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Original Article

Consumer Responses to AI-Generated Fashion Models: The Roles of Labelling and Product Involvement

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Abstract: *In today's e-commerce environment, visual product presentation is extremely important for online fashion retailers. This research examines how AI-generated fashion models impact consumer trust and purchase intent in e-commerce platforms. Three hypotheses were set regarding the effects of fashion model source, labelling condition and product involvement level. The research is quantitative and uses an experimental online questionnaire to collect primary data. A total of 145 valid responses were analysed using reliability analysis, confirmatory factor analysis, descriptive statistics, one-way analysis of variance and Tukey post-hoc tests. The results showed that website presentations involving human fashion models were evaluated more favourably than presentations involving AI-generated fashion models in terms of both consumer trust and purchase intent. The AI labelled condition produced the weakest results, while the differences between the experimental conditions became stronger in the high-involvement product context. All proposed hypotheses were supported. The findings show that the source of fashion model presentation matters for consumer evaluation, that disclosure of AI use does not necessarily improve consumer reactions, and that product involvement level plays an important role in shaping the strength of these effects.*

Keywords: *AI Disclosure, AI-Generated Fashion Models, Consumer Trust, E-Commerce, Product Involvement, Purchase Intent.*

I. INTRODUCTION

The relevance of artificial intelligence in digital marketing and e-commerce is increasingly discussed in online retail. Many online retailers are currently using AI for personalization, for automating decisions, or to enhance the shopping experience (Davenport et al., 2020). Visualisation plays an important role in fashion e-commerce as customers are unable to test products before purchasing. Numerous companies thus deliver virtual try-on tools powered by AI and visualisations such as fashion models created with the help of artificial intelligence (Gao & Liang, 2025).

Research shows that AI-generated visual content has a significant impact on consumer behavior by using image visuals in videos and images when displaying products or brands online. Studies on virtual try-on and AI-assisted product images found that these tools can enhance perceived enjoyment, immersion and purchase intentions among consumers who trust the brand (Nguyen et al., 2025). Other authors report that consumers perceive more credibility and are then also able to make a purchase decision better when the model (here called as reviewer) is a digital human or even visually similar [18,19].

But there are also negative effects. The threat to social identity is likely when these models emerge from AI (for example, people using a tool like The Avatar Model) and are in themselves seen as profit-motive-focused rather than authentically representing diversity. This can lead to belonging reduction and poor brand attitudes; e.g. for underrepresented demographics (Sands et al., 2024). Recent findings also indicate that consumers' responses are based on perceived realism, source disclosure and emotional response, as well as attitudes towards AI-supported personalisation (Belanche et al., 2025; Lim & Schmälzle, 2024).

This study addresses a relevant business problem and the growing body of research by researching how online fashion retailers that use AI-generated avatar models impact consumer trust and purchase intent. The problem of the research is how the use of AI-generated fashion models impacts consumer trust and purchase intent in e-commerce platforms. The aim is to investigate the impact of AI-generated fashion models on consumer trust and purchase intent in e-commerce platforms.

In particular, this research compares AI-generated and human fashion models under labelled and non-labelled conditions and under low-involvement and high-involvement product conditions. In this way, the research examines whether consumer responses are shaped not only by the source of the fashion model, but also by the way such content is presented and by the involvement level of the evaluated product.

II. LITERATURE REVIEW AND THEORETICAL BACKGROUND

A) Consumer Trust and Purchase Intent in E-Commerce

Consumer trust plays an important role as a precursor for e-commerce because it deals with situations that are full of uncertainty and risk for the consumer, such as payment made before receiving the product and data privacy (Handoyo, 2024). Trust in e-commerce settings is often measured by trusting beliefs, such as beliefs that consumers hold that e-retailers or sellers are trustworthy, responsible and will not misuse information and data (Singh et al., 2024). Consumer trust in e-commerce has always been interpreted as confidence in the reliability, credibility and safety of the seller, platform or transaction environment during online shopping (Jadil et al., 2022; Saxena & Thakur, 2024).

