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Influence Effectuation in Fashion Marketing: Analyzing Mediated Relationships Between Expertise, Credibility, and Consumer Purchase Intentions Among Indian Consumers

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Abstract

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This research examines how different influencer attributes impact consumer purchase intentions in the Indian fashion market. This research focuses on six primary constructs: expertise, credibility, argument quality, interaction between influencer and audience, physical attractiveness of influencers, and matching attitudes between influencers and their followers. Using a quantitative cross-sectional research design, the research employs Structural Equation Modeling (SEM) to examine data from 393 consumers who engage with fashion influencers on Instagram and YouTube. Consumer engagement acts as a crucial intermediary that increases the impact of influencers on their audiences. Future research must explore how influencer marketing affects brand loyalty over extended periods. The presented insights offer helpful strategic direction for fashion marketers seeking to enhance influencer partnerships, which will help boost sales and consumer engagement.

Keywords: *Influencer marketing; Consumer purchase intentions; Fashion industry; Expertise; Credibility; Argument quality; Interaction; Physical attractiveness; Consumer engagement; Mediation analysis*

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1. Introduction

Digital advertising now features influencer marketing as a significant strategy within the fashion industry because visual appeal and trust play essential roles in consumer decision-making processes. Marketing communication underwent significant changes when social media platforms like Instagram enabled influencers to engage directly with consumers (Sokolova & Kefi, 2020; Hsu & Lin, 2020). According to Statista 2023 data, India has surpassed 448 million social media users, making it one of the most significant world and most rapidly expanding digital markets (Ismail, 2017). Studies show that influencer qualities like expertise attractiveness, credibility, and interaction affect consumer trust and engagement (Martínez-López et al., 2020; Sanz-Blas et al., 2019; Bigné et al., 2001; Okazaki & Taylor, 2013). The latest research demonstrates that product-influencer alignment shapes consumer perceptions of advertisements and influencer trustworthiness, affecting purchase behaviours (Janssen, Schouten, & Croes, 2022; Arora et al., 2019). The research fills an existing void by exploring the interaction between cognitive factors like credibility, expertise, and argument quality with affective factors such as attractiveness and parasocial interaction to understand their combined effect on consumer engagement and purchase intent in India's fashion market. This study develops a complete framework for influencer effectiveness based on the Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986), Source Credibility Theory (Hovland & Weiss, 1951), and Parasocial Interaction Theory (Horton & Wohl, 1956).

Numerous studies document that influencer credibility, expertise, and argument quality influence how consumers perceive content. The Elaboration Likelihood Model (ELM) posits that persuasion occurs through two routes: The central route involves consumers analysing argument quality and expertise, while the peripheral route depends on superficial cues like attractiveness and parasocial relationships to influence consumer behaviour (Petty & Cacioppo, 1986; Lou & Yuan, 2019). Source Credibility Theory demonstrates that an influencer's expertise, trustworthiness, and attractiveness increase their persuasive power (Hovland & Weiss, 1951). Study findings indicate that consumers engage more deeply and show increased purchase intent when they perceive influencers as credible and experienced (Kim et al., 2023). An influencer's perceived credibility is partly determined by their follower count, leading to macro-influencers having more influence than micro-influencers in luxury fashion marketing (De Veirman, Cauberghe, & Hudders, 2017). Influencers' trustworthiness suffers when they participate in too many commercial partnerships because it damages their perceived authenticity (Audrezet, Kerviler & Moulard, 2020). Endorsements that show a strong product match increase consumer engagement and trust more effectively than those that seem overly commercialised or poorly aligned (Breves et al., 2019;Luceri & Latusi, 2015). The research fills existing research gaps by incorporating consumer engagement as a mediator to assess how expertise, argument quality, attractiveness, credibility, and parasocial interaction influence purchase behavior.

The research makes practical advancements in influencer marketing strategy while moving past theoretical insights. The latest research demonstrates engagement as the primary factor of purchase decisions, particularly for Gen Z and millennial consumers who seek authentic and interactive experiences (Kim et al., 2023; Djafarova & Bowes, 2021; Casaló et al., 2018;Rehman et al,2014). According to research, influencers who maintain regular two-way communication with their audiences achieve greater relatability and influence, resulting in stronger brand loyalty (Colliander & Dahlén, 2011; Bagozzi & Dholakia, 2006; Boerman, 2019). The success of influencer endorsements depends on trust-building strategies, which include transparent disclosures and personal storytelling to boost consumer identification and persuasion (Dhanesh & Duthler, 2019). When the influencer matches well with the product they endorse (product-influencer fit), it leads to a better brand assessment. According to research from Schouten, Janssen, and Verspaget (2020), influencers need to match their promotional content to their specialization to achieve greater engagement levels; influencers need to match their promotional content to their specialisation to achieve greater engagement levels, influencers need to match their promotional content to their specialization to achieve greater engagement levels. Martínez-López et al. (2020) discovered that Instagram interactive features, including polls and Q&A sessions, and direct influencer responses, increase consumer trust and loyalty. Research demonstrates that Indian market consumers give higher importance to trust than visual appeal, which contrasts with Western digital markets where attractiveness takes precedence (Sokolova & Kefi, 2020). Consumers evaluate influencer credibility through metrics like follower count and engagement but find that too much commercialisation damages trust (Kay, Mulcahy, & Parkinson, 2020). This research establishes an all-encompassing framework that fashion brands can employ to build influencer credibility through social commerce insights and persuasion theory while increasing consumer interaction and boosting purchase conversion rates.

