14, p = .02). However, the AI model without disclosure condition was not significantly different to the human model condition (p= .63).

These findings indicate that respondents perceived human models and AI models with no disclosure as more realistic and humanlike than AI models with disclosure. This suggests that the disclosure of AI use can reduce how realistic and humanlike models appear to consumers. Thus, these findings show that the assigned conditions were able to predict significant differences in perceived anthropomorphism, providing support for hypothesis 3.

To test H4, simple linear regression analyses were conducted to examine the extent to which anthropomorphism as the independent variable predicts dependent variables relating to consumer trust and perceived risk. A significant regression was found for source credibility (b = .27, F (1,200) = 16.30, $p < .001$) with an R^2 of .07, attitude (trust) towards the product listing (b = .25, F (1, 200) =12.86, $p < .001$) with an R^2 of .06, and trust in the online store (b = .28, F (1, 200) = 17.55, $p < .001$) with an R^2 of .08. The positive coefficients indicate that as anthropomorphism increases, so does consumer trust.

Furthermore, a significant regression was found for product risk (b = -.27, F (1, 200) = 15.54, $p < .001$) with an R^2 of .07 and perceived risk (b= -.31, F (1, 200) =21.02, $p < .001$) with an R^2 of .09. The negative coefficients indicate that as anthropomorphism increases, perceived risks of the product (e.g. being defective, lacking in quality, or failing to meet expectations) and perceived risks of the website (e.g. being associated with loss and negative experiences) decrease.

Additionally, a significant regression was found for related marketing variables such as purchase intentions (b = .20, F(1, 200) = 8.41, p = .004), attitude towards the brand (b = 21, F(1,200)= 9.60, p = .002), attitude towards the product (b= .25, F(1, 200) = 13.65, $p < .001$), and attitude towards the model (b = .28, F(1, 200) = 17.31, $p < .001$).

Overall, these findings suggest that when consumers perceive models as more anthropomorphic in e-commerce fashion sites, this can promote trust and reduce perceived risk. Similarly, more realistic and humanlike models can positively influence attitudes towards the brand, featured model, product, and even purchase intentions. Therefore, these findings provide support for hypothesis 4.

4.3.2. Mediation Results

To further investigate the relationship between condition (model type) and anthropomorphism, mediation analyses were conducted using Model 4 of Hayes' PROCESS Macro. The aim of the analyses was to determine whether the effects of condition (human model vs. AI model with disclosure) as the independent variable, on perceived risk and trust, as the dependent variables, are mediated by anthropomorphism. Due to the multicategorical nature of the study's experimental conditions as the independent variable, prior to conducting the mediation analyses, an indicator coding strategy was used by dummy-coding (*k* -1) the condition groups (Hayes & Preacher, 2014). Considering the lack of significant differences found between the human condition group and the AI model without disclosure condition group in the findings for hypothesis 3, the latter group was removed for this analysis. This resulted in two groups being used for the condition variable (0= human condition, 1= AI model with disclosure condition). Consequently, this allowed a more accurate comparison of interest with a more equal number of participants per comparison group (human condition = 67, AI condition with disclosure =68), resulting in a total sample size of 135 for the analyses.

The mediation analysis resulted in a significant model (R^2 =.109, F (1, 133) =16.25, p < .001), indicating that condition (human model vs. AI model with disclosure) explains 10.9% of the variance in anthropomorphism. Furthermore, the coefficients indicate that condition has a significant negative effect on anthropomorphism (b = -.84, p < .001), which shows that the AI source was perceived as significantly less anthropomorphic compared to the human source. This is shown as path a in Figure 4. In the combined regression model predicting perceived risk, both condition (model type) and anthropomorphism were included as predictors, resulting in a model that was also significant (R^2 = .091, F (2, 132) = 6.58, p = .002). The coefficients demonstrate that anthropomorphism predicted significantly lower perceived risk (b = -.34, p < .001), as shown through path b in Figure 4. This indicated an indirect effect of condition on perceived risk through anthropomorphism (b = .29, 95% CI = [.10, .54]), which was significant based on 5,000 bootstrap samples which did not contain zero. However, the direct effect of condition on perceived risk was not significant in this model (b = -.04, SE = .25, t = -.17, p = .86, 95% CI = [-.54, 45]), indicating that the effects of condition are fully mediated through anthropomorphism, as illustrated in path c' in Figure 4.

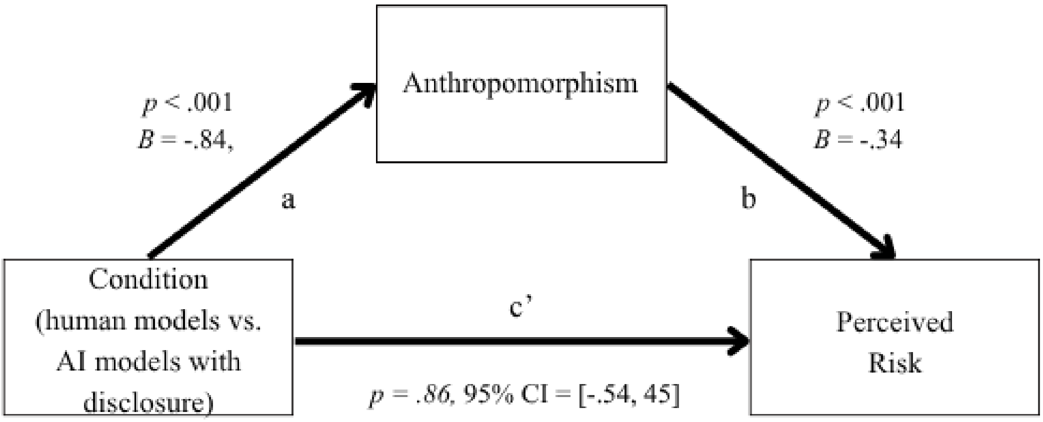

Figure 4. Mediation effects of anthropomorphism

Similarly for product risk, both condition and anthropomorphism, as the predictors, resulted in a significant model (R^2 = .10, F (2, 132) =7.69, p = .00). The coefficients table shows that anthropomorphism predicted significantly lower product risk (b = -.26, p = .00). This indicates a significant indirect effect of condition on product risk, which is fully mediated through anthropomorphism (b = .21, 95% CI = [.04, .47]) as the direct effect of condition on product risk was nonsignificant (b = .08, SE = .19, t = .43, p = .66, 95% CI = [-.28, .45]).