Trust in e-commerce can be beneficially seen as multi-level and multidimensional. Trust can be examined at three levels: the platform, seller or brand trust level and content environment (Soleimani, 2022). Such cues can signal competence (e.g., proper design) or consistency, which increase consumers' cognitive trust, while social presence increases emotional trust and offering a safe atmosphere increases their consumer comfort level (Wu et al., 2023). Reviews, reputation, website design, structural assurance, security, privacy and service quality also shape trust in online shopping environments (Mayayise, 2024; Saoula et al., 2023).

Purchase intent in online shopping is treated mostly as behavioural intention, namely the consumer's readiness or likelihood to purchase online rather than the actual purchase. It is an important outcome variable because it captures consumers' purchase intentions under uncertainty even if the actual purchase is not made (Ghosh, 2024). Online purchase intention is formed through product evaluation and evaluation of the online purchasing environment and is shaped by perceived utility, reliability, reputation cues and contextual or experience-based factors (Espírito Santo & Marques, 2021; Nguyen et al., 2023).

A consumer's involvement deals with product-related thinking and behaviour and represents the level of personal relevance, importance or perceived risk that a consumer associates with a product or shopping category. For high-involvement products, consumers engage in information search and more detailed information processing, whereas low-involvement products require less cognitive effort. Product involvement can affect intentions to buy online through involvement with advertisements and website product presentations (Arora & Sharma, 2018; Wirya & Syah, 2022).

The relationship between consumer trust and purchase intention is central in e-commerce research because it explains how consumers move from evaluating an online seller or platform to developing readiness to buy. Trust can reduce consumers' feeling of vulnerability and weaken the negative effect of perceived risks on buying intentions (Phamthi et al., 2024). Although trust is an important antecedent of purchase intention, its influence can vary across markets and online shopping platforms (Quintus et al., 2024). Thus, visual presentation may be another cue by which consumers judge the trustworthiness, reliability or credibility of the online offer.

B) Artificial Intelligence and AI-Generated Fashion Models

Artificial intelligence, particularly generative AI, is rapidly developing in digital marketing and advertising. AI in marketing helps organisations to learn, identify, predict and create or curate relevant marketing content (Huang & Rust, 2021). The applied area includes predictive analytics, targeting and campaign optimisation, automated decision-making support in personalisation recommendations for customer interactions (Davenport et al., 2020; Ziakis &Vlacho-poulou, 2023). Generative AI is now writing marketing messages, designing visuals, thus giving rise to wide scale experimentation and cost savings, as well as the challenges of transparency, uniqueness and over-automation (Dwivedi et al., 2021; Grewal et al., 2025).

AI can produce natural-looking product images, interactive models, in addition to happy content through systems trained on extremely large datasets (Ramesh et al., 2022). On the other hand, traditional product visual content is generated through photography and creates time, cost and logistical challenges, whereas AI-generated content gives online retailers much-needed flexibility (Kumar et al., 2024). Computer-generated fashion and lifestyle marketing models can also be either generated entirely by computer or based on real human images altered with the help of AI algorithms (Buyukaslan et al., 2023). Online consumers rely on high-quality product images to eliminate uncertainty and evaluate products pre-purchase (Chrimes et al., 2022).

AI created fashion models are being used in ads and content for e-commerce sites. In the fashion domain, new research suggests that a significant proportion of people believe AI-generated images appear realistic and high-quality (Hartmann et al., 2025). Drawing on visual cues like realism, attractiveness and appropriateness (Kiper & Liang, 2025), consumers respond to fashion models based on the impressions they form, which could influence trust formation or purchase intention. On the other hand, if models are perceived as being artificial or manipulative rather than authentic, then consumption scepticism may be amplified (Brüns & Meißner, 2024; Yu).

Trust is also about disclosure. Telling consumers that a visual was artificially made may be an indicator of transparency, but it can also emphasize the lack of authenticity for this content type and trigger persuasion knowledge. Empirical research on AI disclosure in advertising indicated that disclosures can have a detrimental impact on attitudes toward the ad; however, other studies found evidence that transparency has favorable effects because marketers and consumers become more engaged (Wang & Qiu, 2024; Wortel et al., 2024). Moreover, credibility-related characteristics and contextual fit are also related to how participants respond with trust toward AI-generated presenters (Alboqami, 2023).

