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Evaluating the Influence of Social Network Sites on Consumer Purchase Intentions: A Comprehensive Study of Indian Social Network Users

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Abstract

This study investigates what drives purchase intention in Indian SNS-based fashion commerce by analysing how attitude toward SNSs acts as a mediator while examining the effects of perceived enjoyment, emotional value, usefulness, quality, price, risk, and electronic word of mouth (eWOM). The study gathered 423 valid responses through Instagram and Facebook using a descriptive-correlation approach and stratified random sampling for proper representation. The research employed confirmatory factor analysis (CFA) and structural equation modelling (SEM) in AMOS 26 to evaluate direct and indirect effects as well as mediation effects in the data analysis process. Purchase intention is driven by perceived quality along with emotional value and SNS attitude, but not affected by perceived risk or eWOM, which indicates that consumer engagement and brand trust surpass traditional purchasing concerns such as risk evaluation and product pricing. The research integrates TAM with Social Exchange Theory to advance digital consumer behavior understanding and provides actionable insights for fashion brands as well as policymakers and marketers to improve SNS engagement and build trust and personalization in online retail experiences.

A b s t r a c t

Keywords: *Perceived risk, social commerce, eWOM, perceived enjoyment, emotional value, purchase intention, social networking sites, influencer marketing, perceived quality, consumer behaviour.*

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Introduction

The fashion industry worldwide has changed due to social networks such as Instagram, Facebook, WhatsApp and numerous e-commerce platforms. Modern marketplaces in digital platforms now dictate consumer purchasing patterns according to Molinillo et al. (2021). Social networking platforms have become vital for social commerce in India, where more than 500 million people utilise them to find and buy fashion items with ease (Yadav & Rahman, 2017). Social media marketing enables marketers to target audience groups accurately because 73% of users believe it works well (Buffer, 2018). Fashion brands partner with trustworthy influencers as intermediaries to establish consumer trust while boosting their sales (Kaplan & Haenlein, 2019). Brands achieve greater consumer interaction by building direct relationships and combining user-generated content with in-app purchase options (Blázquez, 2014). The achievement of two billion monthly active Instagram users in 2021 has prompted fashion brands to utilize its visually appealing advertisements and interactive features (Rodriguez, 2021).

Product quality issues alongside data privacy breaches and fraudulent activities in social commerce platforms create consumer concerns, as shown in various studies (Chen et al., 2022; Rehman & Al-Ghazali, 2022). To reduce consumer risks social commerce platforms need to improve perceived enjoyment alongside trust and positive virtual conversations which ultimately boost purchase intentions (Sokolova & Kefi, 2020). User interactions through comments, likes, image swiping, and tag tapping prompt quick engagement and boost impulsive purchasing behaviors (Kim et al., 2019; Xiang et al., 2016; Sreejesh et al., 2020). Customer trust, along with purchasing behaviour, gets reinforced through secure navigation on websites and the combination of effective delivery systems and straightforward pricing approaches (Amin & Naqvi, 2020; Shin & Jeong, 2020). According to Djafarova & Bowes (2020), brand-enhanced influencer endorsements build emotional value while boosting consumer engagement and loyalty. The research provides essential guidance for fashion businesses seeking to enhance their social network marketing practices and consumer interaction methods.

2. Literature Review

The research explores the connection between perceived risk, enjoyment, eWOM, emotional value, usefulness, quality, price factors and purchase intention while the attitude toward social networking sites (SNSs) serves as a mediating variable. According to TAM1 researchers Kim & Eastin (2011), Koufaris (2002), and Zhang et al. (2007) have identified perceived usefulness (PU) and perceived ease of use (PEOU) as essential elements for technology adoption. Chan et al. The research by Chan et al. (2017) expands the existing framework by connecting PU with utilitarian motivations while associating PEOU with hedonic motivations through the SOR model.

2.2. Theory of Reasoned Action

This study deploys the TAM1 framework to analyse the impact of usability together with system design and navigation ease on social network site adoption for shopping. Bagozzi's 2007 research highlights that TAM1's simplicity contrasts with UTAUT's complexity and therefore serves as the best framework for understanding online impulse buying. The Theory of Reasoned Action (TRA) extends TAM1 by illustrating how consumer attitudes along with social advertising and brand perceptions impact buying choices (Ajzen & Fishbein, 1980; Hussein, 2017). The research uses TRA to show how the credibility of SNS platforms and influencer recommendations impact consumer trust and engagement levels (Familmaleki et al., 2015). The combination of TAM1 with TRA and the SOR model demonstrates that system usability and social marketing generate cognitive responses, including PU and PEOU, which result in purchase intentions (Lin & Yang, 2018). In India's fashion industry shoppers are primarily driven by price sensitivity according to Amin & Naqvi (2020) and influencer marketing strengthens customer trust and social connections as per Djafarova & Bowes (2020).