2. Review of Literature

2.1. Theoretical framework

The expanding reach of social media and digital marketing now requires theoretical models to clarify consumer behaviour patterns within digital marketplaces. The Elaboration Likelihood Model (ELM) is a foundational model that defines how consumers interpret persuasive messages through logical analysis or heuristic cues (Petty & Cacioppo, 1986). The effectiveness of influencer marketing relies mainly on the peripheral route of persuasion because consumers make decisions based on the influencer's attractiveness and credibility, combined with their ability to connect with audiences. Trust is the most important aspect of influencer marketing because authentic engagement drives audience loyalty and increases purchase intentions (Su, Cheng, & Huang, 2021). The Source Credibility Theory supports this view by demonstrating how consumer influencer message assessments are affected by expertise, consumer influencer message assessments are affected by expertise, trustworthiness, and attractiveness (Torres, Augusto, & Matos, 2019). The Parasocial Interaction (PSI) Theory demonstrates how users build one-sided connections with influencers they see as relatable friends (Horton & Wohl, 1956). PSI strengthens the brand image and increases buying intention, especially among youth audiences, according to Sokolova & Kefi (2020). Through social interactions like comments and likes, consumers develop trust and community bonds with influencers, enhancing their influence power (Labrecque, 2014). Researchers will thoroughly investigate influencers' strategic use of credibility and engagement to direct consumer behaviour in digital commerce.

Conceptual framework

2.2.1. Argument Quality

Argument Quality (ARQ) encompasses how powerful and clear an influencer's message is at influencing consumers and includes its ability to persuade (Petty & Cacioppo, 1986). The Elaboration Likelihood Model (ELM) demonstrates that messages with well-structured arguments trigger central route processing, which subsequently produces stronger purchase intentions, according to Martínez-López et al. (2020). Studies reveal that influencers who deliver factual reviews and testimonials and perform comparative analyses achieve excellent trustworthiness and audience involvement (Lou & Yuan, 2019). Fashion marketing research demonstrates that product details combined with sustainability claims and expert opinions boost perceived authenticity, which drives purchase intent (Haikel-Elsabeh et al., 2023; Sokolova & Perez, 2021). In India, consumers value influencers who deliver detailed stories based on personal experiences when deciding on purchases (Gupta et al., 2023). Research by Kim et al. (2023) shows that influencer posts gain trust from their audience when they feature user-generated content and customer testimonials to support their arguments. High-quality arguments generate social validation, which results in higher engagement rates, as demonstrated by Erkan & Evans (2021). The results indicate that influencers who utilise robust reasoning techniques in their content creation show better success rates in impacting consumer purchasing decisions.

H1: Higher argument quality in influencer marketing positively influences consumer purchase intention.

2.2.2. Physical Attractiveness

Physical attractiveness (PAT) describes an influencer's visual appeal, which improves their perceived credibility and audience engagement because of the Halo Effect. According to this psychological phenomenon, consumers perceive attractive people as possessing positive characteristics (Nisbett & Wilson, 1977). Studies confirm that influencers who possess physical attractiveness gain higher levels of likes and shares and greater trust from their audience, which results in increased purchase intentions (Djafarova & Bowes, 2021; Schouten et al., 2020). Visually appealing content is essential for brand exposure and fostering consumer loyalty on platforms such as Instagram, where aesthetic appeal is essential, according to Sanz-Blas et al. (2019). Indian consumers value authenticity more than attractiveness and view relatability and credibility as essential elements that drive their purchase decisions (Gupta et al., 2023). The initial appeal of attractive influencers draws attention, but their sustained influence depends primarily on the informational value and engagement methods of their content of their content (Tiwari et al., 2024). Kim and Kim's 2023 research indicates that consumer trust strengthens when physical attractiveness pairs with credibility and expertise. The study shows that aesthetic appeal does not lead to purchases but is a secondary signal that backs essential purchasing decisions based on trustworthiness and argument quality.

H2: Influencer's physical attractiveness positively affects consumer trust and purchase intention.

2.2.3. Attitude Homophily

The concept of attitude homophily (ATT) describes how influencers reflect similar values and lifestyle choices to their consumer audience. According to Byrne (1971), similarities in values and beliefs help build relatability between individuals, leading to trust and further engagement. According to Djafarova and Bowes (2021) and Schouten et al. (2020), people tend to follow and purchase from influencers who match their personal tastes and social identity; people tend to follow and purchase from influencers who match their personal tastes and social identity, people tend to follow and purchase from influencers who match their personal tastes and social identity. The research presented by Sokolova and Perez (2021) illustrates that influencer effectiveness improves when homophily creates an emotional connection with the audience. Research reveals that influencers achieve higher engagement rates when they match their language and style preferences to their audience's (Haikel-Elsabeh et al., 2023). Research demonstrates that consumers are more likely to purchase when they experience increased community bonding and trust through homophily (Kim et al., 2023). The marketing power of influencers grows stronger because consumers trust influencers who share similar values (Casaló et al., 2020). These insights demonstrate that homophily is key to influencer marketing success.

H3: Attitude homophily strengthens consumer trust and enhances purchase intention.

2.2.4. Influencer Expertise

Consumer trust and purchase intention heavily depend on an influencer's expertise (EXP). This concept evaluates how consumers perceive an influencer's professional competence and expertise, according to the research by Hovland and Weiss (1951). Source Credibility Theory maintains that consumers demonstrate increased trust toward influencers they perceive as knowledgeable and follow their recommendations (Ohanian, 1990). Marketing research reveals that fashion-focused influencers who show competence in styling techniques, fabric quality assessment, and trend analysis substantially drive consumer behaviour (Martínez-López et al., 2020; Sokolova & Kefi, 2020). Research shows that Indian consumers favour influencers who demonstrate expertise above those who are just popular. Consumer preferences lean towards influencers delivering comprehensive product evaluations and personalised style recommendations (Kim et al., 2023; Gupta et al., 2023). According to the Elaboration Likelihood Model (ELM), expert content triggers central route processing, increasing the persuasiveness of factual information delivered by influencers (Petty & Cacioppo, 1986; Lou & Yuan, 2019). Studies indicate that micro-influencers with 50,000 to 200,000 followers generally show higher expertise and trustworthiness than celebrity influencers. Casaló et al. (2020) say this increases engagement and conversion rates. Expertise is important in India's fashion market because consumers demand products that align with current trends and cultural relevance while maintaining authentic quality (Djafarova & Bowes, 2021). The research proposes that expertise directly affects expertise directly affects consumer trust and purchase intention, demonstrating, demonstrating that fashion marketing benefits from knowledgeable influencers.

H4: Influencer expertise positively affects consumer trust and purchase intention.

