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CLO 3D VISUALIZATION AND INFLUENCER MARKETING IMPACT ON CONSUMER BUYING BEHAVIOR IN THE FASHION INDUSTRY: A COMPARATIVE ANALYSIS OF TRUST, ENGAGEMENT, AND PERSONALIZATION

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ABSTRACT

This study compares the effects of influencer marketing and CLO 3D–based garment visualization on consumers' purchase intention in the fashion industry. The paper investigates trust and involvement as mechanisms by which both strategies function and estimates the two strategies on six consumer outcomes including personalization. A cross-sectional study involving 250 online fashion shoppers with a prior experience of influencer-marketing and CLO 3D and virtual try-on technology was conducted through purposive and snowball sampling methods. Hypotheses were evaluated by means of hierarchical multiple regression, parallel mediation analysis with Monte Carlo confidence intervals, and Steiger's tests of difference of dependent correlations. Influence marketing predicted purchase intention ($\beta = .49$), as did CLO 3D visualization ($\beta = .56$) when both were introduced more than once ($\beta = .31$ and $\beta = .43$; $R^2 = .39$). Trust and engagement were partial mediators of both influences; together, they carried about 58% of influencer marketing influence and about 31% of CLO visualization influence. The connection of the CLO 3D visualization with understanding of the product, personalization, and purchase confidence was considerably stronger than that of influencer marketing with brand attachment and awareness of trends. However, there were no significant differences in the strategies' overall connections to purchase intention. The cross-sectional self-reported non-probability design does not allow for causal conclusions and generalizability of the findings and the use of experimental and longitudinal approaches is recommended. Fashion brands need to consider both strategies as complementary, mostly by employing influencers in the discovery phase and using CLO 3D visualization in the evaluation period in order to create a better understanding about their products and purchase confidence among consumers. The incorporation of parasocial interaction theory and the Technology Acceptance Model in the study highlights that both approaches achieve the same goal – purchase intention – through different although overlapping psychological methods.

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Introduction

The fashion industry's promotional landscape has been reshaped by two parallel digital developments. The first development is the emergence of influencer marketing on social media platforms like Instagram, TikTok, and YouTube, where influencers influence opinions and buying decisions through content that is relatable as well as visually appealing. Influencer marketing has a significant impact on attitude, engagement, purchase intention, and sales, as seen in a meta-analysis that takes into consideration 1,531 effect sizes from 251 studies (Djafarova & Rushworth, 2017; Ki & Kim, 2019; Pan et al., 2025). Another major development is the use of CLO 3D and other 3D garment simulation tools for simulating garments digitally, rendering digital garments and their drape, texture, and movement accurately which allows for virtual try-on and personalized shopping experiences (Beck & Crié, 2018; Merle et al., 2012).

While these methods are often approached individually, they are becoming more prevalent in one consumer journey at a time, as a consumer sees a garment through an influencer and later uses 3D visualization to analyze the fit (Evans et al., 2017). Despite the continued skepticism around influencer marketing, technology-powered visual tools have become popular due to their focus on products and personalized approach (Mollel & Chen, 2025). Empirical studies actually measuring the two approaches' similarities are few. Fashion brands must now pin down a challenging pragmatic question: whether it pays off more to invest their marketing budget into influencers or 3D visualization, or some combination of both, and if so, what criteria to use.

This research relies on the application of two separate theoretical frameworks. The theory of parasocial interaction emphasizes that consumers develop unilateral and quasi-relational relationships with celebrities, leading to consumers' trust in them and compliance with their recommendations (Horton & Wohl, 1956; Labrecque, 2014; Tripopsakul & Hoonsopon, 2025). Meanwhile, the Technology Acceptance Model (TAM) addresses the rationale for the acceptance of technology solutions such as virtual trials based on their perceived usefulness and ease of use (Davis, 1989; Mollel & Chen, 2025). Such cross-comparison helps clarify not just whether either of the strategies works, but also how exactly the latter works. Four research questions are stated for the study.

RQ1. Does influencer marketing have a significant relationship with consumer purchase intention in the fashion industry?

RQ2. Does CLO 3D visualization have a significant relationship with consumer purchase intention?

RQ3. Do trust and engagement mediate the relationships of influencer marketing and CLO 3D visualization with purchase intention?

RQ4. Do the two strategies differ in the strength of their association with specific consumer outcome dimensions?