2.3. Perceived Risk

Perceived risk influences the purchasing decisions of online shoppers because they worry about product authenticity and both payment security and personal data privacy. E-commerce systems depend on trust, yet perceived risk remains the dominant factor influencing purchase choices, particularly in developing countries like India, according to Dowling & Staelin (1994).Research indicates that perceived risk has multiple dimensions, such as financial risk, along with security risk and performance risk, together with social risk (Featherman & Pavlou, 2003). Platforms using secure payment gateways along with verified seller programs and lenient return policies reduce perceived risk which leads to higher consumer confidence (Garcia & Sokolova, 2020). Positive eWOM alongside influencer endorsements and peer recommendations builds trust that consequently reduces online purchase hesitation (Rehman et al., 2020). Current research shows a lack of cohesive analysis about how various demographic groups experience risk differently within social commerce environments. Future studies need to explore how AI-based fraud detection systems combined with blockchain technology can reduce perceived risks and boost trust among consumers.

Hypothesis 1: Perceived risk negatively influences purchase intention by increasing uncertainty and hesitation in online shopping.

2.4. Perceived Enjoyment

The level of entertainment consumers find in SNS-based shopping determines their degree of engagement because users tend to prefer shopping experiences which are both visually immersive and interactive. Perceived enjoyment represents the natural satisfaction users obtain from online activities which establishes a strong connection to impulse buying patterns and user interaction according to Davis et al. (1992). Platforms that combine gamification features with live shopping events and AR try-ons increase user enjoyment, which drives longer engagement durations and boosts purchase figures according to research by Jin & Ryu (2020). The social features of SNSs such as likes, shares, and comments create an enjoyable shopping experience while providing social benefits (Kim et al., 2019). Research shows AI personalisation improves shopping enjoyment through feeds that match consumer preferences which boosts browsing satisfaction (Park & Kim, 2020). The current literature fails to provide information about the relationship between consumer enjoyment perception and cultural shopping behaviors across various social network platforms. Research needs to investigate how short videos together with influencer marketing affect consumer enjoyment in purchase decisions.

Hypothesis 2: Perceived enjoyment positively influences purchase intention by increasing engagement and shopping satisfaction.

2.5. Perceived eWOM (Electronic Word of Mouth)

The consumer trust and purchase decisions depend on eWOM since online shoppers turn to peer opinions before buying. Online posted consumer evaluations of products and services known as eWOM serve as a social proof mechanism which reduces uncertainty while building brand trust, according to Hennig-Thurau et al. (2004). Research by Garcia & Sokolova (2020) shows verified reviews and influencer recommendations serve as major factors in consumer decision-making while the amount and quality of eWOM combined with credibility influences customer purchase intentions. Video testimonials, along with interactive Q&A sessions, hold more authenticity and influence for users compared to text-based reviews (Leong et al., 2018). Studies demonstrate the substantial impact of eWOM but there is insufficient research into how short video social media content from platforms such as Instagram Reels and TikTok shapes consumer trust evaluations. AI recommendation systems structure eWOM content but researchers lack comprehensive knowledge on their impact on consumer decision-making. The research community needs to explore how automated review curation together with influencer authenticity affects purchase decisions driven by electronic-word-of-mouth.

Hypothesis 3: Perceived eWOM positively influences purchase intention by enhancing trust and reducing purchase uncertainty.

2.6. Perceived Emotional Value

The psychological attachment consumers develop toward a product or brand indicates perceived emotional value, which affects their purchasing decisions. Brand storytelling along with influencer marketing and relatable advertising create emotional connections that strongly affect customer loyalty and engagement as shown by Djafarova & Bowes (2020). Research shows individuals who establish emotional connections with brands tend to buy more frequently and promote the brand through digital channels (Kaplan & Haenlein, 2019). Indian buyers who let emotions drive their purchasing decisions show preference toward brands which match their personal values and represent their cultural identities as well as their aspirational lifestyles according to Garland & Reed (2018). SNS platforms build communities which create strong emotional connections to enhance personal and interactive brand relationships. Research on brand loyalty and emotional value exists in abundance but remains scarce in the area of emotional engagement on SNS shopping and its effects on consumer behavior over time. Upcoming research needs to evaluate how emotional advertising and interactive brand stories with influencer partnerships create impulse buying behavior on social networking sites.

Hypothesis 4: Perceived emotional value positively influences purchase intention by fostering brand attachment and trust.

2.7. Perceived Usefulness

The Technology Acceptance Model (TAM) defines perceived usefulness as the ability of social network shopping platforms to improve convenience and operational efficiency including effectiveness according to Shin & Jeong (2020). The combination of AI personalization features with seamless site navigation and chatbot-aided customer service increases customers' satisfaction levels and their intention to make a purchase (Park & Kim, 2020). SNS shopping attracts more customers because voice commerce together with AR shopping experiences and automated checkout systems improve perceived usefulness according to Hsu et al. (2013). Researchers keep advancing their studies on how AI predictive analytics affects people's perceptions of shopping efficiency on SNS platforms. Future research should evaluate how digital automation combined with AI virtual assistants influences consumer behaviour in SNS commercial activities.