In another use, AI-generated images can be helpful for an assessment when it comes to clothing, footwear and accessories. The use of AI (Ruiz-Viñals et al., 2024); online fashion purchase intent, attitudes towards AI, perceived quality and usefulness. Intention to buy can also be influenced by value-for-money, design sophistication, model similarity and social presence or human-likeness factors (Huang et al., 2025; Stein et al., 2024). Thus, the effect of AI-generated fashion models on trust and purchase intention is context-specific and can depend on visual source, disclosure cues and product involvement.

C) Hypotheses

Previous studies suggest that AI-generated content may be evaluated differently from human-generated content because consumers associate AI use with lower authenticity, sincerity and brand-related trust. Brüns and Meißner (2024) showed that the use of generative AI in brand content diminishes perceived brand authenticity. Lefkeli et al. (2024) found that consumers trust brands less when information is disclosed to AI rather than to humans. Song et al. (2024) showed that AI and human endorsers can produce different purchase responses depending on product context, while Zhang and Hur (2025) found that consumer evaluations differ between AI-generated and human-made images when source information is disclosed.

Hypothesis 1 (AI-generated vs. human fashion models). *AI-generated and human fashion models used in website presentations lead to significant differences in (H1a) consumer trust and (H1b) consumer purchase intent.*

The effect may also depend on whether AI involvement is explicitly disclosed. Wortel et al. (2024) found that disclosures regarding AI involvement decreased advertising attitudes, while Wang and Qiu (2024) reported that increased transparency related to AI in digital endorsers positively influenced consumer engagement. Thus, labelling does not have uniform effects, and it is relevant to investigate whether the effect of fashion model source influences consumer perceptions in labelled and non-labelled conditions.

Hypothesis 2 (Effect under different labelling conditions). *The effect of AI-generated and human fashion models used in website presentations on (H2a) consumer trust and (H2b) consumer purchase intent differs under labelled and non-labelled conditions.*

Consumers' reactions to AI-generated content are expected to become stronger for products that are more personally relevant and require more careful consideration. The effect of AI-generated content disclosed to consumers relative to human-generated content may differ across low-involvement and high-involvement product categories (Israfilzade, 2025). Zhang and Hur (2025) also showed that disclosed AI-generated images receive less favourable evaluations in more sensitive product contexts.

Hypothesis 3 (Effect under different product involvement levels). *The effect of AI-generated and human fashion models used in website presentations on (H3a) consumer trust and (H3b) consumer purchase intent differs between low-involvement and high-involvement product conditions.*

The model of the research is presented in Figure 1.

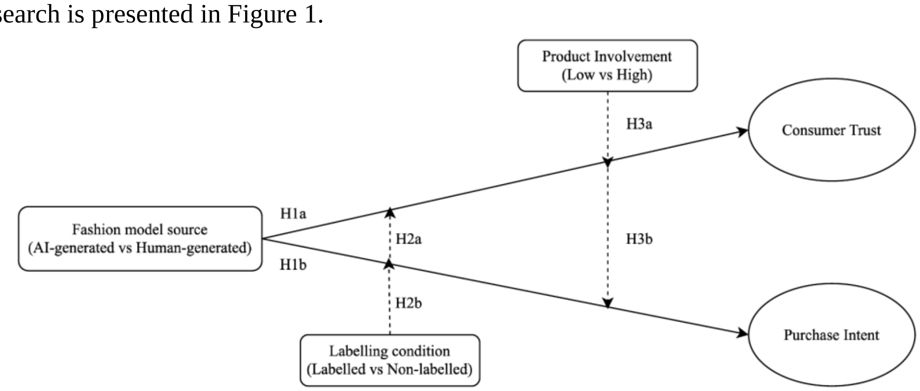

Figure 1. The Model of the Empirical Research

III. METHODOLOGY

A) Research Design and Procedure

A quantitative research method was chosen because the purpose of the study was to obtain accurate and reliable measurements and to analyse differences between variables using statistical methods (Queirós et al., 2017). Survey-based data collection is appropriate when questionnaire structure, respondent selection and standardised administration are carefully designed (Taherdoost, 2022). The present research combined experimentally prepared website stimuli with an online questionnaire in order to measure consumer trust and purchase intent under different conditions (Stoner et al., 2023).