The research contributes to the advancement of knowledge and practice in three ways. First, it offers an empirical comparative evaluation of the effects of relationally-based and technology-based fashion marketing strategies in one model rather than looking at each method separately. Second, it explains the relationship between marketing strategy and purchase intention in terms of direct and indirect effects stating that trust and engagement have much bigger impact on influencer marketing than on CLO3D effect. Third, it provides the information about outcomes on the basis of which marketers can choose the strategy. The study focuses on consumers who consume fashion online and have some experience with both types of content. The remainder of the paper is organized as follows. Section 2 develops the hypotheses and conceptual framework. Section 3 describes the methodology, and Section 4 presents the results. Section 5 discusses the findings, Section 6 sets out theoretical and practical implications, Section 7 addresses limitations and future research, and Section 8 concludes.

Literature Review and Hypothesis Development

Theoretical Foundations

Parasocial interaction theory posits that repeated, non-mutual exposure to a media figure results in feelings of intimacy and closeness akin to a person-to-person relationship, though the relationship is non-reciprocal (Horton & Wohl, 1956). The role of social media is that it enhances the process since influencers interact with their followers, unveil their private lives, and answer comments which underlines the fantasy of intimacy (Labrecque, 2014). Thus, the theory describes persuasion because of relational processes: trust and emotional closeness with the source.

The Technology Acceptance Model, in contrast, interprets use in terms of the individual's assessment of the technology. Perceived usefulness (the extent to which a technology enhances effectiveness in task performance) and perceived ease of use jointly affect the intention to accept the technology (Davis, 1989). In online clothing shopping, "task" refers to evaluating whether the clothing will fit and look right, and as such, visualization is useful to the extent that it eliminates this doubt (Kim and Forsythe, 2008). Thus, the two theories suggest reaching the same goal in different ways: while influencer marketing is effective in persuading the individual, CLO 3D visualisation is persuasive through the product itself. The common outcome is defined as the purchasing intention, which is the intention to buy (Ajzen, 1991).

Influencer Marketing and Purchase Intention

One of the bases of influencer marketing is the credibility of the spokesperson, which is usually broken down into three components: expertise, trustworthiness, and attractiveness (Ohanian, 1990). Thus, people who consider an influencer credible are likely to accept their advice and use the same product or lifestyle (Djafarova & Rushworth, 2017; Lou & Yuan, 2019). The wish to imitate an influencer also helps in turning this credibility into purchasing intention (Ki & Kim, 2019). Influencers might outdo usual celebrities in terms of a bigger connection with their audience and a higher trust level (Schouten et al., 2020). In general, the endorsement effect for product fit with the endorser (McCormick, 2016). Moreover, some research has shown that parasocial relationships are

partially the mediator between influencer credibility and purchasing intentions (Sokolova & Kefi, 2020; Tripopsakul & Hoonsopon, 2025).

Despite the benefits of influencer marketing, it still faces challenges related to authenticity. The nature of sponsorship disclosures is important for determining how followers view content as advertising (Evans et al., 2017). Since too much commercialization may affect the parasocial relationships that influencers build, it can be said that influencer marketing still gives good results in terms of purchase intention as well as other consumer outcomes.

H1. Influencer marketing has a significant positive effect on consumer purchase intention in the fashion industry.

CLO 3D Visualization and Purchase Intention

CLO 3D is a garment-simulation platform that converts two-dimensional patterns into three-dimensional digital garments, rendering drape, texture, and movement on configurable avatars. Its consumer-facing outputs—realistic product renders, 360-degree views, and virtual try-on—address the central weakness of online apparel retail: the inability to touch, inspect, and try on a garment before buying. Early work showed that virtual try-on adoption depends on both its usefulness and its entertainment value (Kim & Forsythe, 2008), and that try-on with personalized virtual models shapes consumer responses to apparel websites (Merle et al., 2012). Virtual fitting rooms have since been shown to increase exploratory behaviour, patronage, and purchase intentions both online and offline (Beck & Crié, 2018). Extending TAM, Mollel and Chen (2025) found that perceived usefulness, perceived ease of use, fit confidence, and body esteem all significantly affect attitudes towards augmented reality virtual try-on and the intention to purchase apparel.

Two further mechanisms strengthen this effect. Consumers may extend a distinct form of trust to technology: the "machine heuristic" describes a tendency to treat machines as more objective and reliable than humans, which has been demonstrated in contexts such as the disclosure of personal information (Sundar & Kim, 2019). In addition, artificial intelligence enables personalized engagement at scale by tailoring content and recommendations to individual preferences (Kumar et al., 2019), and immersive technologies at the point of sale increase consumer enjoyment and satisfaction (Pantano & Servidio, 2012). Hence:

H2. CLO 3D visualization has a significant positive effect on consumer purchase intention in the fashion industry.