Hypothesis 5: Perceived usefulness positively influences purchase intention by improving shopping efficiency and reducing friction.

2.8. Perceived Quality

Online shopping depends heavily on perceived quality since consumers use visual and textual indicators to evaluate the credibility of products. The purchase decisions of consumers are greatly affected by trust signals such as high-quality product images alongside influencer reviews and user-generated content according to Bilro et al, 2018. According to Koo & Lee (2019) research indicates that brand credibility along with third-party authentication and AI-driven fraud detection mechanisms enhance perceived quality which reduces customer worries about counterfeit products. Consumer trust improves through augmented reality (AR) and 3D product visualisation which delivers an enriched shopping experience. There are insufficient insights about the influence of real-time product demonstrations and interactive product reviews on perceived quality. Subsequent studies need to explore the effects of AI-driven product verification systems together with interactive social network shopping functions on consumers' quality assessments.

Hypothesis 6: Perceived quality positively influences purchase intention by reinforcing trust in product authenticity.

2.9. Perceived Price

Consumers in price-sensitive markets such as India make purchase decisions based on perceived price because they look for value-for-money deals. Consumer perceptions are shaped by competitive pricing methods along with flash sales and influencer-exclusive discounts, which work together with dynamic pricing strategies to target buyers (Amin & Naqvi, 2020). Studies show transparent pricing approaches combined with AI-based personalized discounts build consumer trust which makes shopping on Social Networking Sites more attractive (Rehman & Al-Ghazali, 2022). Research remains scarce on how social commerce platforms develop pricing strategies to target various consumer groups. Upcoming studies should examine how AI price matching combined with gamified discount systems affects purchase intention.

Hypothesis 7: Perceived price positively influences purchase intention by increasing affordability and perceived value.

2.10. Attitude Toward SNSs (Mediator)

The way users perceive SNSs mediates their purchase intentions through their engagement with social commerce platforms. When users trust SNSs and find them convenient and enjoyable to use, they engage more and show increased buying behaviour (Perez & Gutierrez, 2020). People who feel positive about SNS shopping engage with brands and share their evaluations which increases their intention to purchase according to Kim et al. (2019). Social network commerce becomes more attractive and personalised through influencer campaigns and real-time shopping features alongside AI-driven personalization (Park & Kim, 2020). The scientific exploration into how different generations and cultures develop their attitudes towards shopping on social networking sites has not been extensively conducted. Younger users view SNS shopping positively while older users express skepticism driven by security and privacy concerns according to Rehman & Al-Ghazali (2022). The next research should examine how AI-assisted engagement methods combined with personalized recommendation engines and social game features affect different demographic groups' views on SNS shopping.

Hypothesis 8: Attitude toward SNSs mediates the relationship between perceived constructs and purchase intention.

2.11. Purchase Intention (Dependent Construct)

Purchase intention on SNS platforms depends on psychological and social factors as well as technological aspects according to Ajzen (1991). Multiple factors including trust and credibility combined with perceived risk and enjoyment lead to purchase intention as eWOM and emotional value join usefulness quality and price to create a strong influence (Chen & Zhang, 2021). The interactive shopping sections of SNS sites where users engage with influencers and peer feedback create stronger purchase intentions (Djafarova & Bowes, 2020). Personalized urgency generated from the combination of AI product recommendations with impulse purchases and time-limited offers heightens SNS shopping activity as demonstrated by Garcia & Sokolova (2020). It remains unclear how modern technologies such as augmented reality shopping experiences along with AI chatbots and voice commerce influence purchase intentions on social networking services. The effects of predictive analytics together with immersive social shopping features plus cross-platform brand integrations on consumer purchasing choices in SNS commerce demand investigation by researchers.

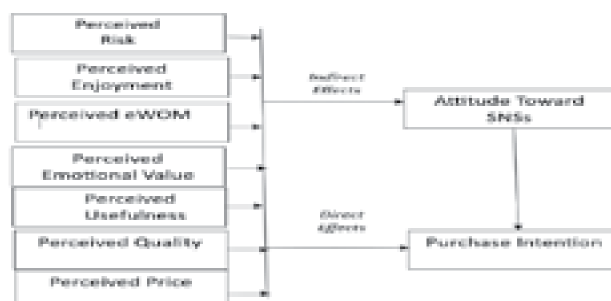

Figure 1.

Conceptual framework developed by the Authors.