For source credibility, both condition and anthropomorphism as predictors also result in a model that was significant (R^2 = .06, F (2, 132) = 3.89, p = .02). The coefficients table demonstrates that anthropomorphism predicted significantly higher source credibility (b= .24, p = .00). This indicates a significant indirect effect of condition on source credibility, which is fully mediated through anthropomorphism (b = -.20, 95% CI= [-.42, -.03]) as the direct effect of condition on source credibility was nonsignificant (b = .14, SE = .22, t = .63, p = .53, 95% CI = [-.30, .58]).

For trust in the online store, both condition and anthropomorphism as predictors result in a model that was significant (R^2 = .06, F (2, 132) = 4.14, p = .01). The coefficients table demonstrates that anthropomorphism predicted significantly higher trust in the online store (b = .27, p = .00). This indicates a significant indirect effect of condition on trust in the online store, which is fully mediated through anthropomorphism (*b* = -.22, 95% CI = [-.47, -.03]) as the direct effect of condition on trust in the online store was nonsignificant (*b* = -.03, *SE* = .25, *t* = -.10, *p* = .91, 95% CI = [-.53, .47]).

Lastly, in predicting attitude (trust) towards the product listing, both condition and anthropomorphism as predictors result in a model that was significant (R^2 = .06, *F* (2, 132) = 4.16, *p* = .02). The coefficients table demonstrates that anthropomorphism predicted a significant positive effect on attitude (trust) towards the product listing (*b* = .25, *p* = .01). This indicates a significant indirect effect of condition on attitude (trust) towards the product listing, which is again fully mediated through anthropomorphism (*b* = -.21, 95% CI = [-.46, -.03]) as the direct effect of condition was nonsignificant (*b* = -.01, *SE* = .23, *t* = -.02, *p* = .98, 95% CI = [-.46, .45]).

Overall, these results show that the effects of the condition (human model vs. AI with disclosure) on trust and risk variables are fully mediated through anthropomorphism, providing support for hypothesis 5. This shows that when some consumers are exposed to an AI model in an online product image, the decrease in perceived anthropomorphism negatively affects their perceptions of trust and risk. This was observed with an increase in their perceived risk and product risk, as well as a decrease in their trust in the online store, attitude (trust) towards the product listing, and the credibility of the featured model.

Chapter 5: Discussion

5.1. Introduction

Prior research, discussed in the literature review, has shown that AI imagery has the ability to impact consumer responses. For instance, To et al. (2025) showed that AI imagery in email ads can lead to negative consumer evaluations, perceived authenticity and effort, as well as lower click-through rates. Grigsby et al. (2025) has shown that disclosure of AI imagery in service advertisements can lead to a reduction in consumer trust and negative attitudes towards the ad. Similarly, the use of non-human sources, such as virtual influencers in social media marketing content was previously shown to negatively impact credibility and trust (Hofeditz et al., 2022; Nissen et al., 2023, Muiz et al. 2023).

The current study, focusing on the use of AI-generated models in product imagery, has demonstrated that similar patterns can be observed in the online retail setting. While results demonstrate that AI-generated models can negatively impact consumer trust and perceived risk, as well as other marketing measures, these findings were shown to be limited to specific conditions. Nevertheless, these results highlight the significant role that AI disclosure and perceived anthropomorphism can play on consumer responses when viewing AI-generated models in product imagery.

The current chapter will discuss the study's findings in more detail, linking to similar findings from past research, while also considering the possible implications the results have in online retail settings. Following this discussion, the chapter will address potential contributions that this study can offer to academics and practitioners. Lastly, the chapter will discuss the study's limitations and directions for future research.

5.2. Summary of Findings

Main study findings reveal that there are no differences between consumer responses in trust and perceived risk regardless of whether they are exposed to online product images that feature human models, undisclosed AI models, or disclosed AI models. As a result, both hypotheses one and two were rejected. Despite this, the null findings offer meaningful insights which indicate that consumers view human models and AI models as equal, even when their artificial identity is explicitly communicated. This implies a potential consumer indifference toward the type of model used in online fashion imagery. Furthermore, it shows that the use of AI-generated models in online retail is unlikely to negatively impact consumers' trust towards the models, store, or product listing, nor increase perceptions of risk related to the product or website. Given the growing adoption of AI technology in the fashion industry, this outcome holds positive implications for the continued development and implementation of AI-driven visual marketing strategies in online retail environments.

However, the study also reveals that there are significant differences in perceived anthropomorphism between the different types of models, whereby disclosed AI models are perceived as less anthropomorphic than human models and undisclosed AI models. Accordingly, this result showed support for hypothesis three. While no differences were observed between human models and undisclosed AI models, this indicates that consumers cannot visually distinguish between human and AI models, unless AI disclosure is present. This suggests that in online fashion retail, the same level of realism in appearance presented by human models in product images can be similarly achieved with AI-generated models.

Additionally, the findings demonstrate that increased perception of anthropomorphism in the featured models was associated with greater consumer trust and lower perceived risk, providing support for hypothesis four. This indicates that models that are more realistic and humanlike in their appearance can promote higher levels of trust towards themselves, the store, and product listing, as well as reduce perceived risk towards the product and website. These findings align with previous research by Luo et al. (2019) and Muniz et al. (2024), which similarly demonstrated that the disclosure of AI-powered entities, such as chatbots and influencers, led to a reduction in perceived anthropomorphism and negatively impacted consumer responses.

The study further reveals that the effects of different model types on consumer responses in trust and perceived risk are fully mediated by perceived anthropomorphism. That is, when viewing AI-generated models with disclosure in a product image online, some consumers perceive the models as less anthropomorphic compared to the human models, which in turn negatively impacts their trust and perception of risk. This suggests that it is the level of realism and human-likeness that is subjectively perceived in the appearance of the model which ultimately affects how consumers respond. This not only provides support for hypothesis five but also aligns with previous findings from Baek et al. (2024), who show that the degree of anthropomorphism perceived by consumers can influence consumer attitudes and credibility of the ad in response to disclosure of AI use in marketing imagery. The current study extends these findings by drawing on the role of perceived anthropomorphism as a mediator, while also showing its ability to influence consumer responses including trust towards the model, online store, and product listing, as well as perceived risk in relation to the product and website.

Thus, as regulations on the use of AI in marketing content evolve, these findings may present potential foresight on the consequences of disclosing AI imagery in retail settings. Furthermore, it highlights the importance of employing strategies that prioritise realism and human-likeness in the appearance of fashion models which are featured in online retail imagery, particularly when AI is used and disclosed. However, at this stage, it is also evident that more research is warranted to expand on the current findings of the study in order to draw more definitive conclusions.

