ADVANCE SOCIAL SCIENCE ARCHIVE JOURNAL
Available Online: https://assajournal.com
Vol. 05 No. 01. Jan-March 2026.Page#.3989-4009
Print ISSN: 3006-2497 Online ISSN: 3006-2500
Platform & Workflow by: Open Journal Systems

Determinants of Consumer Purchase Intention on Community E-Commerce Platforms: A Stimulus-Organism-Response Analysis of a Collectivist Developing Market

Sana Saleem
Mohammad Ali Jinnah University, Karachi, Pakistan
sanasaleem567@gmail.com
Amir Adam
Mohammad Ali Jinnah University, Karachi, Pakistan
amir.adam@jinnah.edu.pk

Abstract
Community e-commerce, where buying is embedded in social interaction, peer discussion, and influencer endorsement, has become one of the fastest growing retail channels in emerging economies. Yet the psychological process that converts social exposure into a decision to buy remains thinly studied outside Western and East Asian settings. Drawing on the Stimulus-Organism-Response (SOR) framework, this study treats influencer credibility, social media content quality, and online community trust as social stimuli, perceived value as the organism, and purchase intention as the response, and it tests whether perceived value mediates each stimulus-to-intention relationship. Survey data were gathered from 386 active community e-commerce users aged 25 to 40 in Pakistan and analysed with partial least squares structural equation modelling (PLS-SEM) using 5,000 bootstrap resamples in SmartPLS 4. All seven hypotheses were supported. Influencer credibility exerted the strongest effect on perceived value, ahead of online community trust and content quality, and perceived value was in turn the strongest single predictor of purchase intention. Perceived value partially transmitted the effect of each stimulus; because the direct paths remained significant, the mediation was complementary rather than full. The model accounted for meaningful variance in perceived value ($R^2 = 0.366$) and purchase intention ($R^2 = 0.416$). The study extends the SOR framework to a collectivist developing market, positions perceived value as a genuine but non-exclusive channel between social cues and intention, and offers direction for influencer selection, content strategy, and community trust infrastructure. Psychometric limitations of the shortened measures are acknowledged and addressed.

Keywords: *community e-commerce; influencer credibility; social media content quality; online community trust; perceived value; purchase intention; Stimulus-Organism-Response model; PLS-SEM; Pakistan*

1. Introduction

Over the past decade the way people find and buy products online has changed in a manner that runs deeper than the arrival of new platforms. Shopping has moved out of the static catalogue and into the social feed, where goods are discovered, debated, and bought inside streams of user-generated content, peer reviews, and influencer endorsement (Appel, Grewal, Hadi, & Stephen, 2020). This fusion of commerce and social interaction is now widely described as community e-commerce. It is not an ordinary online store with a comment box attached. The community, the conversation, and the sense of belonging form part of the product experience rather than a decoration on top of it.

The shift is most visible among younger consumers, who increasingly treat peer recommendation, community discussion, and influencer opinion as their first source of pre-purchase information (Lin & Shen, 2023; Kumar & Gupta, 2021). A recommendation from a person who appears sincere tends to carry more weight than a polished advertisement, and this preference is consistent across a range of cultures and product categories. The practical consequence for firms is considerable, because the levers that shape a purchase are no longer confined to price and placement but extend to who is speaking, how the content is made, and whether the surrounding community is trusted.

Pakistan offers a particularly informative setting in which to study these mechanisms. Smartphone adoption has risen quickly, the cost of mobile data has fallen, and social media has become part of daily routine, especially for adults between 25 and 40 years of age. The Pakistan Telecommunication Authority (2024) estimates an online population of roughly 45 to 50 million, which places the country among the fastest growing digital consumer markets in South Asia. Community platforms such as Daraz Live, TikTok Shop, Instagram Shops, and Facebook Marketplace have become a normal route to discovering and buying products for the urban, connected middle class. Because Pakistan is a collectivist society with strong reliance on social proof, high uncertainty avoidance, and family-centred decision making, the influence of peers and communities on buying is likely to be pronounced, which makes the market a strong test case for social-commerce theory.