3. Research methods

3.1. Study Setting, Population, and Sampling

The study explores the purchasing habits of Indian fashion consumers who utilise social media platforms such as Facebook, Instagram and WhatsApp to make their purchases. The study examines online shopping behaviour. To address internet access disparities between urban, semi-urban and rural areas the research team used stratified random sampling based on age group, gender category, geographic location and educational background which ensured balanced representation as explained by Lohr in 2010. The research method increased sampling accuracy while reducing selection bias and enhanced external validity. The sample size of 441 resulted from applying Taro Yamane's formula in 1967 for a 95% confidence level with a 5% margin of error.

The online survey that reached tech-savvy digital consumers achieved a response rate of 95.9% from which 423 valid responses were collected. Diverse SNS fashion shoppers throughout India could relate to these findings due to the use of a robust sampling technique (Hair et al., 2014)..

3.2. Measurement Tools

The questionnaire utilized dependable scales confirmed through social commerce and fashion consumer behavior studies (Hajli, 2015; Kim & Park, 2020; Djafarova & Bowes, 2020) to evaluate constructs. The study measured perceived risk, enjoyment, electronic word-of-mouth (eWOM), emotional value, usefulness, quality and price, while social network site (SNS) attitudes served as mediators of purchase intention. The questionnaire used a 5-point Likert scale which ranged from 1 meaning strongly disagree to 5 meaning strongly agree as described by Sokolova & Kefi (2020). The study's scales evaluated product authenticity and privacy risks (Featherman & Pavlou, 2003) while assessing interactive shopping satisfaction (Park & Kim, 2020) together with eWOM effects (Garcia & Sokolova, 2020). Perceived emotional value was assessed by Kaplan & Haenlein (2019) while usefulness was evaluated by Shin & Jeong (2020) and quality was measured by Lin & Yang (2018) and price sensitivity was examined by Amin & Naqvi (2020). Trust and satisfaction regarding SNS attitudes were evaluated based on Perez & Gutierrez (2020), while purchase intention analysis was conducted according to Chen & Zhang (2021). The instrument underwent validation and testing.

3.3. Data Collection and Analysis

The research team sent out surveys through Instagram and Facebook to collect data from people who buy fashion items on social media (Hajli 2015; Kim & Park 2020). The survey functioned for three months across India targeting people who regularly interacted with fashion brands and influencers together with online shopping advertisements on SNS platforms (Sokolova & Kefi, 2020). To attract a heterogeneous respondent pool with varying demographics and shopping preferences and digital skills we applied both natural reach and targeted advertising strategies based on Kaplan & Haenlein (2019). The research team examined construct-to-construct relationships and mediation effects plus latent variable interactions through Structural Equation Modeling (SEM) using SPSS and AMOS 26. Structural Equation Modeling (SEM) became the preferred method because it allows simultaneous hypothesis testing and measurement error correction which leads to comprehensive and reproducible results according to Chin (1998) and Gefen et al. (2000). The study first validated the measurement model's reliability and validity using confirmatory factor analysis (CFA) as per Fornell & Larcker (1981) before path analysis explored direct and indirect effects along with mediating impacts based on Baron & Kenny (1986). Through SEM techniques and model fit indices and factor loadings, the research demonstrated statistical strength in hypothesis verification while explaining how perceived constructs influence consumer attitudes and purchase intentions for SNS-based fashion shopping (Shin & Jeong, 2020; Djafarova & Bowes, 2020).

4. Data analysis

The researchers started their data analysis process by conducting an exhaustive demographic analysis of the participants to establish their sample profile. The study incorporated demographic information including gender, age group, educational background, geographical areas and social media usage. By analysing multiple demographic factors the research created a comprehensive profile of Indian social media users who buy products online. The research compared the relationships between independent variables and purchase intention across users of different social networking sites after finishing the demographic breakdown.

4.1. Demographic profile

The demographic data for the survey participants who use social networks to buy fashion items online can be found in table 1 below. The descriptive statistics which used frequency and percentage transformed the data set to display the range of the sample.

Table 1.