5.3. Contributions

This study offers several contributions to academic literature in the marketing and retailing fields. First, given the novel emergence of AI-generated models, particularly within the context of online fashion retail, this research represents one of the earliest studies to investigate this phenomenon's potential effects on consumer responses. While previous studies have examined the effects of various AI sources, such as virtual influencers or chatbots (Luo et al., 2019; Nissen et al., 2023, Muniz et al., 2024), the current study is able to expand on this research by focusing on AI-generated models, specifically those featured in online product images, as a new kind of AI source. Moreover, previous research has heavily focused on AI imagery in advertising contexts (To et al., 2025, Hartmann et al., 2025; Grigsby et al., 2025), while the current study has specifically examined this in the online retail setting. Thus, by addressing these gaps, this study provides novel and valuable insights into the implications of the increasing adoption of AI-generated imagery in marketing and retail settings. This can help to pave way for future research, giving directions for further investigation on the research topic.

Second, the study can offer some valuable theoretical contributions. The study's results help to inform theoretical understanding by identifying perceived anthropomorphism as a key mediating mechanism between source (model) type and consumer responses such as trust and perceived risk. This finding provides empirical support for the idea that consumers' reactions to AI entities depend less on their artificial identity itself and more on how realistic and human-like they appear to the consumer. Additionally, the null differences in trust and perceived risk across model types contribute to theory by suggesting that AI identity alone does not inherently diminish consumer trust in online retail contexts. That is, AI-generated models do trigger a different response in consumers, compared to human models, but only in those who perceive the models as less anthropomorphic when disclosure labels are included. This challenges assumptions in earlier literature, such as those by Grigsby et al. (2025) and To et al. (2025), which suggested that disclosure of AI itself leads to negative outcomes and instead proposes that the degree of anthropomorphism influences how consumers interpret and respond to AI-generated imagery in online retail contexts.

Lastly, as global authorities are expected to enforce increasingly more stringent regulations around the use of AI imagery in marketing content, it will be important to understand how more ethical and transparent use of AI will affect consumers, marketers, and retailers. By investigating the potential consequences of AI disclosure in an online retail setting, the current study is able to give some insight for practitioners and stronger direction for academics to explore this issue further to be able to better inform future practices.

5.4. Limitations and Future Research

The limitations of this study suggest several avenues for future research. Due to the novelty of the phenomenon, the study simply sought to assess whether AI-generated models are capable of influencing consumer responses with a less complex research design in a single study. This may have overlooked several factors that could have contributed to the findings of the study. For instance, although there was a significant difference in responses observed between each condition in the manipulation check, the responses for the disclosed AI-model condition were still lower than expected. This means that despite seeing the AI label on the model images, some participants were still uncertain whether the models were AI or not. This may have been the result of participants not paying enough attention to the details of the image. This lack of captured attention may then have contributed to the insignificant findings observed in trust and perceived risk between the three conditions. To avoid this issue, it would be recommended for future research to ensure that participants are exposed to the stimuli for a sufficient amount of time, for instance, by either setting a fixed timer for the stimuli, or including an open-ended question requiring participants to describe the observed image.

The study may also present some limitations in relation to its experimental design. As disclosure was only manipulated in the AI-generated model condition and not in the human model condition, the study does not present a fully crossed 2 x 2 design. This limits its ability to observe the isolated main effect of disclosure and to test a disclosure × model type interaction. This experimental design can be justified in the present time as human models represent the majority of models observed in fashion e-commerce sites, while in comparison AI-generated models are still a novel development in this setting. However, as the use of AI-generated models becomes more common, it would be necessary for future studies to investigate the effects of disclosure in both AI and human conditions to understand this interaction in more depth.

Other limitations in the study may have been related to the stimuli itself, such as the choice of the featured product in the image. A basic t-shirt was chosen as the featured product in the study due to its versatility and simplicity, which not only allowed for the participation of all genders but also enabled high replicability of the study. However, the simplicity of this chosen product, as well as its price, may have also led consumers to perceive it as a low involvement product, relative to other kinds of clothing items. As low involvement products tend to involve less decision making effort and investment risk for consumers compared to high involvement products (Jain, 2019), the way they are visually presented may not be as significant. For instance, a t-shirt may involve less intensive evaluation to determine the correct fit and size, compared to more complex clothing, such as pants or dresses or higher-dollar and identity relevant luxury fashion items, which may carry higher product risk. Thus, the chosen product for the study's stimuli may have influenced how participants responded to the AI models in the product image. For future research, it would then be recommended to include different types of clothing items, including high-involvement products with variations in price, to explore whether the featured product can be a moderating variable in this context.

Additionally, the use of a picture to present the mock website in the study's experimental stimuli may have also affected the outcomes of the study. Despite the realistic appearance of the website, simply observing a picture of a website may not have offered participants a sufficiently realistic and engaging online retail experience. Future research may then consider using a more realistic and interactive online shopping experience instead of a static image, to enable participants to scroll through multiple product listings, featuring either AI models or human models.

Other limitations in the study may also include the lack of survey questions relating to participants' experience with AI, as well as attitudes towards AI. This could have given the study more conclusive insight for understanding whether the lack of significant differences found between the three conditions was due to a mere indifference towards AI-generated models, a lack of awareness, or something else. Thus, future research could benefit from including such questions to gain a deeper understanding of other potential factors that can influence consumer responses towards AI imagery in online retail settings, while also giving more conclusive answers to the research question raised in the current study.

Furthermore, the results of the study, particularly those relating to the observed effects of anthropomorphism, show the need for further investigation and academic insight to draw clearer conclusions about the practical and ethical implications of using AI-generated models in e-commerce. At this stage in particular, the current study provides inconclusive answers regarding the cause of the effects observed. Further empirical tests are necessary to clarify whether the outcomes in trust and perceived risk were the result of the disclosure of AI or perceived anthropomorphism. Future studies could probe this by experimenting with disclosed and undisclosed stimuli that varies the degree of realism in the models, such as using more cartoon-like styles, to compare with the more realistic imagery that was generated with AI in this study. This may help to determine whether the trigger that lowers trust in online retail use of AI generated models is due to the degree of realism or the disclosure of AI itself.