Trust and Engagement as Mediating Mechanisms

Although both strategies are expected to increase purchase intention, the literature suggests that they activate trust and engagement in different forms. Trust in influencer marketing is both interpersonal and parasocial, with consumers attributing social trust to the influencer (Lou & Yuan, 2019; Sokolova & Kefi, 2020). Trust in CLO 3D visualization is mainly based on the technology as it comes from such experience as testing and inspecting the product firsthand (Sundar & Kim,

2019). When it comes to engagement, it is believed to be emotional and social for influencers (Tripopsakul & Hoonsopon, 2025) and exploratory for CLO (Beck & Crié, 2018). Because trust and engagement each plausibly transmit part of both strategies' effects on purchase intention, the following hypotheses are proposed:

H3. Trust mediates the positive effects of (a) influencer marketing and (b) CLO 3D visualization on purchase intention.

H4. Engagement mediates the positive effects of (a) influencer marketing and (b) CLO 3D visualization on purchase intention.

Comparative Effectiveness and Conceptual Framework

Direct comparisons between relationally driven and technology-driven fashion marketing remain scarce, but converging evidence suggests that the two strategies are not equally strong across all outcomes. Influencer marketing should hold an advantage on relational and affective outcomes—engagement, brand attachment, and awareness of fashion trends—because its persuasive power derives from socially mediated identification and emotional attachment (Chiu & Ho, 2023; Ki & Kim, 2019). CLO 3D visualization should hold an advantage on product-evaluation outcomes—product understanding, personalization, and purchase confidence—because its value derives from resolving uncertainty about fit and appearance (Kim & Forsythe, 2008; Mollel & Chen, 2025). This pattern implies that the two strategies are complements rather than substitutes. Hence:

H5. The comparative strength of the two strategies differs by outcome dimension: influencer marketing is more strongly associated with relational and affective outcomes (engagement, brand attachment, and trend awareness), whereas CLO 3D visualization is more strongly associated with product-evaluation outcomes (product understanding, personalization, and purchase confidence).

Methodology

Research Design

The study adopted a cross-sectional, quantitative survey design, which is standard in consumer behaviour research that compares the relative strength of several predictors on a common outcome (Hair et al., 2019). A structured, self-administered online questionnaire enabled standardized measurement across a geographically dispersed sample of online fashion consumers.

Population, Sample, and Procedure

The target population comprised adult online consumers who actively engage with fashion content on social media (Instagram, TikTok, YouTube, and Facebook) and who had prior exposure to both influencer-promoted fashion content and CLO 3D-based or virtual try-on features on e-commerce platforms. Because no sampling frame exists for this population, respondents were recruited through purposive and snowball sampling via fashion-focused online communities and e-commerce user groups. Screening questions confirmed that each respondent met both exposure criteria. Data collection took place in Lahore, Islamabad, Faisalabad and yielded 250 usable

responses. This sample exceeds the guideline of 15 to 20 observations per predictor for multiple regression (Hair et al., 2019) for the largest model estimated, which contained four predictors.

Figure 1 presents the conceptual framework. Influencer marketing and CLO 3D visualization are modelled as parallel independent variables, trust and engagement as parallel mediators, and purchase intention as the dependent variable; H5 is tested across the six outcome dimensions.

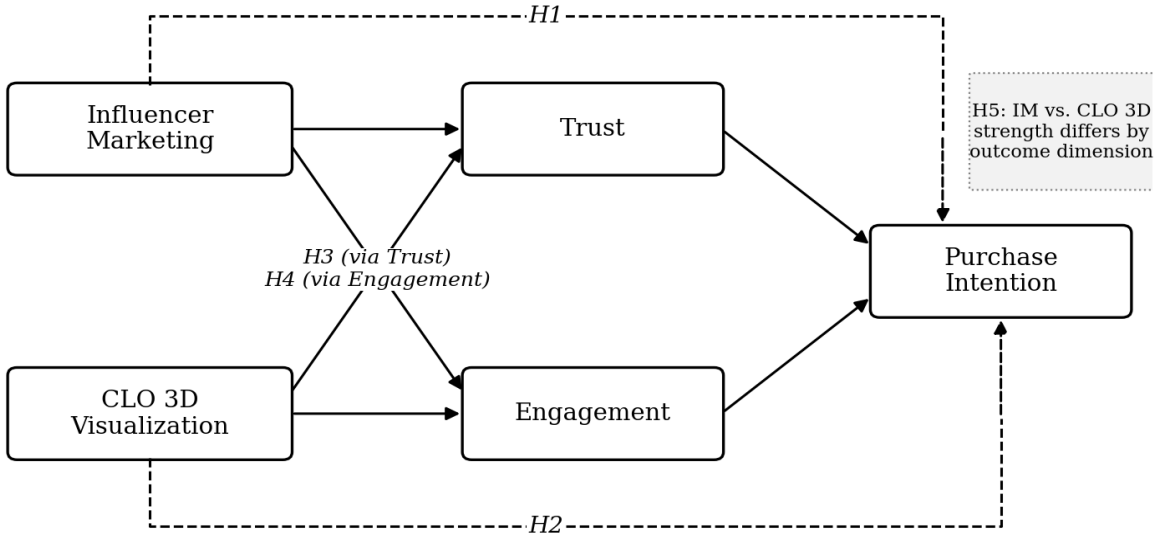


Figure 1: Conceptual Framework

Note. Solid arrows represent paths through the mediators (H3–H4); dashed arrows represent the direct effects (H1–H2). H5 compares the two strategies across six outcome dimensions. IM = influencer marketing.