Despite this growth, empirical understanding lags well behind practice, and three gaps stand out. The first is geographic and cultural. Most evidence on digital consumer behaviour comes from Western Europe, North America, or East Asia, where trust norms and institutional guarantees differ substantially from those in Pakistan, so findings do not transfer cleanly (Sheth, 2020; Lim, Radzol, Cheah, & Wong, 2017). The second is the absence of an integrated model. Influencer credibility, content quality, and community trust have each been examined in isolation, yet few studies estimate their combined contribution to value and intention within a single framework (Lou, Tan, & Chen, 2019; Zhang, Liu, & Chen, 2022). The third concerns mechanism. It is not enough to know that social cues matter; managers need to know how they matter, that is, through what psychological state a social cue is turned into a willingness to buy. The role of perceived value as that intervening state has rarely been tested in the community e-commerce context of a developing collectivist market.

This study addresses the three gaps together. Using the Stimulus-Organism-Response framework (Mehrabian & Russell, 1974; Jacoby, 2002), it models influencer credibility, social media content quality, and online community trust as stimuli, perceived value as the organism, and purchase intention as the response, and it estimates both the direct effects of the stimuli on intention and their indirect effects through perceived value. The model is tested with partial least squares structural equation modelling on survey responses from 386 active community e-commerce users in Pakistan.

The contribution is threefold. Theoretically, the paper extends and validates an SOR-based account of community e-commerce in an under-researched, Muslim-majority, collectivist developing market, and it shows that perceived value functions as a genuine but non-exclusive channel through which several distinct social stimuli are converted into buying intention. Empirically, it establishes the relative weight of the three stimuli in this setting, with influencer credibility emerging as the strongest driver of value. Practically, it offers evidence-based guidance for influencer selection, content investment, and community trust infrastructure, and it speaks to policy questions about disclosure and review integrity. The remainder of the paper reviews the theory and develops the hypotheses, describes the method, reports the results, discusses their implications, and closes with limitations and directions for future work.

2. Theoretical Background and Hypothesis Development

2.1 The Stimulus-Organism-Response Framework

The Stimulus-Organism-Response model of Mehrabian and Russell (1974) provides the theoretical spine of this study. Its central claim is straightforward but consequential. Environmental stimuli do not act on behaviour directly. They first generate an internal state within the organism, and that state, once formed, gives rise to an observable response (Jacoby, 2002). The model therefore replaces the stimulus-response determinism of classical behaviourism with a cognitive and evaluative account in which the consumer's internal processing is the decisive link between what is encountered and what is done.

The framework has been applied widely and successfully in digital commerce, where the stimulus is typically a feature of the online environment, the organism is a cognitive or affective state such as perceived value or arousal, and the response is an intention or behaviour (Lin & Shen, 2023; Wang & Yu, 2020; Zhang et al., 2022). In the present study the stimuli are influencer credibility, social media content quality, and online community trust; the organism is perceived value, understood as the consumer's overall appraisal of benefit relative to cost; and the response is purchase intention. The design assumes that the path from stimulus to intention runs through perceived value, so that a social cue influences the decision to buy by first shaping how much the offering is judged to be worth.

2.2 Community E-Commerce and Perceived Value

Community e-commerce is a digitally mediated form of shopping in which social interaction, peer exchange, and community participation are integral to the transaction (Wang & Yu, 2020). Platforms such as Instagram Shops, TikTok Shop, and Facebook Groups have evolved into full commerce environments where user-generated content, influencer reviews, live product demonstrations, and peer feedback drive attention and shape decisions (Appel et al., 2020; Kumar & Gupta, 2021). The change is qualitative rather than cosmetic. A fixed catalogue is replaced by product information that is created, evaluated, and circulated across peer and influencer networks, and increasingly through live streaming in which a seller answers questions in real time while other viewers add commentary and social proof (Lin & Shen, 2023).

A recurring finding in this literature is that consumers consult online communities before buying and that they do so to reduce uncertainty and to compare their own judgments against those of others (Hajli, 2015; Cheung & Thadani, 2012). Social comparison provides one explanation, since community content gives the consumer an additional reference point against which to test a preference (Vogel, Rose, Roberts, & Eckles, 2014). In a collectivist culture the pull of the reference group is stronger still, and social validation carries particular force. What unites these strands is that the social features of the platform are not valued for their own sake but for the sense of worth they help the consumer construct. Perceived value is therefore the natural organism variable through which the stimuli of community e-commerce are expected to operate.