Demographic profile of the respondents

Variables	Category	Frequency	Percent
Gender	Male	61	18.2%
	Female	251	74.7%
	Prefer not to say	24	7.1%
	Total	336	100.0%
Age of the respondents	Below 18	40	11.9%
	18-27	227	67.6%
	28-40	48	14.3%
	Above 40	21	6.3%
	Total	336	100.0%
Educational level	High School or Less	11	3.3%
	Junior College	68	20.2%
	Undergraduate	175	52.1%
	Postgraduate	69	20.5%
	Doctorate/ Others	13	3.9%
	Total	336	100.0%
Currently Reside	Urban area	206	61.3%
	Suburban area	29	8.6%
	Rural area	101	30.1%
	Total	336	100.0%
Frequency	Daily	223	66.4%
	Many times, a week	31	9.2%
	Once a week	26	7.7%
	Many times, a month	12	3.6%
	Rarely	37	11.0%
	Never	7	2.1%
	Total	336	100.0%
social network platform is used frequently	Facebook	26	7.7%
	Instagram	221	65.8%
	Twitter	3	0.9%
	TikTok	0	0.0%
	LinkedIn	7	2.1%
	Snapchat	18	5.4%
	Other	61	18.2%
	Total	336	100.0%
purchase products through social networks	Daily	51	15.2%
	Weekly	19	5.7%
	Monthly	76	22.6%
	Few times a year	105	31.3%
	Rarely/Never	85	25.3%
	Total	336	100.0%
device do you primarily use	Smartphone	289	86.0%
	Tablet	6	1.8%
	Laptop	17	5.1%
	Desktop computer	3	0.9%
	Others	21	6.3%
	Total	336	100.0%
Time Spent Daily	Less than 30 minutes	61	18.2%
	30 mins to 1 hour	108	32.1%
	1 to 2 hours	83	24.7%
	2 to 3 hours	40	11.9%
	More than 3 hours	44	13.1%
	Total	336	100.0%

The survey sample consisted of 85% women and many respondents were aged between 18 and 27 when young people typically buy things online using SNSs. The educational level of participants varied starting at high-school graduation and went up to college graduation but most participants were undergraduates. The survey results showed geo-diversity because participants came from both metropolitan areas and from suburban and rural regions. Accessing SNSs through social media platforms and devices reveals further details about this consumer group. Understanding the demographic details of the respondents requires

4.2. Exploratory factor loadings – Quality criteria

Through EFA the researcher identified underlying factors and verified discriminant validity using cross-loading assessments (Hair et al., 2010; Henseler et al., 2015). The calculated composite reliability exceeded 0.70 and AVE surpassed 0.50 which confirmed the model's validity and reliability as a preparation for SEM analysis (Nunnally & Bernstein, 1994; Fornell & Larcker, 1981).

Table 2.

Exploratory factor loadings and Quality criteria of Constructs

Construct	Items	Factor Loading	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Risk	PRI1	0.853	0.88	0.884	0.737
	PRI2	0.879			
	PRI3	0.832			
Perceived Enjoyment	PRE1	0.757	0.73	0.793	0.575
	PRE2	0.783			
	PRE3	0.666			
Perceived eWOM	PWM1	0.761	0.83	0.841	0.621
	PWM2	0.817			
	PWM3	0.741			
Perceived Emotional Value	PEV1	0.704	0.77	0.798	0.575
	PEV2	0.804			
	PEV3	0.747			
Perceived Usefulness	PUS3	0.740	0.80	0.835	0.616
	PUS4	0.818			
	PUS5	0.749			
Perceived Quality	PQU1	0.653	0.71	0.725	0.488
	PQU2	0.755			
	PQU3	0.677			
Perceived Price	PPR2	0.715	0.80	0.815	0.621
	PPR3	0.801			
	PPR4	0.804			
Attitude Towards SNS	ATT1	0.781	0.78	0.805	0.561
	ATT2	0.807			
	ATT3	0.672			
Purchase Intention	PUI2	0.652	0.67	0.688	0.474
	PUI3	0.769			
	PUI4	0.616			

Table 2 presents the reliability assessments and convergent validity measurements for various constructs. The Perceived Risk construct meets most convergent validity standards according to Fornell & Larcker (1981) with high internal consistency ($\alpha = 0.88$, CR = 0.884, AVE = 0.737). The Perceived Enjoyment construct shows moderate reliability based on alpha = 0.73, composite reliability = 0.793, and average variance extracted = 0.575. The perceived electronic word of mouth demonstrates strong convergent validity as shown by its metrics ($\alpha = 0.83$, CR = 0.841, AVE = 0.621). The constructs Perceived Emotional Value and Usefulness demonstrate strong reliability coefficients of 0.87 and 0.80 respectively while maintaining AVE values exceeding 0.50. The Perceived Quality metric maintains acceptable standards with $\alpha = 0.71$ and AVE of 0.488. Overall, the measurement model is robust.

5.3. Validity Assessment Table (HTMT and Fornell-Larcker Criterion)

The measurement model demonstrated reliability and validity after factor and cross-loading analysis through convergent (CR > 0.70; AVE > 0.50) and discriminant validity tests employing MSV and MaxR(H) (Fornell & Larcker, 1981; Hair et al., 2010; Henseler et al., 2015). These tests validate accurate, reliable variable relationships.

Table 3.