2.2.5. Source Credibility

In influencer marketing, credibility (CRE) represents an essential attribute through its components of trustworthiness and honesty combined with perceived expertise, which plays a significant role in shaping consumer trust and buying decisions based on research by Hovland & Weiss (1951). Studies reveal that influencers who establish credibility can better persuade audiences, resulting better persuade audiences, resulting in increased consumer trust in their endorsements (Martínez-López et al., 2020; Tiwari et al., 2024). Research indicates that Indian consumers value trustworthy information more than visual appeal since they appreciate straightforward and genuine reviews (Gupta et al., 2023; Erkan & Evans, 2021; Evans et al., 2017). Partnerships Between brands and credible influencers result in superior brand loyalty and engagement (Casaló et al., 2020). The likelihood of consumer purchases increases when an influencer possesses genuine experience within a specific product category, according to Djafarova and Bowes (2021). Fashion micro-influencers who maintain engaged followership receive better perceptions of relatability and trustworthiness (Schouten et al., 2020).

H5: Higher influencer credibility leads to increased consumer engagement and purchase intention.

2.2.6. Parasocial Interaction.

Parasocial Interaction (PSI) involves the one-sided relationships consumers create with influencers, impacting their engagement, trust levels, and purchasing decisions (Horton & Wohl, 1956). Consumers view influencers as similar to real people, which helps them form emotional bonds that mimic face-to-face social connections (Jin et al., 2019; Djafarova & Bowes, 2021). According to research by Sokolova & Perez (2021) and Kim et al. (2023), consumers exhibit stronger brand loyalty and purchase behavior when experiencing higher degrees of Parasocial Interaction (PSI). Research findings indicate that audiences who develop emotional bonds with brands show higher brand commitment and trust toward influencer endorsements (Haikel-Elsabeh et al., 2023). Casaló et al. (2020) note that Instagram stories and live Q&A sessions enable brands to strengthen consumer engagement through direct interaction. The fashion industry relies heavily on PSI to create brand affinity since Gen Z and millennials prefer genuine digital connections over prefer genuine digital connections over traditional advertising methods (Tiwari et al., 2024). The research demonstrates that parasocial interactions significantly strengthen consumer trust and influence digital purchase decisions.

H6: Parasocial interaction mediates the relationship between influencer credibility and consumer purchase intention.

2.2.7. Consumer Engagement (CEG) serves as a crucial mediator

Consumer Engagement (CEG) strengthens the link between influencer characteristics and consumer buying decisions by building trust and facilitating brand interaction and active participation (Casaló et al., 2018). The most common metrics for measurement include likes, shares, comments, and direct messages, which drive increased conversion rates (Martínez-López et al., 2020). Indian consumers respond positively to engagement-driven marketing because social interaction forms a core part of their digital behavior patterns (Gupta et al., 2023; Jiménez-Castillo & Sánchez-Fernández, 2019). According to the Elaboration Likelihood Model (ELM) proposed by Petty & Cacioppo (1986), engagement boosts both central and peripheral processing, enhancing influencer attributes. Increased engagement results in improved influencer credibility and enhances purchase probability, according to Haikel-Elsabeh and colleagues (2023). The development of parasocial relationships through this process makes consumers more open to endorsements (Sokolova & Perez, 2021; Arora et al., 2019). The fashion industry relies on engagement to build brand communities that support trust in influencer recommendations (Schouten et al., 2020). This research proposes that consumer engagement mediates the influence of credibility, expertise, argument quality, attractiveness, and parasocial interaction on purchase intention (De Veirman & Hudders, 2019).

2.2.8. Purchase Intention as the Dependent Variable

Purchase Intention (PUI) represents the final stage in the digital marketing funnel, which describes the consumer's likelihood of purchasing a product following an influencer's endorsement (Lou & Yuan, 2019). Credibility, engagement, and expertise are the core factors that drive purchase intent, underscoring the importance of trust within influencer marketing (Schouten et al., 2020; Martínez-López et al., 2020). According to the Theory of Reasoned Action (TRA), consumer purchase intentions develop from their attitudes and subjective norms; therefore, influencers' credibility, attractiveness, and engagement significantly affect consumer decisions (Ajzen & Fishbein, 1980). Indian audiences respond best to influencers who deliver honest reviews and engaging materials, according to research by Gupta et al. (2023). The alignment between influencers and products and authenticity strongly determines how well engagement translates into sales, according to Kim et al. (2023). Purchase intentions receive reinforcement from different social proof types, including testimonials from influencers and audience interactions, according to Tiwari et al. (2024). Fashion brands boost consumer purchase intentions when influencers collaborate with brands to promote their merchandise through discounts and exclusive time-sensitive offers (Casaló et al., 2020). Sokolova and Perez (2021) found that influencers who maintain high engagement levels and credibility achieve tremendous success in encouraging purchases. The research demonstrates influencer marketing effectiveness by showing that purchase intention strengthens with credibility, engagement, argument quality, expertise, and parasocial interaction. (Bigné et al., 2001).

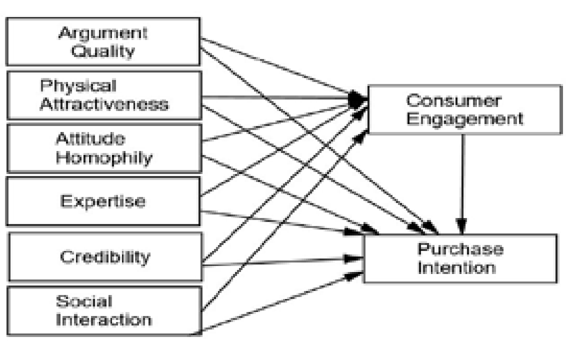

Figure 1

Conceptual framework

3. Research Methodology

3.1. Research Design and Approach

This research uses a quantitative cross-sectional approach to evaluate how influencer characteristics affect purchasing intentions among consumers in India's fashion market. Influencer marketing research frequently employs cross-sectional methodologies to measure consumer perceptions and behaviours at one moment (Jin et al., 2019; Sokolova & Kefi, 2020). Quantitative methodology enables structured data collection and hypothesis testing while ensuring the generalizability of results (Hair et al., 2021). Current research underscores the strong impact of digital channels on buying choices in fashion, which depends heavily on user interaction and trustworthiness as key factors in shaping customer attitudes (Blanche et al., 2021; Ong et al., 2024). The study addressed common method bias in its cross-sectional analysis through procedural measures such as counterbalancing questionnaire sections and adding reverse-coded items (Podsakoff et al., 2003). Harman's single-factor test confirmed that no single construct was responsible for over 50% of the variance, demonstrating that common method bias did not substantially influence the findings (Kock, 2015; Hair et al., 2021).