2.3 Influencer Credibility and Perceived Value

Influencer credibility refers to the consumer's perception of an influencer's trustworthiness, expertise, authenticity, and appeal (Lou & Yuan, 2019). The construct draws on Source Credibility Theory (Hovland, Janis, & Kelley, 1953), which holds that the knowledge and trustworthiness of a source shape how persuasive its message will be. When an influencer is seen as credible, the endorsement is processed more readily and is more likely to be acted upon, because a trusted recommendation serves as a quality signal that reduces information asymmetry and lowers perceived risk (Spence, 1973; Erdem & Swait, 2004).

The link between credibility and value is likely to be especially strong in Pakistan, where formal guarantees of product quality and consumer protection are comparatively weak, so a trusted human voice does more of the reassurance work. Evidence from neighbouring Southeast Asian markets supports this reasoning. Lim et al. (2017) found that trustworthiness and authenticity related most strongly to downstream outcomes and that credibility influenced intention through evaluative states rather than directly. Casalo, Flavian, and Ibanez-Sanchez (2020) reported that authenticity, more than reach, produced genuine perceptions of value. These findings suggest that credibility raises the perceived worth of an endorsed offering before it raises any intention to buy it. Accordingly:

H1. Influencer credibility has a positive effect on perceived value.

2.4 Social Media Content Quality and Perceived Value

Social media content quality captures several attributes of the material a consumer encounters, including visual appeal, accuracy and completeness of information, contextual relevance, capacity to engage, and narrative consistency (Ashley & Tuten, 2015; Tafesse & Wood, 2021). Where credibility is a property of the source, quality is a property of the message. The distinction matters theoretically because the Elaboration Likelihood Model (Petty & Cacioppo, 1986) proposes that persuasion can proceed through a central route of careful argument evaluation or a peripheral route of quick reliance on cues, and content quality feeds the central route by giving the consumer the substance needed to reason about an offering.

Tafesse and Wood (2021) distinguished informational, visual, entertainment, interactive, and brand dimensions of content, each engaging the audience in a different way. Informative material helps consumers build an accurate mental model of a product; strong visuals contribute hedonic and affective value; entertaining and interactive content deepens processing; and consistent brand content sustains coherence across the feed. Zhang et al. (2022) showed that the effect of content quality on intention was largely carried by perceived value, and related work on vlog content reached similar conclusions (Lee & Watkins, 2016; Lin, Bruning, & Swarna, 2019). As feeds fill with competing material and as short vertical video reshapes what content looks like, the decisive factor appears to be whether the content answers a real question about the product rather than how expensive it looks to produce. This reasoning yields:

H2. Social media content quality has a positive effect on perceived value.

2.5 Online Community Trust and Perceived Value

Online community trust is the degree of confidence a consumer places in the information shared by other members of a community. It has cognitive, affective, and behavioural components: a rational judgment of competence and reliability, a sense of goodwill toward fellow members, and a readiness to act on community information when buying. Wang and Yu (2020) found that trust in a social network raised the perceived value of shared information, which in turn raised purchase intention, with value mediating the relationship. Lu, Fan, and Zhou (2016) reported a similar pattern working through perceived usefulness and social support, and a meta-analysis by Cheung and Thadani (2012) identified information trustworthiness as the strongest predictor of the adoption of electronic word of mouth.

Two mechanisms help explain why trust lifts perceived value. Trust reduces cognitive load, since a consumer who trusts the community need not scrutinise every claim to extract what is useful, and it reduces perceived risk, because trusted claims appear more legitimate. Both mechanisms are amplified in Pakistan, where reliance on in-group trust and social endorsement is high. Trust also transfers: confidence in a platform or a respected member tends to extend to the products and content associated with them (Gefen, Karahanna, & Straub, 2003; McKnight, Choudhury, & Kacmar, 2002), and in a densely networked social environment a favourable community judgment can spread quickly and carry social currency beyond any single review. This leads to:

H3. Online community trust has a positive effect on perceived value.