Convergent and Discriminant validity

Con	CR	AVE	MSV	MaxR(H)	PRI	PRE	PWM	PEV	PUS	PQU	PPR	ATT	PUI
PRI	0.884	0.737	0.485	0.884	1.000								
PRE	0.793	0.575	0.479	0.793	0.784	1.000							
PWM	0.841	0.621	0.393	0.841	0.653	0.727	1.000						
PEV	0.798	0.575	0.410	0.798	0.667	0.698	0.755	1.000					
PUS	0.835	0.616	0.441	0.835	0.670	0.689	0.744	0.754	1.000				
PQU	0.725	0.488	0.441	0.725	0.654	0.643	0.681	0.673	0.662	1.000			
PPR	0.815	0.621	0.479	0.815	0.701	0.710	0.702	0.702	0.692	0.701	1.000		
ATT	0.805	0.561	0.499	0.805	0.689	0.695	0.694	0.695	0.694	0.689	0.702	1.000	
PUI	0.688	0.474	0.410	0.688	0.664	0.676	0.672	0.663	0.671	0.664	0.674	0.661	1.000

The research evaluates construct reliability and validity through the metrics of Composite Reliability (CR), Average Variance Extracted (AVE), Maximum Shared Variance (MSV), and MaxR(H) as shown in Table 3. The study shows strong internal consistency for all constructs because their CR values surpass 0.70 according to Nunnally & Bernstein (1994). The construct PRI demonstrates strong reliability with a CR of 0.884 and AVE of 0.737 which means it accounts for more than 73% of the variance according to Fornell & Larcker (1981). Perceived Enjoyment (PRE) and Perceived eWOM (PWM) both show construct reliability coefficients of 0.793 and 0.841 respectively and average variance extracted values of 0.575 and 0.621. The validation of discriminant validity occurs when all constructs show AVE values exceeding their MSV according to Hair et al. (2010) criteria, and MaxR(H) measures correlate with CR thereby reinforcing reliability. The measurement model displays strong reliability and valid performance.

5.4. Model fit indices

The research team evaluated SEM model fit indices to determine how well the model matched the observed data and variable relationships (Byrne, 2016). The essential fit indicators for the SEM analysis were CMIN/DF together with CFI, TLI, SRMR and RMSEA according to Kline (2015) and Hu & Bentler (1999). The model demonstrates acceptable fit with CMIN/DF values between 1 and 3 alongside CFI/TLI greater than 0.90 while SRMR remains under 0.08 and RMSEA stays below 0.06. These indices boost robustness and credibility.

Table 4.

Model Fit Measures

Measure	Estimate	Threshold	Citation
CMIN	728.746	--	(Byrne, 2010)
DF	288	--	(Kline, 2015)
CMIN/DF	2.530	Between 1 and 3	(Marsh & Hocevar, 1985)
CFI	0.922	> 0.95	(Hu & Bentler, 1999)
NFI	0.960	> 0.95	(Bentler & Bonett, 1980)
TLI	0.955	> 0.95	(Tucker & Lewis, 1973)

GFI	0.920	> 0.90	(Jöreskog & Sörbom, 1984)
SRMR	0.045	< 0.08	(Hu & Bentler, 1999)
RMSEA	0.068	< 0.06	(Steiger, 1990)
PClose	0.000	> 0.05	(Jöreskog & Sörbom, 1993)

The research team used model fit indices from Table 5 to determine how well the SEM model performed. The CMIN/DF value of 2.530 demonstrates good model fit according to Marsh & Hocevar (1985). The CFI value stands at 0.922 while both NFI and TLI show satisfactory fit levels at 0.960 and 0.955 respectively as per Bentler & Bonett (1980) and Tucker & Lewis (1973). The SRMR value of 0.045 and the RMSEA score of 0.058 fulfil the standards established by Hu & Bentler (1999).

4.5. Hypothesis testing

Model fit evaluation works together with direct effects hypothesis testing to reveal the impact of independent variables on dependent variables through correlation analysis. Standardized regression coefficients demonstrate both the strength and directionality of relationships (Kline, 2015) while statistically significant results require a critical ratio exceeding 1.96 and a p-value less than 0.05 (Schumacker & Lomax, 2010). Direct effects testing explores how risk perceptions, along with usefulness and emotional value, affect consumer purchasing behaviour in social fashion commerce, which supports digital marketing strategies and system development through empirical evidence (Hair et al., 2010).