Another avenue for future empirical testing based on this study could include an examination of how clearly the AI disclosure label is perceived by consumers. As previously noted, the outcomes in the manipulation check suggested that consumers displayed some uncertainty in identifying whether the AI-generated models with disclosure were in fact created by AI or not. This could indicate that they did not pay enough attention to the featured disclosure label or the label was not sufficiently visible to the consumers. To heighten awareness of the disclosure, future research could implement a different design for the label, which may include either a different colour, size, or placement, to better emphasize the disclosure for AI models on the website.

5.5. Conclusion

Although AI-generated models are in their early stages of adoption, it is evident that this technology has the potential to transform product imagery in online fashion retail. This is particularly true with the substantial advantages it offers to online retailers as a significantly more cost-and-time effective alternative to traditional product photoshoots. However, while it can benefit online retailers, it is not yet known how this technology affects consumers. This is particularly important to understand in the online fashion retail context, as a high-risk setting. Compared to brick-and-mortar stores, the online retail environment can involve significantly more risks for consumers by lacking opportunities for physical interaction with products. Such interactions are particularly important for fashion-related products as they require higher precision in size and fit. Due to this, consumers must have a high reliance on available product information such as product imagery to reduce their perception of risk when shopping online for clothing. As AI-generated models offer a lower degree of visual realism, it raises questions about the consumers' evaluation of products online. To address such questions, the current study aimed to understand how AI-generated models impact consumer trust and perceived risk in the online fashion retail setting by comparing consumer responses to human models and AI-generated models, with and without disclosure.

The main findings of the study demonstrate that there are no differences in responses in trust and perceived risk between those exposed to online product images that either feature human models, undisclosed AI-generated models, or disclosed AI-generated models. However, the findings also show that compared to human models, AI-generated models with disclosure can be perceived as less human-like and realistic, which can result in lower consumer trust and higher perceived risk. Overall, these findings suggest that the use of AI-generated models in product imagery does not inherently provoke more negative consumer responses compared to human models. This study suggests that the use of disclosure alone does not affect consumer trust and perceived risk if AI-generated models portray a high degree of realism and human-likeness. Together, these findings offer positive implications for the continued use of AI models in the future and suggest that as regulations move towards enforcing more transparent communication in the use of AI, fashion brands and retailers may not face negative consequences when disclosures are implemented on e-commerce sites. However, it should be noted that the study does present some limitations that need be addressed in future research to gain more conclusive understandings on the role of perceived anthropomorphism and AI disclosure in this context.

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Appendices

Appendix A: Ethics Approval

Auckland University of Technology Ethics Committee (AUTEC)

9 September 2025

Sommer Kapitan
Faculty of Business Economics and Law

Dear Sommer

Re Ethics Application: **25/270 AI-Generated Models and Their Impact on Consumer Trust and Perceived Risk in Online Fashion Retail**

Thank you for your responses to AUTEC's conditions.

Your ethics application has been approved for three years until 9 September 2028.

Standard Conditions of Approval

1. The research is to be undertaken in accordance with the Auckland University of Technology Code of Conduct for Research and as approved by AUTEC.
2. All public facing documents must have the AUTEC approval number and be of a high standard of spelling and grammar. Dates on the Information Sheet(s) and Consent Form(s) must be consistent.
3. Any amendments to the project must be approved by AUTEC prior to being implemented.
4. A progress report is due annually on the anniversary of the approval date.
5. A final report is due at the expiration of the approval period, or, upon completion of project.
6. Any serious or adverse events must be reported to AUTEC, this includes unforeseen issues that might affect continued ethical acceptability of the project.
7. AUTEC grants ethical approval only. You are responsible for obtaining management permission for access from any institution or organisation at which your research is being conducted and you need to meet all ethical, legal, public health, and locality obligations or requirements for the jurisdictions in which the research is being undertaken.

The application number and title need to be referenced on all correspondence related to this project.

All forms are available online http://www.aut.ac.nz/research/researchethics

For any enquiries, please contact the Secretariat at ethics@aut.ac.nz
(This is a computer-generated letter for which no signature is required)

The AUTEC Secretariat
Auckland University of Technology Ethics Committee

Cc: qmk8761@autuni.ac.nz

Appendix B: Information Sheet and Survey Materials

Trust and Risk in Online Fashion Retail

Start of Block: Intro

Participant Information Sheet

Date that data collection will start: 25/08/2025
Project Title: Consumer Trust and Perceived Risk in Online Fashion Retail

Dear Participant,

You are invited to participate in a research study on the use of different models in fashion e-commerce. This study is being conducted by Milana Melamed, an Honours marketing student, and supervised by Sommer Kapitan, an associate professor in marketing from Auckland University of Technology, New Zealand. This study is being carried out as a requirement for the completion of a dissertation in the Bachelor of Business (Honours) programme.

What is the purpose of this research?
The aim of this research is to gain an understanding of how different models used by online fashion retailers affect consumer trust and perceived risk towards products and brands. Due to the current lack of existing research on the issue, the findings of the study are expected to bring a valuable contribution to academic literature and inform future marketing and retailing practices. The findings of this research may be used for academic publications and presentations.

How was I identified and why am I being invited to participate in this research?
This study is targeting individuals over the age of 18 who shop online. You as a participant have been selected to take part in this study based on this criteria indicated by your CloudResearch Connect profile.

How do I agree to participate in this research?
At the beginning of the survey, you are given the option to click “I agree” to give your consent to participate. Your participation in this research is voluntary (it is your choice) and whether you choose to participate will neither advantage nor disadvantage you. You are free to withdraw at any time. To do this, simply close your browser window or the application

(App) the survey is presented on. Any information you have entered up to that point will be deleted from the data set.
As this is an anonymous survey it will not be possible to withdraw your information after you have completed the survey. This means that the submission of completed questionnaires will imply agreement to participate and use your responses as data in this research.

What will my participation involve?
This experiment will include images of a clothing brand's website featuring three variations of models. As a participant, you will be allocated to one of the three types of models. You will then be asked to briefly analyse the image and answer a number of questions (based on your allocated model type) evaluating your level of trust and perceived risk in regard to the website, brand, product, and models. This experiment is expected to take approximately 10 minutes of your time.

What are the benefits?
This study is expected to contribute to a better understanding of how AI imagery can influence consumer trust and perceived risk in the online fashion retail setting. This can add on to the limited academic literature on the subject as an area that has not yet been extensively explored. While there may be no direct benefits for participants, the findings may provide useful insights for researchers, marketers, and e-retailers by informing future studies and potentially offering guidance for developing more transparent and ethical retail and marketing practices.