Measures

All constructs were measured on five-point Likert scales (1 = strongly disagree, 5 = strongly agree) using multi-item scales adapted from established research; illustrative items are listed in the Appendix. Influencer marketing items captured the perceived credibility and persuasive influence of fashion influencers' content (Djafarova & Rushworth, 2017; Ki & Kim, 2019; Ohanian, 1990). The items for 3D visualization addressed usefulness perceptions of 3D visualization in terms of evaluating garment fit and appearance (Davis, 1989; Kim & Forsythe, 2008). The items that measure trust is used to show the level of trust in the source of fashion information or technology (Lou & Yuan, 2019); those for engagement measure cognitive, emotional, and behavioral engagement in this technology (Hollebeek et al., 2014). The purchase intention variable was taken from Dodds et al. (1991). For analysis purposes (H5), six types of outcomes were measured: engagement (measurement for engagement was used), brand attachment, trend awareness, product

knowledge, personalization, and purchase confidence. As necessary, the items underwent translation and back-translation processes (Brislin, 1970) and were tested for clarity in pilot studies.

Data Analysis

The data was screened for missing values and outliers prior to analysis. The internal consistency was assessed using Cronbach's alpha against the 0.70 guideline (Hair et al., 2019). Bivariate relationships were tested by means of Pearson correlations. The first two hypotheses were tested using hierarchical multiple regression with influencer marketing and CLO 3D visualization being entered first into Models 1 and 2, respectively, and then jointly, after which trust and engagement variables were added into Model 3. H3 and H4 were tested with a parallel mediation model following the regression-based approach of Hayes (2022), in which trust and engagement were specified as simultaneous mediators and both independent variables were entered together so that each indirect effect is estimated net of the other strategy. Because the product of two coefficients is not normally distributed, the significance of indirect effects was judged with 95% Monte Carlo confidence intervals based on 20,000 draws (Preacher & Selig, 2012); an indirect effect is significant when its interval excludes zero. H5 was tested by comparing, for each outcome dimension, the correlation with influencer marketing against the correlation with CLO 3D visualization using Steiger's (1980) Z test for dependent correlations that share a variable.

Common Method Bias and Multicollinearity

Because all variables were collected from the same respondents with the same instrument, procedural remedies recommended by Podsakoff et al. (2003) were applied: anonymity was guaranteed, respondents were told that there were no right or wrong answers, and predictor and outcome items were placed in separate sections. Statistically speaking, the greatest correlation between constructs (r = .58) was well under the .90 threshold that would imply considerable common method bias (Bagozzi et al., 1991). Multicollinearity was not an issue: the highest variance inflation factor (VIF) for all models was 1.68, which is significantly less than the usual threshold of 10 and even below the more conservative cut-off of 5 (Hair et al., 2019).

Results

Respondent Profile

The participants in the survey were mainly young adults who have used Instagram or TikTok on a regular basis and also have had the experience of having availed at least one feature of virtual try-on or 3D garment visualization.

Descriptive Statistics, Reliability, and Correlations

Table 1 shows means, standard deviation, reliability coefficients, and inter-construct correlations. The mean scores lie above the midpoint of 3, which shows that respondents had positive attitude towards both strategies; purchase intention had highest mean (M = 3.89) and trust accordingly

lowest (M = 3.54). Cronbach's alpha ranged from .82 (trust) to .88 (CLO 3D visualization) which is higher than .70 showing good internal consistency (Hair et al., 2019).

Table 1: Descriptive Statistics, Reliability Coefficients, and Correlation Matrix

Variable	M	SD	α	1	2	3	4	5
1. Influencer marketing	3.62	0.84	.85	—				
2. CLO 3D visualization	3.78	0.79	.88	.42**	—			
3. Trust	3.54	0.81	.82	.51**	.48**	—		
4. Engagement	3.71	0.76	.84	.55**	.44**	.53**	—	
5. Purchase intention	3.89	0.73	.87	.49**	.56**	.58**	.52**	—

Note. N = 250. M = mean; SD = standard deviation; α = Cronbach's alpha. All constructs measured on five-point scales. **p < .01 (two-tailed).