3.2. Sample Selection and Demographic Profile

The research team used purposive sampling to select social media users who actively interact with fashion influencers. This non-probability sampling technique is used in influencer marketing research because it enables researchers to examine individuals with firsthand experience with influencer-driven purchases (Casaló et al., 2018; Djafarova & Rushworth, 2017). To qualify for the study, participants needed to be active social media users who spent a minimum of two hours daily on platforms such as Instagram, YouTube, and Facebook while following at least one fashion influencer with 50,000 or more followers and actively interacting with the influencer content through likes, shares, comments or purchases within the previous six months. Researchers selected participants between 18 and 35 years old because studies show this age group is most impacted by fashion marketing through social media (Kim et al., 2021; Ong et al., 2024). The study's selection criteria filtered participants to obtain pertinent consumer insights while excluding those who were passive social media users or showed minimal interaction with influencer content. This research examines how social media influencers market clothing and beauty products within the Indian fashion industry. The sector's importance stems from its heavy dependency on visual content, making influencer marketing vital for brand promotion (Kadekova & Holienčinova, 2018). The fashion e-commerce market in India will expand at an exceptional annual rate of 13.5%, while social media platforms will shape more than 60% of these transactions (Statista, 2023). The study targets Millennials and Gen Z individuals between 18 and 35 years as its primary active demographic, validating the research's focus on this vibrant market segment (Belanche et al., 2021; Kim & Kim, 2021). The study collected data by implementing structured online surveys strategically distributed through social media platforms, email services, and fashion communities to reach followers of fashion influencers and people who used specific Instagram hashtags (Ong et al., 2024). During its one-month availability period, the survey received 393 valid responses from the 500 distributed copies. The survey showed that most respondents fell within the 18-35 age bracket and comprised 70% females, 28% males, and 2% non-binary participants. Half of the study participants had achieved undergraduate education levels, demonstrating the educational variety among respondents. Sixty per cent of survey participants originated from metropolitan cities, providing extensive insight into the shopping practices of urban and semi-urban populations across India.

3.3. Measurement of Constructs

We adapted measurement scales from established, validated constructs used in previous influencer marketing studies to ensure content validity. The research utilised a 7-point Likert scale that ranges from 1 representing Strongly Disagree to 7 representing Strongly Agree, which has broad acceptance for its ability to capture detailed consumer perceptions (Revilla et al., 2014; Ong et al., 2024). The study measured credibility alongside parasocial interaction and argument quality, while engagement was a mediator in predicting purchase intention. Researchers modified Ohanian's (1990) credibility scale and integrated elements from Chetioui et al. (2019) for their study. Scholars used the scales introduced by Horton and Wohl (1956) alongside Sokolova and Kefi (2020) to measure parasocial interaction. Researchers assessed argument quality using criteria from Petty and Cacioppo (1986) and Casaló et al. guidelines (2018). The concept of engagement as a mediator was developed from research by Lou and Yuan (2019) and Kim et al. (2021). The modeling of purchase intention in this study was based on frameworks established by Martins et al. (2017) and Djafarova and Rushworth (2017). The study employed Cronbach's Alpha to test reliability and validity and found that all constructs displayed internal consistency values exceeding 0.7, according to Nunnally & Bernstein (1994). The research team calculated Composite Reliability (CR) and Average Variance Extracted (AVE) to confirm that each construct accurately represented its targeted variable through convergent validity procedures.

3.4. Statistical Analysis

Structural Equation Modelling (SEM) performed in AMOS and SPSS served as the analytical method because it is a standard approach in influencer marketing research to examine complex variable relationships (Fornell & Bookstein, 1982). The research applied Exploratory Factor Analysis (EFA) to identify distinct factor structures before using Confirmatory Factor Analysis (CFA) to establish measurement model validity and construct validity testing. Researchers confirmed the model's statistical validity by evaluating fit indices against GFI (>0.90), RMSEA (<0.06), and CFI (>0.95) standards (Hair et al., 2021). The study tested the indirect effects of influencer credibility on purchase intention through consumer engagement by conducting a mediation analysis with 5,000 bootstrapped resamples following the method of Preacher & Hayes (2008). This study produces dependable findings through advanced statistical techniques that provide important insights into influencer marketing's effects on consumer behaviour within India's fashion sector.

3.5. Ethical considerations

Each participant received information about the study and agreed to participate through their consent. Researchers implemented rigorous ethical standards throughout data collection to safeguard respondent confidentiality and privacy. The study participants received confirmation that their data would stay anonymous and serve solely academic research ends. The research adhered strictly to the ethical standards established by the [Institutional Review Board] to ensure all procedures followed the highest ethical research standards (Sean & Bougie, 2011).

4. Data analysis

4.1. Demographic profile

The study began its data analysis by examining the demographic characteristics of 393 respondents from different parts of India. Women accounted for 76.6% of the participants, while men represented 15.8%, and

7.6% opted to keep their gender private. The survey shows that 66.4% of participants were between 18 and 27 years old, proving that young adults are the leading group interacting with influencer-based fashion marketing. The group of respondents aged 28 to 40 accounted for 18.1%, followed by 11.2% younger than 18 and 4.3% older than 40. The survey showed that 50.1% of participants had undergraduate degrees, 23.7% finished junior college, and 20.4% achieved postgraduate qualifications—a minimal segment of respondents, representing 3.3%, achieved a doctorate or equivalent degree. Geographically, the respondents were well-distributed: Most % lived in urban areas, 62.1%, 26.7% were based in rural regions, and 11.2% lived in suburban areas. The varied sample strengthens the generalizability of the findings, which represent a wide range of consumers interacting with social media influencers in the Indian fashion sector (Ong et al., 2024; Djafarova & Rushworth, 2017) and creates a robust basis for further statistical evaluation.