What are the costs?
Participation in the study will only take 10 minutes of the participant's time. Participants will receive monetary compensation that is determined and administered by the CloudResearch Connect website.

Will the results of the study be published?
The results of this research will be published in a dissertation. This dissertation will be available to the general public through the AUT library. Results may be published in peer-reviewed, academic journals and may be presented during conferences or seminars to wider professional and academic communities. Participants will not be identifiable in any publication.

What are the discomforts and risks?
The study does not involve any serious risks; however, it may potentially trigger experiences of mild discomfort in answering questions asked about trust in online shopping experiences. Participants have the right to withdraw at any time during the study if they do not wish to continue.

What will happen to information about me?
The study will not collect any identifiable participant information. Participant responses will be anonymous which means that the study's researchers and any third parties outside CloudResearch Connect will not have access to any identifiable data. Personal information

will only include basic demographic information such as age and gender. All data collected in the study will be securely stored on the university OneDrive for 6 years.

What opportunity do I have to consider this invitation?
The invitation to participate in the study will be available for a minimum of 2 weeks.

Will I receive feedback on the results of this research?
Yes, a summary of the findings of this research will be made available via a URL once the survey has been completed. Since this is an anonymous survey, we will not be able to provide individual results to participants. However, the summary available at the URL will provide an overview of the overall findings. Participants can access a summary of the findings via the URL pasted below: https://www.sommerkapitan.com/study-results

What do I do if I have concerns about this research?
Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor, Sommer Kapitan. Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, ethics@aut.ac.nz, (+649) 921 9999 ext 6038.

Who do I contact for further information about this research?
Please keep this Information Sheet (or screenshot it) for your future reference. You are also able to contact the research team as follows:
Researcher Contact Details:
Name: Milana Melamed
Email: qmk8761@autuni.ac.nz
Project Supervisor Contact Details:
Name: Sommer Kapitan
Email: sommer.kapitan@aut.ac.nz

Approved by the Auckland University of Technology Ethics Committee on 09.09.2025, AUTEC Reference number: 25/270

Agreement
Please select "agree" to continue with this study. Thank you!

○ Agree (1)

○ Disagree (2)

Page Break

Part 1: Evaluate a website
Welcome to the study on online fashion retail.

Main Character, a new clothing apparel brand, will soon be launching a website to sell their fashion products online. The brand is experimenting with different features and looks for its website to create an optimal online shopping experience. As a potential customer, you will be viewing and evaluating a picture of this website to gain some insight for its development.

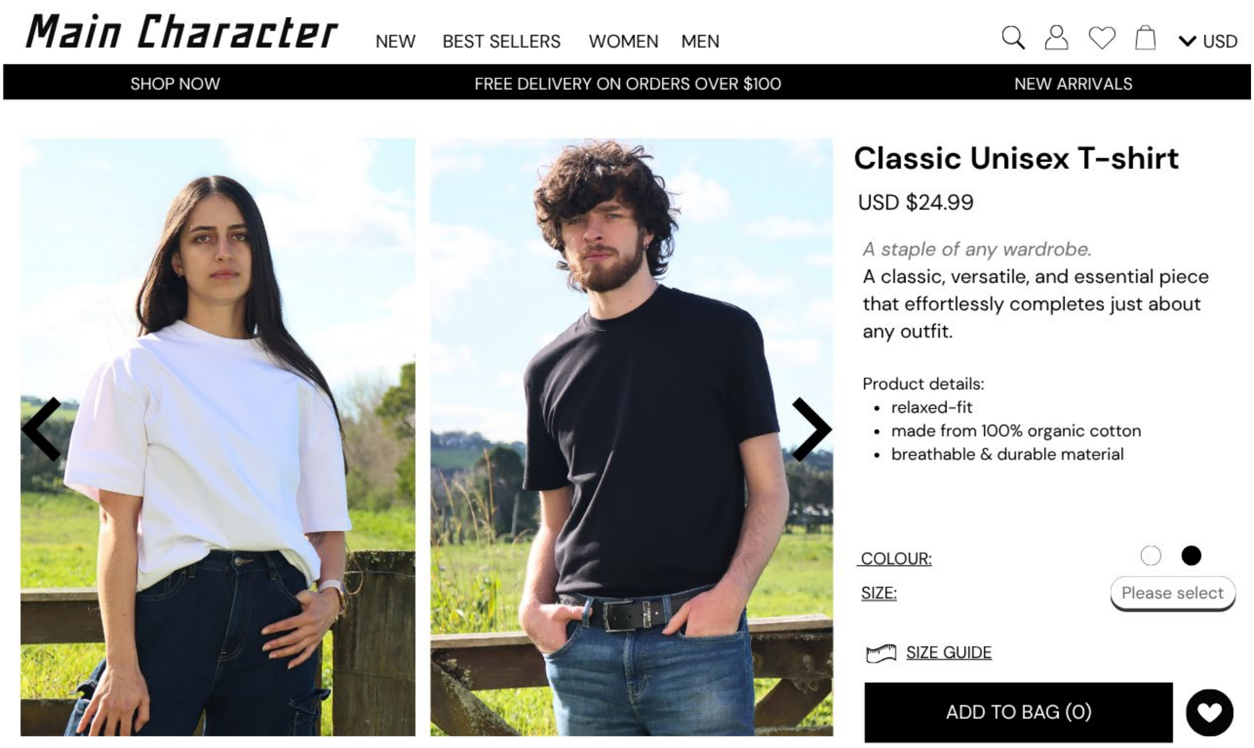
In part 1, please evaluate the new website for clothing brand Main Character.
In part 2, we'll ask for a few demographics.

Thank you for your participation.