All the correlations were found to be positive and significant (p < .01) being in the range of .42 to .58 which indicates that the two are related but distinct concepts. CLO 3D visualization has the highest correlation with purchase intention (r = .56), while influencer marketing has the strongest correlation with engagement (r = .55). The moderate correlation between the two strategies (r = .42) suggests that consumers who respond to one strategy in most cases respond to the other as well.

Direct Effects: Hierarchical Regression (H1 and H2)

Table 2 presents the hierarchical regression results. Entered alone, influencer marketing explained 24% of the variance in purchase intention (Model 1) and CLO 3D visualization explained 31% (Model 2).

Table 2: Hierarchical Multiple Regression Predicting Purchase Intention

Predictor	Model 1	Model 2	Model 3	Model 4
Influencer marketing	.49***	—	.31***	.13*
CLO 3D visualization	—	.56***	.43***	.30***
Trust	—	—	—	.28***
Engagement	—	—	—	.17**
Model statistics				
R^2	.24	.31	.39	.48
Adjusted R^2	.24	.31	.39	.47
ΔR^2	—	—	.15***[a]	.09***[b]
F	78.36***	113.31***	79.77***	56.68***

Predictor	Model 1	Model 2	Model 3	Model 4
df	(1, 248)	(1, 248)	(2, 247)	(4, 245)
Maximum VIF	1.00	1.00	1.21	1.68

Note. N = 250. Standardized coefficients (β) are reported. VIF = variance inflation factor. [a]Change relative to Model 1. [b]Change relative to Model 3. *p < .05. **p < .01. ***p < .001.

When both methods were combined (Model 3), they continued to play a role in the process—the role of influencer marketing was .31 (p < .001) and CLO 3D visualization .43 (p < .001)—and they led to the explained variance of 39 percent. By implementing CLO 3D visualization the explained variance increased by 15 dependencies, thus showing that the two methods work separately. Therefore, H1 and H2 have been confirmed. Adding trust and engagement (Model 4) made it possible to explain 9 percent of variance (F change = 20.81, p < .001). Both mediators were significant and the values of both methods fell with the values for influencer marketing declining from .31 to .13 and from .43 to .30 for CLO 3D visualization, still staying significant. This is the very first sign of partial mediation and indicates that the role of trust and engagement in obtaining the influence of influencer marketing already is high enough.

Mediation Analysis (H3 and H4)

Table 3 decomposes each strategy's total effect on purchase intention into direct and indirect components.

Table 3: Parallel Mediation Analysis: Direct, Indirect, and Total Effects on Purchase Intention

Path	a	b	Effect	SE	95% CI
Influencer marketing (IM)					
IM → Trust → Purchase intention	.37***	.28***	.11	.03	[.06, .16]
IM → Engagement → Purchase intention	.44***	.17**	.08	.03	[.02, .13]
Total indirect effect of IM			.18	.04	[.11, .26]
Direct effect of IM (c′)			.13*	.06	[.01, .24]
Total effect of IM (c)			.31***	.05	[.20, .42]
CLO 3D visualization (CLO)					
CLO → Trust → Purchase intention	.32***	.28***	.09	.03	[.05, .14]
CLO → Engagement → Purchase intention	.25***	.17**	.04	.02	[.01, .08]
Total indirect effect of CLO			.13	.03	[.08, .20]
Direct effect of CLO (c′)			.30***	.05	[.19, .40]

Path	a	b	Effect	SE	95% CI
Total effect of CLO (c)			.43***	.05	[.32, .54]

Note. N = 250. Standardized coefficients. a = effect of the strategy on the mediator, controlling for the other strategy; b = effect of the mediator on purchase intention, controlling for both strategies and the other mediator. CIs for indirect effects are 95% Monte Carlo confidence intervals (20,000 draws); CIs for direct and total effects are normal-theory intervals. An indirect effect is significant when its CI excludes zero. *p < .05. **p < .01. ***p < .001.

All four specific indirect effects were positive and significant, as none of their confidence intervals included zero. Trust transmitted part of the effect of both influencer marketing (effect = .11, 95% CI [.06, .16]) and CLO 3D visualization (effect = .09, 95% CI [.05, .14]), supporting H3a and H3b. Engagement likewise transmitted part of the effect of influencer marketing (effect = .08, 95% CI [.02, .13]) and CLO 3D visualization (effect = .04, 95% CI [.01, .08]), supporting H4a and H4b. Because both direct effects remained significant, mediation is partial in each case.