2.6 Perceived Value and Purchase Intention

Perceived value is the consumer's overall assessment of the worth of an offering relative to what must be given up to obtain it (Zeithaml, 1988). It is multidimensional, spanning functional, economic, emotional, and social value (Sweeney & Soutar, 2001), and it sits at the heart of the SOR model as the organism state that integrates external cues and converts them toward a response. Purchase intention, the response in this framework, is the stated likelihood or readiness to buy (Ajzen, 1991; Pavlou & Fygenson, 2006). Intention is the final and most proximal cognitive step before purchase, and meta-analytic evidence confirms a strong association between measured intention and subsequent behaviour (Sheppard, Hartwick, & Warshaw, 1988).

The Theory of Planned Behavior (Ajzen, 1991) offers a complementary reading in which intention follows from attitude, subjective norms, and perceived control. In community e-commerce, credibility and content quality feed the attitudinal component, community trust feeds the normative component, and perceived value can be understood as the consolidated judgment that carries both toward intention. Studies of live-stream and community commerce consistently identify value as the most immediate antecedent of intention (Lin & Shen, 2023; Chan, Cheung, & Lee, 2017; Zhang et al., 2022). Hence:

H4. Perceived value has a positive effect on purchase intention.

2.7 The Mediating Role of Perceived Value

The logic of the SOR model implies that the three stimuli should influence intention primarily by way of perceived value rather than independently of it. There are three grounds for expecting mediation. First, the framework itself specifies that stimuli activate an organism state before any response, so a consumer who encounters credible influencers, strong content, and a trusted community still forms an intention only after judging the offering to be worthwhile. Second, dual-route persuasion theory holds that processing culminates in an overall evaluation rather than an immediate act (Petty & Cacioppo, 1986). Third, the evidence is convergent: the effect of credibility on intention weakened once value was modelled (Lou & Yuan, 2019), and the same held for content quality (Zhang et al., 2022) and for community trust (Wang & Yu, 2020). These considerations lead to three mediation hypotheses:

H5a. Perceived value mediates the relationship between influencer credibility and purchase intention.

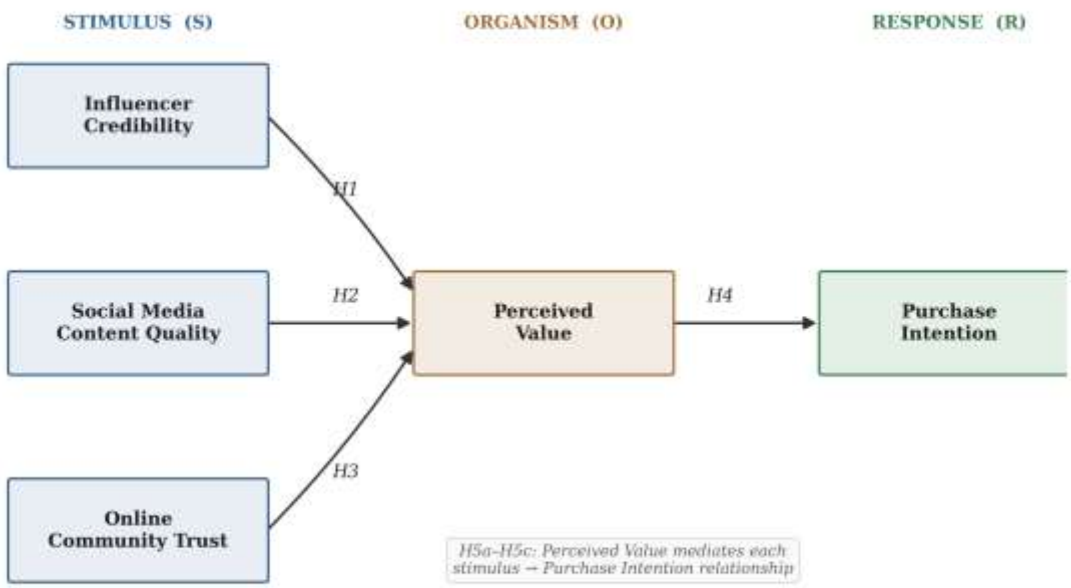
H5b. Perceived value mediates the relationship between social media content quality and purchase intention.

H5c. Perceived value mediates the relationship between online community trust and purchase intention.