End of Block: Intro

Start of Block: Human model

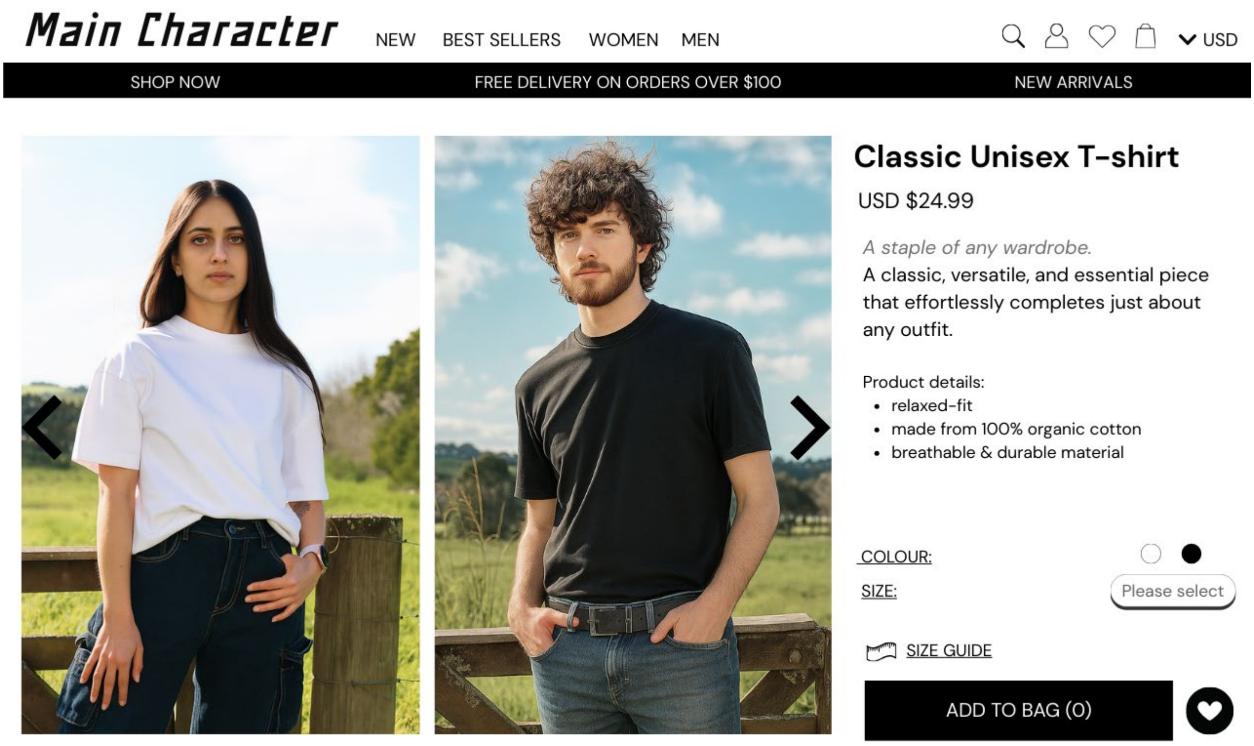
The following picture is a screenshot of Main Character's new website, please take a couple of minutes to analyse it. Imagine that you have encountered this website while shopping online to buy a new t-shirt for yourself or for someone else.



End of Block: Human model

Start of Block: AI model no disclosure

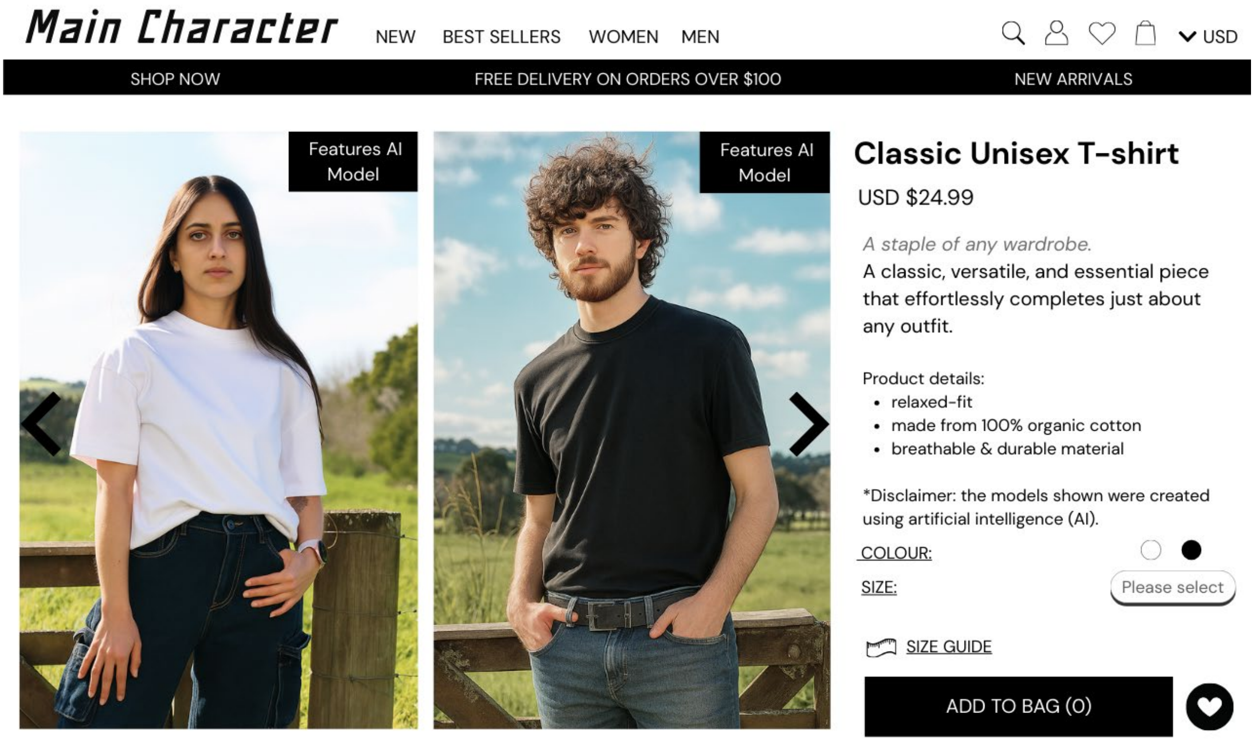
The following picture is a screenshot of Main Character's new website, please take a couple of minutes to analyse it. Imagine that you have encountered this website while shopping online to buy a new t-shirt for yourself or for someone else.



End of Block: AI model no disclosure

Start of Block: AI model disclosure

The following picture is a screenshot of Main Character's new website, please take a couple of minutes to analyse it. Imagine that you have encountered this website while shopping online to buy a new t-shirt for yourself or for someone else.