4.2. Exploratory factor analysis

After completing descriptive statistical analysis, researchers used exploratory factor analysis (EFA) to uncover hidden constructs while minimising dimensions by grouping related variables and confirming an accurate construct representation for each measurement item (Hair et al., 2010). The researchers used EFA to test the structural validity of items by assessing factor loadings to ensure significant loading on respective factors while avoiding excessive cross-loadings with other constructs (Tabachnick & Fidell, 2007). The initial item analysis resulted in 24 modified items for measuring the study constructs. Exploratory Factor Analysis (EFA) led to the non-elimination of any items because they displayed recommended factor loadings and internal consistency. (see Annexure)

Table 2.

Exploratory factor analysis and cross-loading assessment.

Constructs	Items	Factor Loadings	Cronbach's Alpha	Composite Reliability (CR)	AVE	MSV
Argument Quality	ARQ1	0.732	0.678	0.872	0.537	0.366
	ARQ2	0.750				
	ARQ3	0.703				
Physical Attractiveness	PAT1	0.649	0.725	0.886	0.607	0.381
	PAT2	0.832				
	PAT3	0.785				
Attitude Homophily	ATT2	0.707	0.742	0.880	0.542	0.372
	ATT3	0.785				
	ATT4	0.735				
Interaction	INT1	0.732	0.713	0.865	0.527	0.360
	INT2	0.782				
	INT3	0.690				
Expertise	EXP2	0.662	0.711	0.861	0.503	0.355
	EXP3	0.768				
	EXP4	0.695				
Credibility	CRE1	0.751	0.746	0.891	0.562	0.389
	CRE2	0.798				
	CRE3	0.686				
Purchase Intention	PUI1	0.697	0.713	0.865	0.530	0.360
	PUI2	0.668				
	PUI3	0.756				
Consumer Engagement	CEG1	0.667	0.745	0.888	0.533	0.388
	CEG2	0.775				
	CEG3	0.721				

The validation step proved essential for distinguishing each factor and improving the measurement model's overall strength. The argument quality items showed strong construct representation with loadings of ARQ1 = 0.732, ARQ2 = 0.750, and ARQ3 = 0.703, and the physical attractiveness items demonstrated significant loadings with PAT1 = 0.649, PAT2 = 0.832, and PAT3 = 0.785. All constructs passed the internal consistency check because their Cronbach's alpha values surpassed the 0.70 minimum requirements, demonstrating reliable measurement according to Nunnally & Bernstein (1994). High reliability was reflected through a Cronbach's alpha of 0.746 for the credibility construct. All constructs displayed composite reliability (CR) values above 0.70, demonstrating internal reliability according to Fornell & Larcker (1981). The interaction construct demonstrated high reliability with a composite reliability score of 0.865. AVE values surpassed the 0.50 minimum requirement, which confirmed convergent validity, while MSV values stayed below AVE to support discriminant validity, according to Hair et al. (2010). The EFA and cross-loading assessments establish the reliability and distinction between constructs, confirming that the dataset is appropriate for additional statistical analysis.

4.3. Validity concerns – Convergent and discriminant validity

After completing the exploratory factor analysis (EFA) and cross-loading assessments, researchers evaluated their measurement model's convergent and discriminant validity. When items measuring the same construct display strong correlations, and the average variance extracted (AVE) surpasses 0.50, it indicates convergent validity because over half of the construct's variance is accounted for by its indicators (Fornell & Larcker, 1981). Internal consistency of constructs is confirmed by composite reliability (CR) values, which must be above 0.70, according to Hair et al. (2010). Discriminant validity demonstrates the theoretical and statistical distinction between constructs when maximum shared variance (MSV) stays below average variance extracted (AVE), and the square root of AVE for each construct surpasses its correlations with other constructs (Fornell & Larcker, 1981). The validity assessments ensure that the measurement model maintains both reliability and validity, allowing researchers to interpret accurately characteristics that affect consumer purchase intentions accurately.

Table 3.

Convergent and discriminant validity.

Cons	CR	AVE	MaXR (H)	ARQ	PAT	ATT	INT	EXP	CRE	CEG	PUI
ARQ	0.870	0.536	1.021	0.861							
PAT	0.881	0.602	0.990	0.512	0.821						
ATT	0.890	0.540	0.951	0.314	0.300	0.837					
INT	0.856	0.525	0.990	0.268	0.279	0.338	0.757				
EXP	0.816	0.509	0.983	0.376	0.539	0.543	0.547	0.713			
CRE	0.819	0.526	1.019	0.410	0.423	0.302	0.411	0.402	0.745		
CEG	0.824	0.530	1.017	0.509	0.311	0.544	0.522	0.552	0.631	0.750	
PUI	0.854	0.538	0.978	0.545	0.511	0.464	0.442	0.545	0.589	0.710	0.788

Table 3 demonstrates convergent and discriminant validity for constructs such as argument quality (ARQ), physical attractiveness (PAT), attitude homophily (ATT), interaction (INT), expertise (EXP), credibility (CRE), consumer engagement (CEG), and purchase intention (PUI). The composite reliability (CR) scores for all constructs exceeded the 0.70 benchmark, which shows strong internal consistency, according to Hair et al. (2010). The credibility (CRE) construct demonstrated the highest composite reliability (CR) at 0.891, which validated the reliability of this construct's measurement. Physical attractiveness (PAT) reached its peak AVE value at 0.607, indicating that its measurement items demonstrate strong intercorrelations. The discriminant validity of all constructs was confirmed because their respective maximum shared variance (MSV) values fell below their average variance extracted (AVE) values as per Fornell & Larcker (1981). The interaction (INT) construct achieved an AVE of 0.527 and an MSV of 0.238, which shows its distinctiveness from other constructs. (Henseler et al., 2014; Henseler, 2017).