Figure 1 summarises the conceptual model. The three stimuli are hypothesised to raise perceived value, perceived value is hypothesised to raise purchase intention, and perceived value is hypothesised to carry the influence of each stimulus toward intention.

Figure 1

Conceptual model based on the Stimulus-Organism-Response framework



Note. Solid arrows denote the hypothesised stimulus-to-value and value-to-intention paths (H1 to H4). Perceived value is proposed to mediate each stimulus-to-intention relationship (H5a to H5c).

3. Method

3.1 Research Design and Sample

The study adopts a positivist, quantitative, and cross-sectional design, on the assumption that consumer perceptions and intentions can be measured objectively and their relationships tested statistically (Saunders, Lewis, & Thornhill, 2019; Creswell & Creswell, 2018). A descriptive correlational approach suits the aim, which is to establish the nature, direction, and strength of relationships among defined constructs rather than to manipulate them experimentally (Hair, Risher, Sarstedt, & Ringle, 2019). Data were collected at a single point in time, an approach well matched to attitudes and intentions in a fast-moving digital market.

The target population comprised active users of community e-commerce platforms in Pakistan, defined as consumers who follow influencers and engage with buying communities on TikTok Shop, Instagram Shops, Facebook Marketplace, and Daraz Live. The study focused on adults between 25 and 40 years of age with a monthly income between PKR 100,000 and PKR 300,000, a segment chosen for its digital literacy, disposable income, and central role in the growth of community commerce. Because a complete sampling frame for this population does not exist, non-probability purposive sampling was used, with respondents screened on age and on a recent purchase decision informed by an influencer or a buying community, so that every participant had genuine and recent experience of the phenomenon (Saunders et al., 2019).

A self-administered structured questionnaire was distributed through Google Forms across WhatsApp groups, Facebook communities, Instagram, and LinkedIn, supplemented by a small number of face-to-face responses collected at selected points in Karachi to broaden coverage. Data collection ran for more than six weeks. Of 420 questionnaires distributed, 386 were complete and usable, a response rate of 91.9 percent. The achieved sample satisfies established requirements for PLS-SEM: it comfortably exceeds ten times the largest number of paths directed at any construct, and it is well above both the Krejcie and Morgan (1970) benchmark of 384 for a large population at a 95 percent confidence level and a 5 percent margin of error, and the common minimum of 200 cases for stable estimation.

3.2 Measures

All constructs were measured reflectively with five items each, adapted from validated scales and rated on a five-point Likert scale from 1, strongly disagree, to 5, strongly agree. Influencer credibility was adapted from Lou and Yuan (2019) and Lim et al. (2017); social media content quality from Tafesse and Wood (2021) and Zhang et al. (2022); online community trust from Wang and Yu (2020) and Lu et al. (2016); perceived value from Zeithaml (1988) and Chan et al. (2017); and purchase intention from Ajzen (1991) and Lin and Shen (2023). The five-point format was selected for its established reliability in studies of consumer attitudes, its familiarity to respondents in Pakistan, and its suitability for PLS-SEM. Table 1 summarises the operationalisation of the constructs, and the full item wording with individual loadings and item-level descriptives is provided in the Appendix.

Table 1

Operationalisation of study constructs

Construct (role)	Dimensions and indicators	Items	Source
Influencer Credibility (stimulus)	Trustworthiness, expertise, authenticity, appeal, reliability	5	Lou & Yuan (2019); Lim et al. (2017)
Social Media Content Quality (stimulus)	Visual appeal, informativeness, clarity, engagement, relevance	5	Tafesse & Wood (2021); Zhang et al. (2022)
Online Community Trust (stimulus)	Reliability, unbiased information, confidence, participation	5	Wang & Yu (2020); Lu et al. (2016)
Perceived Value (organism)	Benefit-cost appraisal, functional, emotional, epistemic value	5	Zeithaml (1988); Chan et al. (2017)
Purchase Intention (response)	Likelihood to buy, readiness to follow recommendations	5	Ajzen (1991); Lin & Shen (2023)