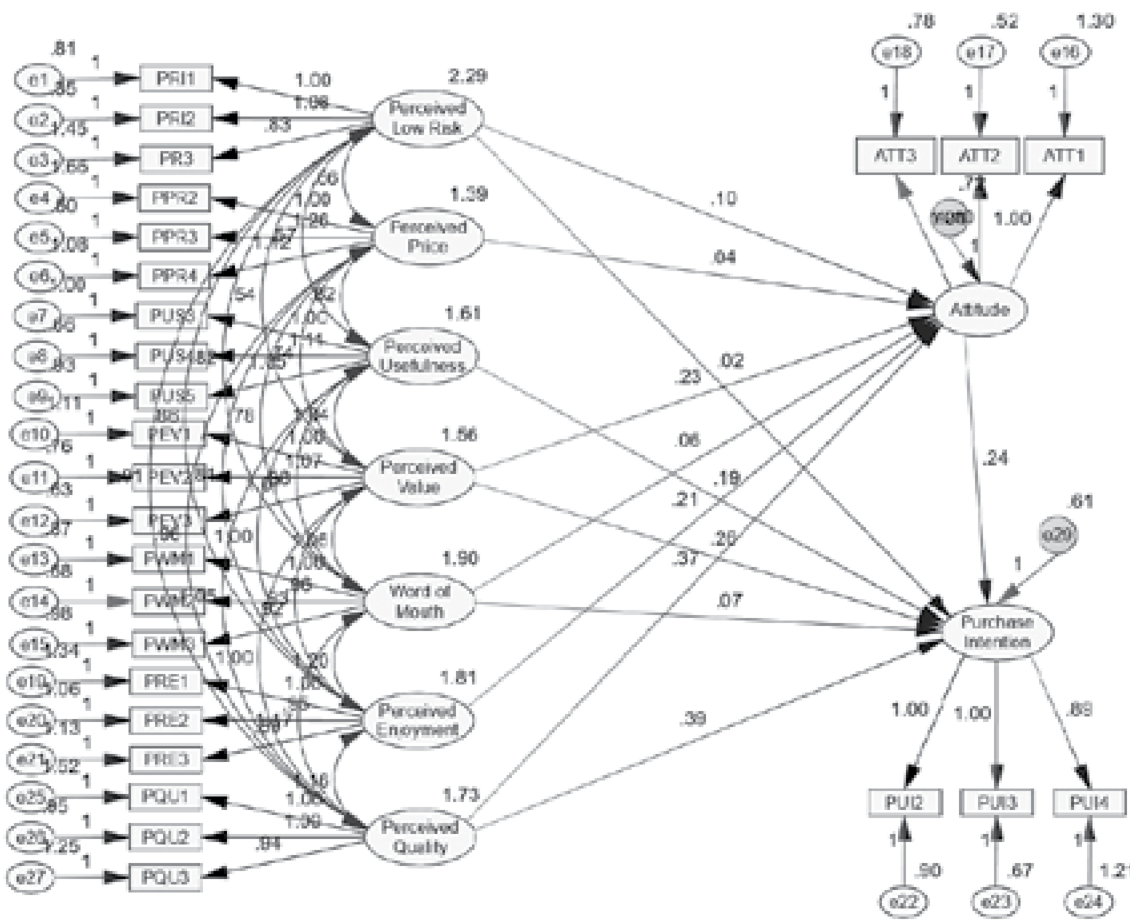

Figure 2

Path analysis

Table. 5:

Hypothesis Testing

Hypothesis	Estimate	S.E.	C.R.	P	Decision
Purchase Intention <--- Perceived Risk (PRI)	0.005	0.046	0.099	0.921	Rejected
Purchase Intention <--- Perceived Usefulness (PUS)	0.154	0.078	1.973	0.049	Accepted
Purchase Intention <--- Perceived Emotional Value (PEV)	0.274	0.083	3.323	0.003	Accepted
Purchase Intention <--- Perceived eWOM (PWM)	-0.138	0.075	-1.832	0.167	Rejected
Purchase Intention <--- Perceived Quality (PQU)	0.355	0.101	3.509	0.001	Accepted
Purchase Intention <--- Attitude Towards SNS (ATT)	0.200	0.080	2.491	0.013	Accepted
Purchase Intention <--- Perceived Enjoyment (PRE)	0.194	0.085	2.278	0.023	Accepted

The results of hypothesis testing on direct effects impacting Purchase Intention in social commerce are shown in Table 5. The analysis demonstrates that perceived risk fails to affect purchasing decisions which suggests that product quality and privacy concerns hold minimal sway. Purchase intent rises significantly when consumers find products useful and shopping enjoyment enhances decision-making through positive emotional value. The research reveals that perceived eWOM exerts no meaningful impact on purchase intention which suggests online reviews fail to influence purchasing choices here. Purchase likelihood heightens when consumers display positive SNS attitudes together with strong perceived enjoyment. Consumer purchases are driven by usefulness along with emotional value and quality and also SNS attitude plus enjoyment while perceived risk and eWOM show no significant effect (Figure 3).

4.6. Mediation analysis

Researchers conducted mediation analysis to examine if a mediator explains the link between independent and dependent variables. For example, perceived usefulness impacts purchase intention via SNS attitude. Bootstrapping with 5000 resamples avoids normality assumptions; a 95% CI excluding zero and $p < 0.05$ confirms significance. Partial and full mediation emerged.