4.4. Model fit assessment

After validating both convergent and discriminant dimensions, the researchers evaluated model fit indices to assess the alignment between the proposed theoretical framework and observed data. This step is pivotal in confirming if the structural equation model (SEM) effectively represents construct relationships while maintaining robust and generalizable findings (Hu & Bentler, 1999; Kline, 2015). The model demonstrates acceptable fit when the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) reach minimum values of 0.90. At the same time, the Root Mean Square Error of Approximation (RMSEA) and Standardised Root Mean Square Residual (SRMR) remain at or below 0.06 and 0.08, respectively (Hu & Bentler, 1999; Barrett, 2007). The established thresholds ensure the model accurately represents latent relationships, confirming its theoretical and empirical validity for subsequent structural analysis. (Bentler, 1990)

Table 4.

Model fit indices

Parameter	Output	Threshold	Reference
CMIN/DF	2.325	Between 1 and 3	Barrett (2007); Kline (2015); Ullman (2001)
CFI	0.937	≥ 0.95	Hu and Bentler (1999); Bentler (1990); Byrne (2016)
TLI	0.95	≥ 0.95	Tucker and Lewis (1973); Marsh et al. (2004); Bentler (1990)
NFI	0.94	≥ 0.90	Bentler and Bonett (1980); Bollen (1989); Schumacker and Lomax (2004)
AGFI	0.89	≥ 0.90	Jöreskog and Sörbom (1984); Schumacker and Lomax (2004)
SRMR	0.042	≤ 0.08	Hu and Bentler (1999); Kline (2015); Schumacker and Lomax (2004)
RMSEA	0.058	≤ 0.06	Hu and Bentler (1999); Steiger (1990); Browne and Cudeck (1993)
PClose	0.020	≥ 0.05	Jöreskog and Sörbom (1993); Muthén and Muthén (2002); Brown (2015)

Table 4 shows that the proposed model meets most goodness-of-fit criteria, proving its appropriateness for hypothesis testing. The CMIN/DF statistic at 2.325 falls between the acceptable range of 1 and 3, which indicates the model demonstrates reasonable fit according to Barrett (2007) and Kline (2015). The Comparative Fit Index (CFI) value of 0.937 falls marginally below the optimal cutoff point of 0.95 yet demonstrates sufficient model fit, according to Hu & Bentler (1999). The model demonstrates structural robustness with a TLI value of 0.95 that aligns with recommended standards. The model demonstrates adequate fit as the Normed Fit Index (NFI) of 0.94 surpasses the minimum requirement of 0.90 (Bentler & Bonett, 1980). The AGFI result of 0.89 falls short of the 0.90 standard, which indicates that the model might benefit from minor improvements (Jöreskog & Sörbom, 1984). The model fits well with the observed data because both SRMR at 0.042 and RMSEA at 0.058 fall within acceptable limits (Hu & Bentler, 1999). Despite the PClose value being outside the recommended range with a score of 0.020 compared to the standard of ≥ 0.05, the model achieves a satisfactory overall fit, validating its statistical reliability and practical relevance for subsequent hypothesis testing and mediation analysis. (Bentler & Bonett, 1980)

4.5. Hypothesis Testing

Following their model fit assessment, the researchers began hypothesis testing through path analysis using structural equation modeling (SEM). SEM represents a multivariate statistical method that enables researchers to analyse multiple relationships between independent and dependent variables while adjusting for measurement errors (Kline, 2015). The analysis estimated standardised regression weights (β) to assess the hypothesised relationships' strength and direction. Researchers evaluated the importance of these estimates with t-values and p-values to establish statistical validity for the proposed relationships (Hu & Bentler, 1999; Byrne, 2016). The study used bootstrapping with 5,000 resamples to improve the robustness and reliability of its results. The technique effectively reduces sampling errors while delivering precise confidence intervals for direct and indirect effects and mediation effects, according to Preacher & Hayes (2008). The study employed a 95% confidence interval (CI) to determine the significance of indirect effects, confirming that the mediation pathways were statistically meaningful (MacKinnon, 2012). Bootstrapping enhances the study findings by minimising standard error biases and providing a more detailed understanding of how variables indirectly affect consumer behaviour (Hayes, 2013). The rigorous methodology ensures empirical support for the structural model, which enables an accurate interpretation of influencer attributes' impact on consumer purchase intentions.

Table 5.

Hypothesis testing

Path	Coefficients (β)	t	p	Decision
Attitude Homophily (ATT) -> Consumer Purchase Intentions (PUI)	0.083	0.884	0.003	Accepted
Credibility (CRE) -> Consumer Purchase Intentions (PUI)	0.247	3.098	0.002	Accepted

Argument Quality (ARQ) -> Consumer Purchase Intentions (PUI)	0.253	2.857	0.004	Accepted
Interaction (INT) -> Consumer Purchase Intentions (PUI)	0.117	1.449	0.003	Accepted
Physical Attractiveness (PAT) -> Consumer Purchase Intentions (PUI)	0.072	0.965	0.003	Accepted
Expertise (EXP) -> Consumer Purchase Intentions (PUI)	0.416	3.886	***	Accepted
Consumer Engagement (CEG) -> Consumer Purchase Intentions (PUI)	0.055	0.585	0.003	Accepted

The path analysis results displayed in Table 5 show that all hypotheses reached statistical significance by illustrating substantial links between independent variables and consumer purchase intentions (PUI). The expertise (EXP) variable demonstrated the most substantial impact on purchase intentions ($\beta = 0.416$, $t = 3.886$, $p < 0.001$), which illustrates how influencer expertise plays an essential role in shaping consumer purchasing decisions. The statistical analysis revealed that argument quality (ARQ) significantly affected purchase intentions with a coefficient of 0.253, demonstrating that well-structured and persuasive arguments are vital for shaping consumer preferences. The substantial impact of credibility (CRE) ($\beta = 0.247$, $t = 3.098$, $p = 0.002$) demonstrates that consumers trust influencers who build confidence through their recommendations. The positive correlation between attitude homophily (ATT) and purchase intentions ($\beta = 0.083$, $t = 0.884$, $p = 0.003$) reveals that consumers trust influencers whose values align with their preferences. The research offers robust empirical support for the theoretical model by demonstrating that consumer purchase intentions are influenced by expertise, credibility, argument quality, and interaction, and fashion brands, and marketers ought to focus on influencer collaborations that convey expertise and trustworthiness since these attributes demonstrate the most significant effect on consumer behavior, according to statistical hypothesis testing results. The research emphasises how meaningful engagement and interaction between influencers and consumers create potent connections that improve purchase decisions.