Note. All items were measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

3.3 Analytical Approach

Data were screened and profiled in SPSS 26, and the measurement and structural models were estimated in SmartPLS 4. Partial least squares structural equation modelling was chosen over covariance-based methods because it accommodates non-normal data, performs well with the moderate sample and the shortened reflective scales used here, and is well suited to models oriented toward prediction and theory extension (Hair et al., 2019). Analysis proceeded in five stages: descriptive statistics for all items; assessment of common method bias; evaluation of the measurement model through indicator loadings, internal consistency, convergent validity, and discriminant validity; estimation of the structural model and testing of the direct hypotheses; and a formal mediation analysis. Significance for all path and mediation estimates was obtained through bootstrapping with 5,000 resamples, and mediation was evaluated using bias-corrected 95 percent confidence intervals.

4. Results

4.1 Sample Profile and Descriptive Statistics

Table 2 reports the profile of the 386 respondents. The gender split was 60.1 percent male and 39.9 percent female. By design, all respondents fell within the target age band of 25 to 40 years and the income band of PKR 100,000 to 300,000. The sample was highly educated, with 92.2 percent holding a bachelor's or master's degree, a profile consistent with the digital literacy that community commerce demands.

Table 2

Demographic profile of respondents (n = 386)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	232	60.1
	Female	154	39.9
Age	25 to 40 years	386	100.0
Education	High school	11	2.8
	Intermediate / diploma	2	0.5
	Professional (ACCA / DAE)	7	1.8
	Bachelor's degree	168	43.5
	Master's degree	188	48.7
	PhD / doctorate	10	2.6
Monthly income (PKR)	100,000 to 300,000	386	100.0

Note. Compiled in SPSS 26.

Item means ranged from 2.63 to 3.59. Skewness values were all below 1.0 in absolute terms and kurtosis values below 1.1, well inside the thresholds of $|\text{skewness}| < 2.0$ and $|\text{kurtosis}| < 7.0$ that indicate distributions suitable for analysis (Hair et al., 2019). A notable pattern emerged in the construct-level ratings. Items measuring content quality and community trust attracted the highest agreement, while items measuring influencer credibility attracted the lowest, with several credibility items averaging below the scale midpoint. Consumers therefore endorsed influencer credibility least strongly on average, a point that becomes important when read against the structural results reported below.

4.2 Common Method Bias

Because the data were self-reported and collected through a single instrument, common method bias was assessed. Harman's single-factor test returned a first factor explaining 21.4 percent of the variance, well under the 50 percent threshold of concern (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Sampling adequacy was confirmed by a Kaiser-Meyer-Olkin value of 0.874, above the recommended 0.60, and Bartlett's test of sphericity was significant (approximately $\chi^2 = 1584.5$, df = 300, $p < 0.001$). Predictor and outcome items were separated in the instrument as a procedural safeguard, and all inner-model variance inflation factors were far below the conservative ceiling of 3.3, with a maximum of 1.58, which indicates that multicollinearity and any method bias arising from it are not a concern (Hair et al., 2019).

4.3 Measurement Model

The measurement model was evaluated for indicator reliability, internal consistency, convergent validity, and discriminant validity, with results in Table 3. Standardised outer loadings ranged from 0.55 to 0.67. Although these fall below the ideal threshold of 0.70, all items were retained because each contributed to the theoretical content of its construct and removing indicators would have narrowed content coverage without materially improving validity (Hair et al., 2019). Composite reliability exceeded 0.70 for all five constructs, ranging from 0.729 to 0.760, which supports internal consistency. Cronbach's alpha ranged from 0.537 to 0.608, below the conventional 0.70; this is a recognised property of short scales with moderate inter-item loadings, and composite reliability was therefore treated as the primary reliability index because it weights indicators by their loadings. Average variance extracted ranged from 0.351 to 0.389. These values are below the 0.50 benchmark of Fornell and Larcker (1981), although Hair et al. (2019) note that an average variance extracted below 0.50 can be acceptable when composite reliability comfortably exceeds 0.60, a condition met by every construct. The below-threshold alpha and average variance extracted values are acknowledged as a limitation of the measurement and are discussed in Section 6.