The decomposition reveals an asymmetry that is central to the study's argument. The two mediators together carried 58% of the total effect of influencer marketing (.18 of .31) but only 31% of the total effect of CLO 3D visualization (.13 of .43). Influencer marketing thus works largely through trust and engagement, whereas most of the CLO 3D effect bypasses them and runs directly to purchase intention. The engagement path in particular was roughly twice as large for influencer marketing (.08) as for CLO 3D visualization (.04), consistent with the argument that engagement is a primarily relational mechanism.

Comparative Mechanism Strength (H5)

Table 4 compares the strength of the two strategies' associations with each outcome dimension and reports Steiger's Z test of whether each difference is statistically significant.

Table 4: Comparative Strength of Influencer Marketing and CLO 3D Visualization by Outcome Dimension

Outcome dimension	β IM	β CLO	Δβ	Steiger's Z	p	Stronger strategy
Relational and affective outcomes						
Engagement	.55***	.44***	.11	1.95	.052	IM (directional)
Brand attachment	.48***	.35***	.13	2.15	.031	IM
Trend awareness	.42***	.28***	.14	2.23	.026	IM
Product-evaluation outcomes						
Product understanding	.31***	.52***	−.21	−3.49	< .001	CLO 3D
Personalization	.29***	.49***	−.20	−3.27	.001	CLO 3D

Outcome dimension	β IM	β CLO	Δβ	Steiger's Z	p	Stronger strategy
Purchase confidence	.34***	.51***	−.17	−2.84	.005	CLO 3D
Overall outcomes						
Trust	.51***	.48***	.03	0.53	.597	No difference
Purchase intention	.49***	.56***	−.07	−1.27	.203	No difference

Note. N = 250. IM = influencer marketing; CLO = CLO 3D visualization. β values are standardized coefficients from separate bivariate models, one per predictor and outcome, and are therefore equal to zero-order correlations. Δβ = β IM − β CLO. Steiger's (1980) Z tests the difference between two dependent correlations sharing an outcome, using r(IM, CLO) = .42. ***p < .001.

The results display a clear crossover pattern. CLO 3D visualization was significantly more strongly associated than influencer marketing with product understanding (Δβ = −.21, Z = −3.49, p < .001), personalization (Δβ = −.20, Z = −3.27, p = .001), and purchase confidence (Δβ = −.17, Z = −2.84, p = .005). Influencer marketing was significantly more strongly associated with brand attachment (Δβ = .13, Z = 2.15, p = .031) and trend awareness (Δβ = .14, Z = 2.23, p = .026). Its advantage on engagement was in the hypothesized direction but fell just short of conventional significance (Z = 1.95, p = .052). Two further comparisons are informative. The strategies did not differ in their association with trust (Z = 0.53, p = .597), indicating that trust is a mechanism shared by both rather than one specific to either. Nor did they differ significantly in their overall association with purchase intention (Z = −1.27, p = .203): the two strategies are comparably effective overall but achieve that effect by strengthening different outcomes. H5 is therefore largely supported.

Summary of Hypothesis Testing

Table 5 summarizes the outcome of each hypothesis test.

Table 5: Summary of Hypothesis Testing

Hypothesis	Relationship	Key evidence	Decision
H1	Influencer marketing → Purchase intention	β = .49 (Model 1); β = .31 (Model 3); both p < .001	Supported
H2	CLO 3D visualization → Purchase intention	β = .56 (Model 2); β = .43 (Model 3); both p < .001	Supported
H3a/b	Mediation through trust	IM: .11 [.06, .16]; CLO: .09 [.05, .14]; direct effects remain significant	Supported (partial mediation)
H4a/b	Mediation through engagement	IM: .08 [.02, .13]; CLO: .04 [.01, .08]; direct effects remain significant	Supported (partial mediation)
H5	Comparative strength by outcome dimension	CLO stronger on product understanding, personalization, and purchase confidence;	Largely supported

	IM stronger on brand attachment and trend awareness; engagement difference directional (p = .052)

Note. IM = influencer marketing; CLO = CLO 3D visualization. Values in brackets are 95% Monte Carlo confidence intervals.

Discussion

This research was conducted in order to investigate the similarities and differences between two related fashion marketing strategies: influencer marketing and CLO 3D visualization. It has been found that both of them generate similar levels of purchase intention by utilizing different but partly overlapping approaches. The interpretation of this finding is provided in the discussion section below and is linked to each research question at hand.