4.6. Mediation analysis

After their direct hypothesis testing, the researchers performed mediation analysis to determine if a mediating variable explained the relationship between an independent variable and consumer purchase intentions (PUI). Mediation analysis helps researchers understand if the independent variable's impact reaches the dependent variable through a mediator, which reveals essential mechanisms in consumer decision-making processes (Baron & Kenny, 1986). The research separates direct and indirect effects to thoroughly examine influencer characteristics and their effects on consumer buying decisions, according to Preacher & Hayes (2008). MacKinnon (2012) reported that this statistical approach delivers more accurate confidence intervals while decreasing estimation biases in mediation pathway analyses. The researchers used this strong statistical method to improve the reliability of their findings and reduce standard errors while clarifying the indirect relationships between influencer attributes and purchase intentions (Hayes, 2013).

Table 6.

Mediation analysis

Path	Total Effect (β)	Sig.	Indirect Effect (β)	Sig.	Direct Effect (β)	Sig.	Type
Expertise (EXP) -> Consumer Purchase Intentions (PUI)	0.417	0.000	0.17	0.000	0.400	0.000	Partial
Physical Attractiveness (PAT) -> Consumer Purchase Intentions (PUI)	0.085	0.085	0.18	0.003	0.083	0.003	Partial
Interaction (INT) -> Consumer Purchase Intentions (PUI)	0.137	0.003	0.20	0.003	0.117	0.003	Partial
Argument Quality (ARQ) -> Consumer Purchase Intentions (PUI)	0.263	0.000	0.62	0.003	0.201	0.000	Partial

Credibility (CRE) -> Consumer Purchase Intentions (PUI)	0.252	0.000	0.50	0.003	0.202	0.003	Partial
Attitude Homophily (ATT) -> Consumer Purchase Intentions (PUI)	0.085	0.000	0.05	0.000	0.050	0.050	Partial

Table 6 demonstrates the mediation analysis results, which show that all independent variables significantly affect consumer purchase intentions through partial mediation. Expertise (EXP) achieved the highest total influence (β = 0.417) through an indirect effect of 0.17 and a direct effect of 0.400, revealing that its impact on purchase decisions includes a significant mediated component. Physical attractiveness (PAT) produced a total effect of 0.085 through both an indirect effect of 0.18 and a direct effect of 0.083, demonstrating that attractiveness exerts minimal direct influence but operates more effectively when mediated. The partial mediation of interaction (INT) is demonstrated through its total effect of 0.137, while its indirect effect of 0.20 and direct effect of 0.117 highlight its indirect impact on consumer purchasing behaviour. The effectiveness of well-constructed arguments with a total effect of 0.263 becomes notably stronger through mediation because of its substantial indirect effect of 0.62 alongside a direct effect of 0.201. The influencer's credibility through partial mediation demonstrated that trustworthiness significantly impacts purchasing choices because of its mediated role, with a total effect of 0.252 and an indirect effect of 0.50 against a direct effect of 0.202. The partial mediation effect of attitude homophily (ATT) at 0.085 shows both direct at 0.050 and indirect effects at 0.05, demonstrating increased trust levels among consumers toward influencers who share similar values when engagement mechanisms exist. All tested constructs demonstrated indirect effects, highlighting the necessity of building robust influencer-consumer relationships through engagement to turn influencer content into purchase decisions. Brands and marketers can benefit from these insights because influencer partnerships need to integrate direct measures of credibility and expertise with engagement tactics that build trust and promote consumer decision-making participation.

5. Findings and discussion

5.1. Findings and discussion on Direct effects

Hypothesis testing results show strong links between influencer characteristics and consumer purchase intentions in fashion commerce, emphasising growing reliance on influencer marketing strategies. The research confirms that EXP emerged as the leading factor influencing purchase intentions (β = 0.416, $p < 0.001$), supporting Djafarova and Rushworth's discovery from 2017. Consumers regard the expertise of fashion influencers as a crucial factor when deciding on purchases. The quality of argumentation (ARQ) showed a substantial impact (β = 0.253, p = 0.004), proving that persuasive and well-organised messaging plays a vital role in consumer behaviour, as Lou and Yuan (2019) highlighted. Influencer credibility (CRE) significantly affects consumer purchase intentions, which boosts consumer confidence and drives purchase behaviour, as De Vries et al. (2012) established. (2012). Despite having comparatively more minor effects (β = 0.117 for INT and β = 0.072 for PAT), interaction and physical attractiveness show statistical importance, supporting their role in influencing purchasing decisions on platforms like Instagram, according to Jin & Ryu (2020). Research findings demonstrate that consumers primarily depend on expertise, credibility, and argument quality for decision-making. Interaction and physical appeal serve important secondary roles in consumer decision-making, with their significance varying across different platforms and contexts.

5.2. Findings and Discussion for the Mediation Table

The mediation analysis reveals a further understanding of the indirect effects that influencer attributes have on consumer purchase intentions (PUI) and identifies partial mediation across every examined construct. The analysis revealed that Expertise (EXP) led to the most substantial total effect (0.417), combining both direct (0.400) and significant indirect effects (0.17), showcasing how expertise affects consumer decisions directly while mediating effects through perceived trust and engagement strengthen its influence (Lou & Yuan, 2019). Argument quality (ARQ) showed substantial indirect influence (0.62) and direct influence (0.201), which demonstrates that persuasive communication strategies significantly affect consumer behaviour when supported by credibility and engagement mediators (Sokolova & Kefi, 2020; Breves et al., 2019). The strong partial mediation effect of credibility (CRE) with an indirect effect of 0.50 and a total effect of 0.252 validated the vital influence of influencer trustworthiness on consumer perceptions, according to De Vries et al. (2012. The indirect impact of physical attractiveness (PAT) reached 0.18, demonstrating that attractiveness boosts consumer perceptions of expertise and indirectly affects purchase behaviour even with limited direct influence (Jin & Phua, 2014). The study by Jin & Ryu (2020) showed that engagement through interactive content creates stronger consumer-influencer relationships, boosting purchase likelihood, with a total interaction effect of 0.137 and an indirect effect of 0.20. The partial mediation of attitude homophily (ATT) showed a total effect of 0.085, while its indirect effect was 0.05 and direct effect was 0.050, confirming that consumers tend to follow influencers who share their fashion preferences (Lee & Watkins, 2016). Research demonstrates that fashion influencers sway consumer purchasing behaviour through direct interactions and complex intermediary processes, highlighting digital marketing's intricate nature. (Amos et al., 2008)