End of Block: AI model disclosure

Start of Block: Part 1: DVs

Attractiveness (source credibility)

Please give your rating of the models based on the following qualities:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Unattractive	○	○	○	○	○	○	○	Attractive
Ugly	○	○	○	○	○	○	○	Beautiful
Inelegant	○	○	○	○	○	○	○	Elegant
Not sexy	○	○	○	○	○	○	○	Sexy
Not classy	○	○	○	○	○	○	○	Classy

Trustworthiness (source credibility)

Please give your rating of the models based on the following qualities:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Undependable	○	○	○	○	○	○	○	Dependable
Untrustworthy	○	○	○	○	○	○	○	Trustworthy
Dishonest	○	○	○	○	○	○	○	Honest
Unreliable	○	○	○	○	○	○	○	Reliable
Insincere	○	○	○	○	○	○	○	Sincere

Attitude – towards model

Please give your rating of the models based on the following qualities:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Uninteresting	○	○	○	○	○	○	○	Interesting
Unpleasant	○	○	○	○	○	○	○	Pleasant
Unlikable	○	○	○	○	○	○	○	Likable
Bad	○	○	○	○	○	○	○	Good

Attitude-towards product

Please give your rating of the product based on the following qualities:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Unappealing	○	○	○	○	○	○	○	Appealing
Unpleasant	○	○	○	○	○	○	○	Pleasant
Unlikable	○	○	○	○	○	○	○	Likable
Bad	○	○	○	○	○	○	○	Good
Not useful	○	○	○	○	○	○	○	Useful

Purchase intention

Please rate the likelihood of purchasing the shown product.

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Unlikely	○	○	○	○	○	○	○	Likely
Definitely would not	○	○	○	○	○	○	○	Definitely would

Purchase intention 2

Please indicate your agreement with the following statements about the product.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I will consider buying the product (1)	○	○	○	○	○	○	○
I will recommend the product to others (2)	○	○	○	○	○	○	○

Attitude- towards brand

Please indicate your agreement with the following statements about the brand.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I like the store brand (1)	○	○	○	○	○	○	○
I believe the quality of the store brand is high (2)	○	○	○	○	○	○	○
I feel confident about the quality of the store brand (3)	○	○	○	○	○	○	○

Attitude -towards ad (trust)

Please indicate your agreement with the following statements about the product listing.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I trust what this product listing has to say (1)	o	o	o	o	o	o	o
The product listing is trustworthy (2)	o	o	o	o	o	o	o
The claims made in this product listing are credible (3)	o	o	o	o	o	o	o
The product listing felt authentic (4)	o	o	o	o	o	o	o

Trust towards online store

Please indicate your agreement with the following statements about the online store.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I trust this online store (1)	○	○	○	○	○	○	○
I think this online store is reliable (2)	○	○	○	○	○	○	○
I think this online store is credible (3)	○	○	○	○	○	○	○

Product risk

Please indicate your agreement with the following statements about the website.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I will get what I ordered through this website (1)	○	○	○	○	○	○	○
I will not receive malfunctioning products from this website (2)	○	○	○	○	○	○	○
It is easy to judge the quality of the product over this website (3)	○	○	○	○	○	○	○

Perceived risk

Please indicate your agreement with the following statements about purchasing from this website.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe that the risk of purchasing online from this website is very high (1)	○	○	○	○	○	○	○
There is a high probability of losing a great deal by purchasing online from this website (2)	○	○	○	○	○	○	○
There is great uncertainty associated with purchasing online from this website (3)	○	○	○	○	○	○	○
Overall, I would label the option of purchasing online from this website as something negative. (4)	○	○	○	○	○	○	○

Anthropomorphism

Please rate the models in the pictures based on the following qualities.

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Does not look human	○	○	○	○	○	○	○	Looks very human
Does not look realistic	○	○	○	○	○	○	○	Looks very realistic
Does not look AI-like	○	○	○	○	○	○	○	Looks very AI-like

Manipulation check

Do you believe the models were AI-generated?

○ Definitely not (1)

○ Probably not (2)

○ Might or might not (3)

○ Probably yes (4)

○ Definitely yes (5)

End of Block: Part 1: DVs

Start of Block: Part 2: Demographics

Gender

Please select your gender.

○ Male (1)

○ Female (2)

○ Non-binary / third gender (3)

○ Prefer not to say (4)

Age
Please indicate your age:

- ◯ 18-24
- ◯ 25-29
- ◯ 30-34
- ◯ 35-39
- ◯ 40-44
- ◯ 45-49
- ◯ 50-54
- ◯ 55-59
- ◯ 60-64
- ◯ 65+

Shopping habits
How often do you shop online for clothing?

- ◯ Very often (1)
- ◯ Often (2)
- ◯ Sometimes (3)
- ◯ Rarely (4)

End of Block: Part 2: Demographics

Appendix C: Reliability Scales

Trustworthiness scale

Reliability Statistics

Cronbach's Alpha	N of Items
.962	5

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
25.03	43.352	6.584	5

Attractiveness scale

Reliability Statistics

Cronbach's Alpha	N of Items
.943	5

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
24.31	49.577	7.041	5

Source credibility scale

Reliability Statistics

Cronbach's Alpha	N of Items
.953	10

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
49.34	155.717	12.479	10

Attitude towards the model scale

Reliability Statistics

Cronbach's Alpha	N of Items
.948	4

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
20.70	32.132	5.669	4

Attitude towards the product scale

Reliability Statistics

Cronbach's Alpha	N of Items
.958	5

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
26.28	45.555	6.749	5

Attitude towards the store brand scale

Reliability Statistics

Cronbach's Alpha	N of Items
.944	3

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
14.38	20.277	4.503	3

Attitude towards the product listing (ad) -trustworthiness scale

Reliability Statistics

Cronbach's Alpha	N of Items
.952	4

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
20.78	24.791	4.979	4

Trust in the online store scale

Reliability Statistics

Cronbach's Alpha	N of Items
.966	3

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
15.16	16.860	4.106	3

Purchase intentions 1 -Thomas and Fowler (2021) scale

Reliability Statistics

Cronbach's Alpha	N of Items
.968	2

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
8.59	15.208	3.900	2

Purchase intentions - Bergkvist and Langner (2017) scale

Reliability Statistics

Cronbach's Alpha	N of Items
.899	2

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
8.63	12.880	3.589	2

Purchase intentions combined scale

Reliability Statistics

Cronbach's Alpha	N of Items
.964	4

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17.22	53.975	7.347	4

Product risk scale

Reliability Statistics

Cronbach's Alpha	N of Items
.744	3

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
15.52	10.519	3.243	3

Perceived risk scale

Reliability Statistics

Cronbach's Alpha	N of Items
.945	4

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
11.46	33.732	5.808	4

Perceived Anthropomorphism scale

Reliability Statistics

Cronbach's Alpha	N of Items
.785	3

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
16.8267	14.144	3.76085	3

Appendix D: SPSS Output

Manipulation Check

Univariate Analysis of Variance

Between-Subjects Factors

		Value Label	N
Condition	0	Human model	67
	1	AI model	67
	2	AI model disclosure	68

Descriptive Statistics

Dependent Variable: Do you believe the models were AI-generated?