Both Strategies Independently Drive Purchase Intention (RQ1 and RQ2)

It can be concluded that both influencer marketing and CLO 3D visualization are positively correlated with purchase intentions, and both retained significant unique positive effects when examined together. The influencer marketing findings support research on credibility and parasocial relationships (Djafarova & Rushworth, 2017; Sokolova & Kefi, 2020) and meta-analyses confirming the positive effects of influencers (Pan et al., 2025). The CLO 3D findings align with research finding that virtual fitting rooms boost consumers' purchase intentions (Beck & Crié, 2018) and the notion that usefulness from virtual try-ons drives apparel purchasing intention (Mollel & Chen, 2025). One noteworthy fact is that CLO 3D visualization showed higher standardized coefficient in joint model (β = .43 as opposed to .31) although the difference between a pair of strategies' zero-order correlation with purchase intention was not statistically significant. The only conclusion that can be drawn here is that the two approaches are equally efficient as none of them is superior. The substantial increase in the role of variance explained when both are used together (from 24% to 39%) shows that both of them capture some of the consumer motivations missed by the other one.

Trust and Engagement as Mechanisms (RQ3)

Trust and engagement partially mediated both strategies, supporting H3 and H4. Three features of this result deserve emphasis. First, trust was the stronger mediator for both strategies and, as Table 4 shows, was equally associated with each. Trust therefore appears to be a common currency of digital fashion persuasion: whether confidence is earned by a relatable person or by a verifiable rendering, it carries a meaningful share of the effect on purchase intention. This finding broadens the interpersonal account of trust in influencer research (Lou & Yuan, 2019) by showing that a technology can generate trust of comparable strength, in line with the machine-heuristic argument (Sundar & Kim, 2019). Second, engagement mattered more for influencer marketing, consistent with the view that engagement in social media is primarily a relational and emotional phenomenon (Hollebeek et al., 2014; Labrecque, 2014). Third, and most importantly, the mediators

carried most of the influencer effect but less than one-third of the CLO 3D effect. This asymmetry fits the theoretical contrast drawn in Section 2.1: parasocial interaction theory locates persuasion in the relationship, so relational mechanisms should absorb most of the influencer effect, whereas TAM locates persuasion in the usefulness of the tool, so the CLO 3D effect should largely bypass relational mechanisms. Although perceived usefulness was not measured directly, the large residual direct effect of CLO 3D visualization is consistent with this TAM-based explanation.

Comparative Advantages by Outcome (RQ4)

The comparative analysis has led to a distinct task distribution. CLO 3D visualization has a clear advantage regarding product comprehension, customization, and purchase assurance—all of which are direct results of solving the problems associated with online garment shopping regarding fit and look (Kim & Forsythe, 2008; Merle et al., 2012). Influencer marketing has proven to be advantageous in terms of brand loyalty and trend knowledge which stem from the idea of identification, aspiration, and social learning (Ki & Kim, 2019; Schouten et al., 2020). The engagement effect of influencer marketing was found to be positive but limited, meaning that interactive 3D may have engaging effects too. This finding also agrees with evidence that virtual fitting rooms encourage exploration (Beck & Crié, 2018). The study highlighted personalization as an important advantage of CLO 3D technology, which agrees with the idea that technological personalization is an additional source of consumer value (Kumar et al., 2019). Thus, the findings imply that the two techniques can complement each other as both of them are most effective at separate stages of the consumer decision making process: influencers being most effective during searching and desiring and 3D technology while evaluating and committing.

Implications

Theoretical Implications

The article presents four theoretical contributions. First, it unites parasocial interaction theory and TAM (Technology Acceptance Model) into one comparative framework. Previous research has usually implemented either theory separately for each strategy, where testing both in the same outcome proves that the theories are not competing but can explain various routes to purchase intention. This dual route perspective is an advancement over the work that has explored cognitive and emotional routes to purchase intention in influencer marketing alone (Tripopsakul & Hoonsopon, 2025).

Moreover, the research indicates that the fraction of effect carried by relational mechanisms is able to serve as a distinguishing parameter between theoretical approaches. This is illustrated by the fact that trust and engagement give 58% of influencer effect and only 31% of CLO 3D effect, thus providing an evidence of the difference between relationally driven and tool-driven persuasion and stimulating empirical research on technology-specific mechanisms that were left out of the model, such as perceived usefulness and fit confidence.

Thirdly, the findings further clarify the understanding of trust within digital fashion marketing. Traditionally, trust is theorized as friendship between people in influencer studies (Lou & Yuan, 2019) and as system-oriented trust in technology studies (Sundar & Kim, 2019). Noting that both approaches generate equal trust, which has equal impact on the corresponding degree of their impact, indicates that trust should be defined as a shared mechanism that may come either from social relations or from technology.

Lastly, this research contributes to the field of fashion technology by shifting the points of discussion of CLO 3D from merely design and production efficiency towards its importance as a marketing tool. According to this study, 3D garment visualization is not just a tool for designers but also a credible technology with its unique set of consumer effects.