Table 6:

Mediation Table

Hyp	Path	Total Effect (β)	Sig.	Indirect Effect (β)	Sig.	Direct Effect (β)	Sig.	Type
H8a	Perceived Quality (PQU) -> Purchase Intention (PUI)	0.431	0.007	0.076	0.066	0.355	0.034	Partial
H8b	Perceived Enjoyment (PRE) -> Purchase Intention (PUI)	0.237	0.070	0.043	0.084	0.194	0.118	Partial
H8c	Perceived eWOM (PWM) -> Purchase Intention (PUI)	-0.152	0.151	-0.014	0.327	-0.138	0.178	No
H8d	Perceived Emotional Value (PEV) -> Purchase Intention (PUI)	0.320	0.008	0.046	0.076	0.274	0.016	Partial
H8e	Perceived Usefulness (PUS) -> Purchase Intention (PUI)	0.154	0.169	0.000	--	0.154	0.169	Direct Only

H8f	Perceived Price (PPR) -> Purchase Intention (PUI)	0.005	0.744	0.005	0.744	0.000	--	No
H8g	Perceived Risk (PRI) -> Purchase Intention (PUI)	0.025	0.663	0.021	0.120	0.005	0.879	No
H8h	Attitude Towards SNS (ATT) -> Purchase Intention (PUI)	0.200	0.141	0.000	--	0.200	0.141	Direct Only

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5. Discussions

Mediation analysis combined with hypothesis testing reveals key factors driving purchase intentions in social network service fashion shopping while building on past academic research. The study demonstrates significant effects of perceived usefulness (β = 0.154, p = 0.049), perceived emotional value (β = 0.274, p = 0.003), perceived quality (β = 0.355, p = 0.001), attitude toward SNSs (β = 0.200, p = 0.013), and perceived enjoyment (β = 0.194, p = 0.023) on purchase intentions which align with prior research suggesting these elements are key drivers of social commerce activities (Shin & Jeong, 2020; Djafarova & Bowes, 2020). The research demonstrates that emotional attachment, along with brand credibility and user satisfaction, are vital elements for online fashion shopping (Kaplan & Haenlein, 2019). eWOM and perceived risk demonstrate no substantial effects (β = 0.005, p = 0.921; β = -0.138, p = 0.167), which reveals consumers place more emphasis on brand messaging and visual marketing strategies. The mediation analysis reveals that perceived quality, enjoyment, and emotional value partially mediate the relationship between SNS attitude and purchase intent demonstrating that SNS attitude affects purchase intent but not exclusively. The direct influence of perceived usefulness together with SNS attitude underscores how effective trust-based shopping interactions can be (Park & Kim, 2020). The marginal impact of perceived price (β = 0.005, p = 0.744) shows that convenience and emotional connection take precedence over cost which directs brands to focus on quality and engagement strategies.

6. Theoretical Implications and Managerial implications

6.1. Theoretical Implications

The research broadens existing frameworks of technology adoption models and theoretical understandings of online consumer behavior within the context of SNS fashion shopping. The research verified emotional value and enjoyment while examining social media attitudes through TAM and TPB as well as Social Exchange Theory (Shin & Jeong, 2020). According to research by Garcia and Sokolova (2020), consumer worries are lessened more effectively through influencer endorsements and community engagement than through standard security measures. The reduced influence of eWOM reveals a trend toward brand-centered experiences which opens new discussions about digital trust and impulse purchasing together with AI-driven personalization within social commerce (Sokolova & Kefi, 2020).

6.2. Practical Implications

These insights provide valuable tools for fashion brands to sharpen their strategies along with digital marketers and SNS developers who can also improve their approaches. Since perceived enjoyment along with emotional connections drive consumer interest, brands need to implement immersive storytelling techniques and interactive shopping experiences together with AI-based personalisation according to Park & Kim (2020). Influencer partnerships combined with AR trials and live commerce strengthen brand loyalty while increasing spontaneous purchases. Secure transactions combined with transparent communication establish trust in social networking services (Perez & Gutierrez, 2020). Due to Indian SNS consumers placing greater importance on brand experience and convenience than price and risk considerations companies need to adopt value-centered engagement strategies (Amin & Naqvi, 2020). The use of improved AI-driven suggestions together with predictive analytics leads to better conversion rates.

7. Limitations and Scope for Further Research

While the research provides important findings about fashion shopping through SNS platforms it needs additional studies to overcome its current constraints. Analyzing only Indian consumers restricts the study's applicability to markets that have distinct cultural dynamics and various economic conditions and digital platform usage (Hajli, 2015). Subsequent studies ought to compare different cultural contexts to understand purchase motivations across multiple SNS platforms according to Shin & Jeong (2020). The use of self-reported data can create bias according to Podsakoff et al. (2003), but the integration of behavioral tracking techniques alongside experimental methods would produce more accurate results. Future research needs to explore moderating variables and critically evaluate the rise of AR technology, virtual influencers and AI chatbots (Djafarova & Bowes, 2020; Park & Kim, 2020).

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