The empirical study employed a 2 × 2 × 2 mixed experimental design. Respondents were randomly assigned to one of four between-subjects conditions combining fashion model source (AI-generated versus human) and labelling condition (labelled versus non-labelled). Within each assigned website condition, respondents evaluated both a low-involvement product and a high-involvement product. For the human-model condition, website presentation images were prepared by a professional marketing team, whereas for the AI-generated condition, website presentation images were created using artificial intelligence tools.

The questionnaire first included demographic and background questions concerning age, gender, general online shopping and online fashion shopping. Respondents were then exposed to one of the prepared website presentations in Google Forms and answered questions measuring consumer trust and purchase intent separately for the low-involvement and high-involvement products. The questionnaire was designed to be clearly understood and not overly demanding on respondents.

The questionnaire was distributed using a non-probability sampling approach combining convenience sampling, snowball sampling and voluntary response sampling. Convenience sampling was selected because of its simplicity, cost-effectiveness and time-efficiency, while respondents were also asked to distribute the questionnaire through their social networks (Golzar et al., 2022; Naderifar et al., 2017). Respondents were randomly assigned to the four questionnaire versions through the Nimble Links tool (Nimble Links Inc., 2026).

A total of 145 respondents took part in the survey. After data collection, responses were reviewed and filtered in order to ensure the validity of the primary data. Incomplete responses and duplicate responses were excluded from further research where necessary. Thus, 145 valid responses were used for the empirical research: 38 in the Human non-labelled condition, 39 in the Human labelled condition, 35 in the AI non-labelled condition and 33 in the AI labelled condition.

B) Measures

The main constructs were measured using statements adapted from previously validated scales. Consumer trust was measured through perceived credibility, perceived authenticity and perceived reliability. Purchase intent was measured through likelihood to purchase, product attractiveness and willingness to pay. Each dimension was measured with two statements, giving six items for consumer trust and six items for purchase intent. Respondents evaluated all statements using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). A seven-point scale provides a broader distribution of responses and is widely used in consumer research (Russo et al., 2021).

Table 1: Measurement of the Main Constructs

Construct	Dimensions	Items	Main literature sources
Consumer trust	Perceived credibility	2	McKnight et al. (2002); Appelman & Sundar (2016)
Consumer trust	Perceived authenticity	2	Park & Lin (2020); Audrezet et al. (2020)
Consumer trust	Perceived reliability	2	McKnight et al. (2002); Park & Lin (2020); Yildirim et al. (2021)
Purchase intent	Likelihood to purchase	2	Spears & Singh (2004); Yildirim et al. (2021); Alalwan (2018)
Purchase intent	Product attractiveness	2	Park & Lin (2020); Israfilzade (2025)
Purchase intent	Willingness to pay	2	Mejía (2024); Yildirim et al. (2021)

C) Data Analysis, Reliability and Research Ethics

All statistical analyses were conducted using Jamovi statistical software (version 2.7.24), including reliability analysis, confirmatory factor analysis, descriptive statistics, skewness and kurtosis analysis, and hypothesis-testing procedures. Cronbach's alpha, McDonald's omega and composite reliability were calculated to assess internal consistency. Average variance extracted was used to evaluate convergent validity, while confirmatory factor analysis was used to evaluate whether the questionnaire items corresponded satisfactorily to the intended constructs (Goretzko et al., 2024; Taber, 2018).

The main statistical procedure was one-way analysis of variance, followed by Tukey post-hoc comparisons. This approach made it possible to determine whether consumer trust and purchase intent differed significantly across the four experimental conditions and, if such differences were found, to identify which specific groups differed from one another.

The study was conducted in accordance with generally accepted ethical standards for academic research and the rules and requirements of Vytautas Magnus University. All respondents were informed about the academic purpose of the study before completing the questionnaire. Participation was voluntary, all responses remained anonymous, and the questionnaire did not require identifying personal or sensitive information. The collected data were used purely for academic research and were not released to other parties.