Practical Implications

Based on the above findings, five recommendations emerge for fashion marketers and brands. Strategize the order of applying both strategies throughout the consumer journey. As the results show that influencer marketing contributes more to brand attachment and trend awareness, while CLO 3D visualization is more important for product understanding and assurance in making a purchase, brands should use influencers for generating discovery and demand, and CLO 3D visualization for converting this demand into an actual purchase.

Invest in the realization of CLO 3D as a conversion and reduction of return tool. The connection between CLO 3D and purchase confidence indicates that realistic 3D images and online fittings can facilitate the reduction of uncertainty during buying and decrease the rate of returns. The brands that integrate CLO 3D technology into the production process can re-use the same digital models for e-commerce at minimal costs.

Safeguard the trust offered by both of the channels. Trust served as the most influential mediator in both of the strategies. In influencer campaigns, this means choosing trustworthy and congruent influencers (McCormick, 2016), and disclosing sponsorship transparently (Evans et al., 2017). In case of using 3D visualization, this means that the visuals must be authentic and represent the color, drape, and fit properly; unrealistic visuals can threaten the trust generated by the technology.

Limitations and Future Research

Several limitations qualify the findings and point to directions for future research. First, the cross-sectional design precludes causal inference; the mediation results show that the data are consistent with the hypothesized process but cannot establish temporal ordering. Experimental designs that randomly assign consumers to influencer-led, 3D-led, and combined conditions, or longitudinal designs that track the same consumers over time, would provide stronger causal evidence.

Second, the purposive and snowball sample limits generalizability, particularly because respondents were predominantly young, social-media-active consumers already familiar with

virtual try-on. Probability-based samples and cross-cultural replications are needed to establish whether the comparative advantages identified here hold across age groups, markets, and levels of technological familiarity.

Third, all data were self-reported by the same respondents at a single point in time. Although procedural remedies were applied and inter-construct correlations were moderate, common method variance cannot be ruled out entirely (Podsakoff et al., 2003). Future studies could combine survey data with behavioural data such as click-through, conversion, and return rates.

Fourth, measurement quality was assessed through internal consistency only. Future research should conduct confirmatory factor analysis to establish convergent and discriminant validity. In addition, trust and engagement were measured as general constructs; separating parasocial trust from technology-based trust, and emotional engagement from interactive engagement, would allow a sharper test of the strategy-specific mechanisms proposed in Section 2.4. Likewise, measuring perceived usefulness and fit confidence directly would clarify what drives the large direct effect of CLO 3D visualization.

Fifth, the study focused on purchase intention rather than actual purchase behaviour. Although intention is the proximal antecedent of behaviour (Ajzen, 1991), the intention–behaviour gap is well documented, and field studies using transaction data would strengthen the managerial conclusions.

Finally, the rapid spread of generative artificial intelligence is blurring the boundary between the two strategies examined here. Virtual influencers and AI-generated fashion models combine a relational persona with a synthetic, technology-generated appearance (Chiu & Ho, 2023). Examining whether such hybrids elicit parasocial trust, technology-based trust, or both is a promising avenue for extending the dual-route framework developed in this study.

Conclusion

This study compared influencer marketing and CLO 3D visualization as drivers of purchase intention in the fashion industry, drawing on parasocial interaction theory and the Technology Acceptance Model. Both strategies significantly and uniquely predicted purchase intention and were comparably effective overall, but they operated through different routes. Influencer marketing worked largely through trust and engagement and held an advantage on brand attachment and trend awareness; CLO 3D visualization worked mainly through a direct route and held an advantage on product understanding, personalization, and purchase confidence. Trust emerged as a mechanism shared by both strategies. These findings indicate that relationally driven and technology-driven fashion marketing are complements rather than substitutes. Brands that use influencers to inspire and 3D visualization to reassure are therefore likely to be best placed to meet consumers' growing demand for online shopping experiences that are both engaging and trustworthy.

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Appendix: Illustrative Questionnaire Items

Note. The items below illustrate each section of the instrument. All attitudinal items used a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Section A: Demographic Information

A1. Gender

A2. Age

A3. Educational qualification

A4. Preferred social media platform

Section B: Influencer Marketing

B1. I trust fashion recommendations made by influencers.

B2. Influencer content affects my fashion choices.

B3. I am likely to purchase products promoted by influencers.

Section C: CLO 3D Visualization

C1. CLO 3D visualization improves my understanding of products.

C2. Virtual try-on experiences increase my confidence in purchasing.

C3. Personalized digital models enhance my shopping experience.

Section D: Trust and Engagement

D1. I trust the fashion technology or content source I interacted with.

D2. I feel engaged when interacting with this fashion content or technology.

Section E: Purchase Intention

E1. I intend to purchase fashion products promoted online.

E2. Realistic product visualization increases my likelihood of purchase.

E3. I prefer brands that provide interactive digital experiences.