Table 3

Construct reliability and convergent validity (n = 386)

Construct	Loading range	Cronbach's α	CR	AVE
Influencer Credibility	0.56 to 0.65	0.557	0.737	0.360
Social Media Content Quality	0.55 to 0.66	0.552	0.735	0.358
Online Community Trust	0.57 to 0.66	0.608	0.760	0.389
Perceived Value	0.56 to 0.66	0.537	0.729	0.351
Purchase Intention	0.58 to 0.67	0.587	0.752	0.378
Recommended threshold	**≥ 0.70 (ideal)**	**≥ 0.70**	**≥ 0.70**	**≥ 0.50**

Note. CR = composite reliability; AVE = average variance extracted. Thresholds follow Hair et al. (2019).

Discriminant validity was examined with the heterotrait-monotrait ratio of correlations (Table 4). Under the Fornell-Larcker criterion the constructs were distinct, since each construct's correlations were below the square root of its average variance extracted. Against the stricter heterotrait-monotrait threshold of 0.85 (Henseler, Ringle, & Sarstedt, 2015), however, five construct pairs exceeded the criterion, most prominently perceived value and purchase intention at 0.962. This indicates that several constructs do not attain full discriminant separation under the heterotrait-monotrait test, which is a genuine limitation of the measurement model. The two most overlapping constructs, perceived value and purchase intention, are theoretically adjacent but conceptually distinct within the SOR sequence: perceived value is the organism's internal appraisal of worth, whereas purchase intention is a conative readiness to act, and the two were measured with separate established scales. They are retained as distinct constructs on these grounds, and every affected relationship is interpreted with corresponding caution.

Table 4

Heterotrait-monotrait (HTMT) ratios (n = 386)

Construct	IC	CQ	OCT	PV	PI
Influencer Credibility (IC)		0.809	0.644	**0.887**	0.818
Social Media Content Quality (CQ)	0.809		**0.869**	**0.869**	**0.876**
Online Community Trust (OCT)	0.644	**0.869**		0.833	0.799
Perceived Value (PV)	**0.887**	**0.869**	0.833		**0.962**
Purchase Intention (PI)	0.818	**0.876**	0.799	**0.962**	

Note. IC = influencer credibility; CQ = content quality; OCT = online community trust; PV = perceived value; PI = purchase intention. Recommended threshold HTMT < 0.85 (Henseler et al., 2015). Values shown in bold exceed this threshold and are treated as a measurement limitation (see Section 6). Diagonal cells are omitted.

4.4 Structural Model and Hypothesis Testing

The structural model was estimated with 5,000 bootstrap resamples, and the direct path results appear in Table 5. All four direct hypotheses were supported. Influencer credibility had the strongest effect on perceived value ($\beta = 0.296$, $t = 6.36$, $p < 0.001$), followed by online community trust ($\beta = 0.261$, $t = 5.43$, $p < 0.001$) and social media content quality ($\beta = 0.207$, $t = 4.15$, $p < 0.001$), supporting H1 through H3. Perceived value in turn predicted purchase intention ($\beta = 0.275$, $t = 5.60$, $p < 0.001$), supporting H4. The model explained 36.6 percent of the variance in perceived value and 41.6 percent of the variance in purchase intention, both above the 0.26 benchmark for substantial explanatory power (Hair et al., 2019). Each stimulus also retained a significant direct path to purchase intention when perceived value was included in the model, with coefficients between 0.18 and 0.20, which signals that the mediation is partial rather than full. Figure 2 displays the estimated model.

Table 5

Direct path results, PLS-SEM (bootstrapping, 5,000 resamples, n = 386)