IV. RESULTS

A) Sample and Measurement Quality

The respondents were distributed relatively evenly across the four experimental conditions. The sample was dominated by younger respondents: 102 respondents (70.3%) were 18–25 years old, 30 (20.7%) were 26–35, 12 (8.3%) were 36–45, and one respondent (0.7%) was 46–55. In terms of gender, 91 respondents (62.8%) were female, 52 (35.9%) were male, one selected Other and one preferred not to say. Most respondents had experience with online shopping and online fashion shopping.

Table 2: Sample Characteristics

Variable	Category	N	%
Experimental condition	Human non-labelled	38	26.2%
Experimental condition	Human labelled	39	26.9%
Experimental condition	AI non-labelled	35	24.1%
Experimental condition	AI labelled	33	22.8%
Gender	Female	91	62.8%
Gender	Male	52	35.9%
Gender	Other	1	0.7%
Gender	Prefer not to say	1	0.7%

All measurement instruments demonstrated good internal consistency for both low-involvement and high-involvement products. Cronbach's alpha ranged from 0.836 to 0.882, while McDonald's omega and composite reliability ranged from 0.837 to 0.883. The AVE values for consumer trust exceeded 0.50. For purchase intent, the AVE values were slightly below 0.50 but remained close to the recommended level, while the corresponding composite reliability values were above 0.70. Therefore, convergent validity was considered acceptable.

Table 3: Scale Reliability and Convergent Validity Statistics

Construct	Involvement	Items	α	ω	CR	AVE
Consumer trust	Low	6	0.875	0.877	0.877	0.543
Purchase intent	Low	6	0.836	0.837	0.837	0.462
Consumer trust	High	6	0.882	0.883	0.883	0.557
Purchase intent	High	6	0.843	0.846	0.846	0.479

The confirmatory factor analysis indicated acceptable to good fit in both product-involvement conditions. For the low-involvement condition, χ^2/df was 1.356, CFI was 0.977, TLI was 0.971, and RMSEA was 0.050. For the high-involvement condition, χ^2/df was 1.103, CFI was 0.993, TLI was 0.991, and RMSEA was 0.027. The item distributions also did not demonstrate substantial deviations from normality. In the low-involvement condition, skewness ranged from −0.465 to 0.376 and kurtosis from −0.563 to 0.473. In the high-involvement condition, skewness ranged from −0.184 to 0.167 and kurtosis from −0.622 to 0.235.

Table 4: Confirmatory Factor Analysis Model Fit Statistics

Product involvement	χ^2	df	χ^2/df	CFI	TLI	RMSEA
Low involvement	71.887	53	1.356	0.977	0.971	0.050
High involvement	58.453	53	1.103	0.993	0.991	0.027

B) Empirical Research Results

The values presented in Table 5 show a clear pattern. In both product-involvement conditions, the human-related presentations received the highest evaluations, while the AI-labelled condition received the lowest evaluations. For the low-involvement product, consumer trust differed significantly across the conditions, $F(3, 141) = 24.10$, $p < .001$, and purchase intent also differed significantly, $F(3, 141) = 49.81$, $p < .001$. For the high-involvement product, the corresponding results were $F(3, 141) = 69.22$, $p < .001$ for consumer trust and $F(3, 141) = 69.36$, $p < .001$ for purchase intent.

Table 5: Descriptive Statistics and One-Way ANOVA Results

Level	Variable	Condition	N	Mean	SD	ANOVA
Low	Consumer trust	Human non-labelled	38	5.09	0.55	F(3, 141) = 24.10, p < .001

Low	Consumer trust	Human labelled	39	5.18	0.76	
Low	Consumer trust	AI non-labelled	35	4.50	0.46	
Low	Consumer trust	AI labelled	33	4.20	0.42	
Low	Purchase intent	Human non-labelled	38	5.00	0.37	F(3, 141) = 49.81, p < .001
Low	Purchase intent	Human labelled	39	5.06	0.54	
Low	Purchase intent	AI non-labelled	35	4.28	0.46	
Low	Purchase intent	AI labelled	33	4.01	0.37	
High	Consumer trust	Human non-labelled	38	5.03	0.57	F(3, 141) = 69.22, p < .001
High	Consumer trust	Human labelled	39	5.28	0.50	
High	Consumer trust	AI non-labelled	35	4.16	0.44	
High	Consumer trust	AI labelled	33	3.78	0.51	
High	Purchase intent	Human non-labelled	38	4.66	0.38	F(3, 141) = 69.36, p < .001
High	Purchase intent	Human labelled	39	4.89	0.49	
High	Purchase intent	AI non-labelled	35	3.96	0.45	
High	Purchase intent	AI labelled	33	3.56	0.43	