6.1. Managerial and practical implications

This study delivers important information that fashion brands and marketers can use to improve influencer marketing approaches. Managers should prioritise partnering with influencers because their expertise and credibility significantly affect consumer trust and purchasing decisions (Alalwan et al.,2017; Elseminas et al., 2015; Godey et al., 2016). Brands should motivate influencers to deliver persuasive and structured product messages because argument quality is essential in successful marketing (Abidin,2016). When communication is both practical and persuasive, it increases consumer interaction while simultaneously improving purchase likelihood. Interactive content creation must be prioritised because platforms like Instagram demonstrate that more significant interaction strengthens consumer-influencer bonds, ultimately leading to increased sales. (Raji et al., 2019) Physical attractiveness draws consumer interest, which strengthens when combined with expertise and trustworthiness. Brands must choose influencers who combine visual appeal with professional expertise (Tafesse & Wood, 2020; Taillon et al., 2020). Selecting influencers who match the fashion preferences of their target audience creates attitude homophily, which leads to better consumer engagement since individuals tend to connect with those who share their style preferences (Stubb et al., 2019; Adeola et al., 2020). Fashion brands that employ these strategies will build more credibility while creating deeper consumer relationships, leading to higher sales.

6.2. Practical Implications

Fashion brands need to leverage these insights to create influencer marketing strategies that boost consumer interaction and lead to increased purchase rates. Brands must work with fashion industry experts because their followers generally show stronger trust and engagement (Vinerean et al., 2013). Brands must motivate influencers to produce engaging content that captures audience attention and demonstrates how effective communication can drive consumer purchase decisions. Physical attractiveness continues to be important, but its effects become much more potent when combined with credibility and expertise, demonstrating why influencer selection must be multi-faceted. Fashion brands must guarantee that influencer collaborations reflect their target audience's style preferences (Sasmita & Suki, 2015; Yadav & Rahman, 2017b). Brands that tap into attitude homophily can build stronger bonds with consumers and develop lasting brand loyalty. Fashion brands achieve improved influencer marketing results and increased consumer trust, resulting in better sales when they concentrate on these strategic elements in the competitive marketplace.

7.1. Limitations of the study and scope for further research

Limitations of the study

The study presents valuable insights, including several aspects that require acknowledgement. The study's sample size of 393 respondents ensures statistical validity but limits the generalization of findings to broader consumer segments within the multi-faceted fashion industry. Using non-probabilistic sampling methods could result in a bias that fails to represent all consumer demographics outside the primary target group. Because the sample mainly consisted of urban and suburban participants, the study might have missed unique social media and fashion influencer interactions among rural consumers. Using self-reported data increases the possibility of response bias concerning subjective elements like engagement and perceived credibility, which may compromise research findings.

7.2. Scope for Further Study

Future research can build upon this study by examining additional theoretical frameworks, like Social Identity Theory, to discover how consumers' connections with influencer personas impact their buying decisions. New mediating factors like emotional connection and brand loyalty could help researchers better understand the development of durable relationships between influencers and their audiences. Subsequent research should investigate how fashion consciousness and consumer involvement are moderators that influence the relationship between personal preferences and influencer marketing outcomes. Research that includes multiple geographical areas and cultural contexts will provide meaningful knowledge about influencer marketing dynamics throughout different consumer markets that extend past urban digital purchasers. Longitudinal research can assess how influencer marketing impacts brand loyalty and repeat purchases over time to provide a complete picture of influencer success. The proposed extensions will help brands develop better strategies for maximum effectiveness by expanding their knowledge of influencer marketing within the transforming digital fashion sector.

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Annexure A

Construct	Item	Final Item Description
Argument Quality (ARQ)	ARQ1	The influencer presents their endorsements with transparent and rational explanations.
	ARQ2	The influencer presents product features through organised and logical arguments.
	ARQ3	The influencer shares content that shows extensive details and strong persuasive elements.
Physical Attractive-ness (PAT)	PAT1	I find the influencer's visual appearance attractive.
	PAT2	The influencer's unique style strengthens the trustworthiness of their content.
	PAT3	The influencer produces visually appealing photos and videos.
Attitude Homophily (ATT)	ATT1	Our fashion values and preferences show a strong similarity between me and the influencer.
	ATT2	I see my attitudes and beliefs mirrored in the way the influencer lives.
	ATT3	The influencer's viewpoints and interests resonate with me on a personal level.
Interaction (INT)	INT1	The influencer maintains active communication by responding to followers and commenting on their posts.
	INT2	The influencer promotes follower engagement through question and answer sessions as well as polls and live broadcasts.
	INT3	I have a sense of belonging within this influencer's digital community.
Expertise (EXP)	EXP1	The influencer exhibits professional understanding of fashion products together with current trends.
	EXP2	The influencer shows extensive knowledge of fashion styling through their recommendations.
	EXP3	The influencer's fashion expertise holds more credibility for me than typical advertisements do.
Credibility (CRE)	CRE1	The influencer seems honest when recommending products.
	CRE2	This influencer presents reliable product reviews and opinions.
	CRE3	The influencer's product reviews appear to be true and impartial.
Consumer Engage-ment (CEG)	CEG1	I actively engage with the influencer's posts through likes/comments/shares.
	CEG2	Engagement between influencers and their audience builds my connection to brands.
	CEG3	The influencer's posts inspire me to either engage in conversations or provide my own feedback.
Purchase Intention (PUI)	PUI1	My purchasing decisions often include fashion products endorsed by this influencer.
	PUI2	The endorsement of a product by this influencer makes me consider purchasing it.
	PUI3	When the influencer features a product it makes me more inclined to purchase it.