Condition	Mean	Std. Deviation	N
Human model	2.40	.854	67
AI model	2.73	.994	67
AI model disclosure	3.71	1.247	68
Total	2.95	1.179	202

Tests of Between-Subjects Effects

Dependent Variable: Do you believe the models were AI-generated?

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	62.104[a]	2	31.052	28.424	<.001	.222
Intercept	1753.933	1	1753.933	1605.477	<.001	.890
Condition	62.104	2	31.052	28.424	<.001	.222
Error	217.401	199	1.092			
Total	2038.000	202				
Corrected Total	279.505	201				

a. R Squared = .222 (Adjusted R Squared = .214)

Mediation Effects

Effects on Perceived Risk

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Perceive
    X  : HumanvsD
    M  : anthro

Sample
Size:  135

**************************************************************************
OUTCOME VARIABLE:
 anthro

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3299      .1089     1.4755    16.2477     1.0000   133.0000      .0001

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.9801      .1484    40.2967      .0000     5.6866     6.2736
HumanvsD     -.8428      .2091    -4.0308      .0001    -1.2564     -.4293

**************************************************************************
OUTCOME VARIABLE:
 Perceive

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3011      .0907     1.9107     6.5812     2.0000   132.0000      .0019
```

```
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3011      .0907     1.9107     6.5812     2.0000   132.0000      .0019

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.8847      .6138     7.9588      .0000     3.6707     6.0988
HumanvsD     -.0442      .2521     -.1753      .8611     -.5428      .4544
anthro       -.3432      .0987    -3.4787      .0007     -.5384     -.1481


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.0442      .2521     -.1753      .8611     -.5428      .4544

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
anthro      .2893      .1111      .1008      .5382

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

WARNING: Variables names longer than eight characters can produce incorrect outp
ut
when some variables in the data file have the same first eight characters. Short
er
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

Effects on product risk

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Product_
    X  : HumanvsD
    M  : anthro

Sample
Size:  135

**************************************************************************
OUTCOME VARIABLE:
 anthro

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3299      .1089     1.4755    16.2477     1.0000   133.0000      .0001

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.9801      .1484    40.2967      .0000     5.6866     6.2736
HumanvsD     -.8428      .2091    -4.0308      .0001    -1.2564     -.4293

**************************************************************************
OUTCOME VARIABLE:
 Product_

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3230      .1043     1.0422     7.6873     2.0000   132.0000      .0007
```

```
OUTCOME VARIABLE:
 Product_

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3230      .1043     1.0422     7.6873     2.0000   132.0000      .0007

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.2770      .4533     9.4356      .0000     3.3804     5.1737
HumanvsD      .0808      .1862      .4343      .6648     -.2874      .4491
anthro       -.2576      .0729    -3.5354      .0006     -.4018     -.1135


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .0808      .1862      .4343      .6648     -.2874      .4491

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
anthro      .2171      .1118      .0441      .4740

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000
```

<u>Effects on source credibility</u>

```
***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : SourceCr
    X  : HumanvsD
    M  : anthro

Sample
Size:  135

**************************************************************************
OUTCOME VARIABLE:
 anthro

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3299      .1089     1.4755    16.2477     1.0000   133.0000      .0001

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.9801      .1484    40.2967      .0000     5.6866     6.2736
HumanvsD     -.8428      .2091    -4.0308      .0001    -1.2564     -.4293

**************************************************************************
OUTCOME VARIABLE:
 SourceCr

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2357      .0555     1.4988     3.8808     2.0000   132.0000      .0230
```

```
OUTCOME VARIABLE:
 SourceCr

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2357      .0555     1.4988     3.8808     2.0000   132.0000      .0230

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.4465      .5436     6.3402      .0000     2.3712     4.5218
HumanvsD      .1409      .2232      .6310      .5291     -.3007      .5825
anthro        .2421      .0874     2.7698      .0064      .0692      .4149


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      .1409      .2232      .6310      .5291     -.3007      .5825

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
anthro     -.2040      .0986     -.4237     -.0378

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000
```

Effects on trust in the online store

```
***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : TrustOnl
    X  : HumanvsD
    M  : anthro

Sample
Size:  135

**************************************************************************
OUTCOME VARIABLE:
 anthro

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3299      .1089     1.4755    16.2477     1.0000   133.0000      .0001

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.9801      .1484    40.2967      .0000     5.6866     6.2736
HumanvsD     -.8428      .2091    -4.0308      .0001    -1.2564     -.4293

**************************************************************************
OUTCOME VARIABLE:
 TrustOnl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2429      .0590     1.9222     4.1382     2.0000   132.0000      .0181
```

```
OUTCOME VARIABLE:
 TrustOnl

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2429      .0590     1.9222     4.1382     2.0000   132.0000      .0181

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.4697      .6156     5.6363      .0000     2.2520     4.6875
HumanvsD     -.0274      .2528     -.1084      .9138     -.5275      .4727
anthro        .2650      .0990     2.6780      .0083      .0693      .4608


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.0274      .2528     -.1084      .9138     -.5275      .4727

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
anthro     -.2234      .1125     -.4676     -.0322

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000
```

Effects on attitude towards the product listing (ad) – trustworthiness

```
***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 4
    Y  : Attitude
    X  : HumanvsD
    M  : anthro

Sample
Size:  135

**************************************************************************
OUTCOME VARIABLE:
 anthro

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3299      .1089     1.4755    16.2477     1.0000   133.0000      .0001

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.9801      .1484    40.2967      .0000     5.6866     6.2736
HumanvsD     -.8428      .2091    -4.0308      .0001    -1.2564     -.4293

**************************************************************************
OUTCOME VARIABLE:
 Attitude

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2436      .0593     1.6051     4.1634     2.0000   132.0000      .0176
```

```
**************************************************************************
OUTCOME VARIABLE:
 Attitude

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2436      .0593     1.6051     4.1634     2.0000   132.0000      .0176

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.7326      .5625     6.6353      .0000     2.6198     4.8453
HumanvsD     -.0055      .2310     -.0238      .9811     -.4625      .4515
anthro        .2456      .0904     2.7161      .0075      .0667      .4245


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.0055      .2310     -.0238      .9811     -.4625      .4515

Indirect effect(s) of X on Y:
           Effect     BootSE   BootLLCI   BootULCI
anthro     -.2070      .1116     -.4623     -.0303

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000
```