More specifically, in the low-involvement condition, consumer trust was highest in the Human labelled group, where the mean reached 5.18, followed closely by the Human non-labelled group, with a mean of 5.09. The AI non-labelled condition showed a lower mean of 4.50, while the AI labelled condition received the lowest mean of 4.20. A similar pattern was observed for purchase intent. The Human labelled and Human non-labelled conditions reached means of 5.06 and 5.00, respectively, compared with 4.28 in the AI non-labelled condition and 4.01 in the AI labelled condition. Thus, at the descriptive level, presentations involving human fashion models were evaluated more favourably than presentations involving AI-generated fashion models.

The same pattern remained visible in the high-involvement condition, but the differences became more pronounced. Consumer trust was highest in the Human labelled condition, with a mean of 5.28, and lowest in the AI-labelled condition, with a mean of 3.78. Purchase intent followed the same tendency, with corresponding means of 4.89 and 3.56. Compared with the low-involvement condition, consumer trust decreased from 4.20 to 3.78 in the AI-labelled condition and from 4.50 to 4.16 in the AI non-labelled condition, while the human-related conditions remained comparatively more stable. The descriptive results therefore indicate that the differences between human-related and AI-related presentations became more pronounced when respondents evaluated a high-involvement product. Figure 2 presents these mean patterns visually.

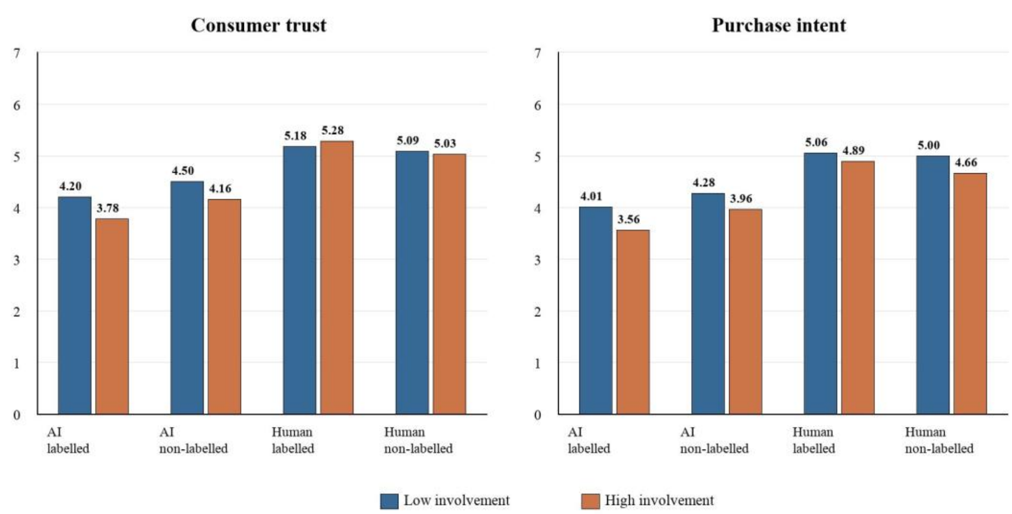

Figure 2. Mean Consumer Trust and Purchase Intent Scores across Product-Involvement Conditions

The Tukey post-hoc comparisons are presented in Table 6. In the low-involvement condition, the main statistically significant division appeared between AI-related and human-related presentations. The differences between the AI-labelled and AI non-labelled conditions were not statistically significant for consumer trust or purchase intent, and the differences between the two human conditions were also not significant. In the high-involvement condition, the AI labelled condition differed significantly from the AI non-labelled condition for both consumer trust and purchase intent. The two human conditions again did not differ significantly.

Table 6: Tukey Post-Hoc Comparisons

Levels	Variables	Comparisons	Mean D	p-value
Low	Trust	AI labelled – AI non-labelled	−0.293	.152
Low	Trust	AI labelled – Human labelled	−0.973***	< .001
Low	Trust	AI labelled – Human non-labelled	−0.886***	< .001
Low	Trust	AI non-labelled – Human labelled	−0.680***	< .001
Low	Trust	AI non-labelled – Human non-labelled	−0.593***	< .001
Low	Trust	Human labelled – Human non-labelled	0.088	.907
Low	Purchase intent	AI labelled – AI non-labelled	−0.271	.059
Low	Purchase intent	AI labelled – Human labelled	−1.046***	< .001
Low	Purchase intent	AI labelled – Human non-labelled	−0.986***	< .001
Low	Purchase intent	AI non-labelled – Human labelled	−0.775***	< .001
Low	Purchase intent	AI non-labelled – Human non-labelled	−0.715***	< .001
Low	Purchase intent	Human labelled – Human non-labelled	0.060	.933
High	Trust	AI labelled – AI non-labelled	−0.379*	.013
High	Trust	AI labelled – Human labelled	−1.495***	< .001
High	Trust	AI labelled – Human non-labelled	−1.244***	< .001
High	Trust	AI non-labelled – Human labelled	−1.116***	< .001
High	Trust	AI non-labelled – Human non-labelled	−0.864***	< .001
High	Trust	Human labelled – Human non-labelled	0.252	.136
High	Purchase intent	AI labelled – AI non-labelled	−0.401**	.001
High	Purchase intent	AI labelled – Human labelled	−1.328***	< .001
High	Purchase intent	AI labelled – Human non-labelled	−1.097***	< .001
High	Purchase intent	AI non-labelled – Human labelled	−0.927***	< .001
High	Purchase intent	AI non-labelled – Human non-labelled	−0.696***	< .001
High	Purchase intent	Human labelled – Human non-labelled	0.231	.103

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

Taken together, the results consistently show that website presentations involving human fashion models were evaluated more favourably than presentations involving AI-generated fashion models for both consumer trust and purchase intent. The AI-labelled condition showed the weakest results, while the differences between the conditions were bigger in the high-involvement product context. On this basis, all proposed hypotheses were supported.

Table 7: Summary of Hypotheses

H	Description	Result
H1a	AI-generated and human fashion models lead to significant differences in consumer trust.	Accepted
H1b	AI-generated and human fashion models lead to significant differences in purchase intent.	Accepted
H2a	The effect on consumer trust differs under labelled and non-labelled conditions.	Accepted
H2b	The effect on purchase intent differs under labelled and non-labelled conditions.	Accepted
H3a	The effect on consumer trust differs between low- and high-involvement conditions.	Accepted
H3b	The effect on purchase intent differs between low- and high-involvement conditions.	Accepted

V. DISCUSSION

The results revealed a clear pattern. In both low-involvement and high-involvement product conditions, website presentations involving human fashion models were evaluated more favourably than presentations involving AI-generated fashion models. This tendency was observed for both consumer trust and purchase intent. The poorest consumer evaluations were obtained for the AI labelled condition, and stronger between-condition differences were found for the high-involvement product.

The results align with earlier studies which have found that marketing content generated by AI may be judged more negatively than human-generated material. Brüns and Meißner (2024) documented that using generative AI to write brand content positions it as less authentic, which elicits unfavourable attitudinal and behaviourual reactions. Results are also in line with Lefkeli et al. (2024), who found lower brand trust when the AI vs human aspect was highlighted, and with Zhang and Hur (2025), who found that disclosed AI-generated images received less favourable evaluations than those by humans.

Disclosure was a relevant factor because the weakest ratings were obtained for the AI labelled condition. Simply stating that fashion models were generated by AI did not increase evaluations. Rather, disclosure made the artificial nature of the content more salient and was associated with more negative evaluations. This is consistent with Wortel et al. (2024), although Wang and Qiu (2024) found that transparency can increase engagement in a different digital endorser context.

The findings also correspond with research showing that product context affects responses to AI content. Song et al. (2024) demonstrated that AI and human endorsers produce different purchase responses depending on product context. In the present research, the differences between experimental conditions increased in the high-involvement product condition. This suggests that higher involvement increases sensitivity to source-related and disclosure-related cues when respondents make a more careful product evaluation.

A) Theoretical Contribution

This research contributes to existing studies on artificial intelligence in digital marketing and e-commerce by applying the analysis to AI-generated visual content in fashion website presentations. Although previous studies have explored consumer responses to AI-generated brand content, AI endorsers and disclosed AI images, there is a need for more research into how consumers respond to AI-generated versus human fashion models.

First, the results confirm that the source of visual presentation content matters in consumer evaluation. Website presentations involving human fashion models were evaluated more favourably in terms of both trust and purchase intent. Second, the results clarify the function of disclosure. The AI-labelled condition consistently produced the weakest outcome, while the differences between Human labelled and Human non-labelled conditions were not statistically significant. Third, the study shows that the effect of AI-generated fashion models differs according to product involvement level, with bigger differences in the high-involvement product context.

The findings show that consumer responses to AI-generated content are shaped by a combination of conditions rather than by a simple positive or negative evaluation of AI content.

B) Managerial Implications

The results have implications for e-commerce companies, online fashion retailers and digital marketing professionals. Website presentations with human fashion models were rated more favourably than presentations with AI-generated models. Consequently, merely replacing human fashion models with AI-generated ones will not automatically be accepted by consumers. Retailers need to weigh the potential savings, speed and flexibility of AI-generated content against possible negative effects on consumer trust and purchase intent.

The findings are also relevant for businesses labelling AI-generated fashion models on their websites. The AI-labelled condition received the weakest evaluations, particularly for a high-involvement product. Businesses should therefore test consumer responses to AI labelling before adopting it as part of website presentation. The results further indicate that the use of AI-generated fashion models may be particularly risky for products that require more careful evaluation.

This does not mean that AI-generated fashion models should be excluded from all situations. The results suggest selective use, evaluation and application in suitable product contexts and target groups. AI may also support content creation, concept development and prototyping while the final consumer-facing presentation retains human visual elements. Thus, AI-generated fashion models should be used strategically rather than automatically.

C) Limitations and Directions for Further Research

The study has several methodological limitations. Since the test was based on non-probability sampling and online questionnaire distribution, it might not fully reflect data that represents all online fashion consumers. In addition, by utilizing experimental designed website presentations rather than a true e-commerce environment and conducting the study in just one field of interest (poverty-stricken fashion), this indicates limited generalizability to real-world settings.

It examined immediate consumer responses using self-reported questionnaire measures. These measures are often used for attitudes and intentions but can be susceptible to being influenced by social desirability, careless responding or the gap between expressed and real-world behaviour. In addition, participants evaluated both low-involvement and high-involvement products within the same website condition, which may create possible order effects.

Future studies could use larger and more diverse samples, more realistic online shopping simulations and behavioural data such as click behaviour or product choice. Future research could also combine quantitative and qualitative methods, examine other product categories, and include additional variables such as perceived realism, brand attitude, advertising attitude or willingness to recommend.

VI. CONCLUSION

The development of AI-generated visual content has become especially relevant in fashion e-commerce, where consumers strongly depend on website presentation in the absence of physical product inspection. Although AI-generated fashion models offer a scalable and cost-efficient alternative to traditional human-based visual presentation, their effect on consumer responses is not uniform.

The results showed that website presentations involving human fashion models were evaluated more favourably than presentations involving AI-generated fashion models in both low-involvement and high-involvement product conditions. The weakest results were found in the AI labelled condition, while the differences between the conditions became stronger in the high-involvement product context. On this basis, all proposed hypotheses were supported.

The overall findings confirm that the source of fashion model presentation matters for consumer evaluation, that disclosure of AI use does not necessarily improve consumer reactions, and that product involvement level plays an important role in shaping the strength of these effects. AI-generated content offers practical advantages, but these advantages do not automatically translate into more positive consumer responses. Therefore, the use of AI-generated fashion models in online retail should be approached with consideration and strategy, especially when trust and purchase readiness are relevant.

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