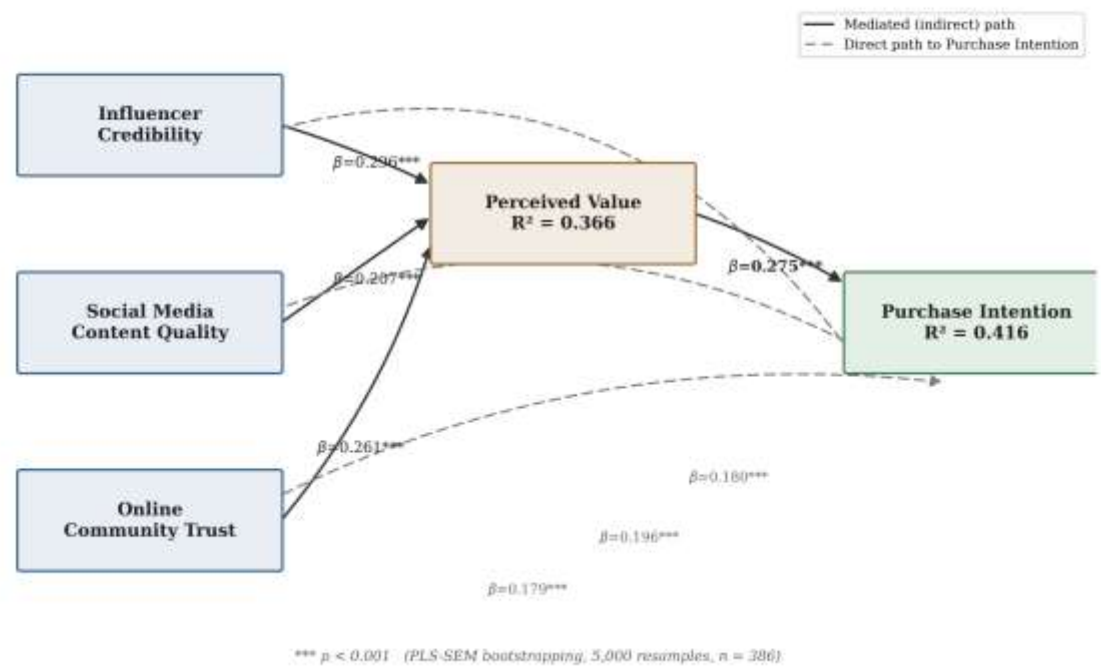
Hyp.	Structural path	β	t	p	Decision
H1	Influencer Credibility → Perceived Value	0.296	6.36	< 0.001	Supported
H2	Social Media Content Quality → Perceived Value	0.207	4.15	< 0.001	Supported
H3	Online Community Trust → Perceived Value	0.261	5.43	< 0.001	Supported

Hyp.	Structural path	β	t	p	Decision
H4	Perceived Value → Purchase Intention	0.275	5.60	< 0.001	Supported
H5a′	Influencer Credibility → Purchase Intention (direct)	0.179	3.81	< 0.001	Significant
H5b′	Social Media Content Quality → Purchase Intention (direct)	0.196	3.98	< 0.001	Significant
H5c′	Online Community Trust → Purchase Intention (direct)	0.180	3.75	< 0.001	Significant

Note. The primed rows report the direct stimulus-to-intention paths with perceived value in the model. All remained significant, which, together with the indirect effects in Table 6, indicates complementary partial mediation (Zhao, Lynch, & Chen, 2010).

Figure 2

Estimated structural model with standardised path coefficients and explained variance



*Note. Solid arrows are mediated paths through perceived value; dashed arrows are direct paths to purchase intention. *** p < 0.001. Estimates from PLS-SEM bootstrapping with 5,000 resamples (n = 386).*

4.5 Mediation Analysis

Mediation was tested through the indirect effects reported in Table 6, using 5,000 bootstrap resamples with bias-corrected 95 percent confidence intervals. All three indirect effects were significant, since none of the intervals contained zero: influencer credibility to perceived value to purchase intention (β = 0.081, 95% CI [0.049, 0.123]); content quality to perceived value to purchase intention (β = 0.057, 95% CI [0.028, 0.100]); and community trust to perceived value to purchase intention (β = 0.072, 95% CI [0.039, 0.116]).

Perceived value therefore mediates each relationship, supporting H5a through H5c. Because each direct path also remained significant, the pattern is one of complementary partial mediation rather than full mediation (Zhao et al., 2010).

This combination of a significant indirect effect alongside a significant, same-signed direct effect is what Zhao et al. (2010) term complementary mediation, and it is recognised as a valid and informative mediation outcome in partial least squares path modelling (Nitzl, Roldán, & Cepeda, 2016; Hair et al., 2019). It indicates that perceived value transmits a meaningful portion of each stimulus's influence while a direct channel remains open, which is a substantive theoretical finding rather than a weak or failed mediation. Figure 3 makes the point visible by decomposing each stimulus's total effect on intention into its direct and indirect components.

Table 6

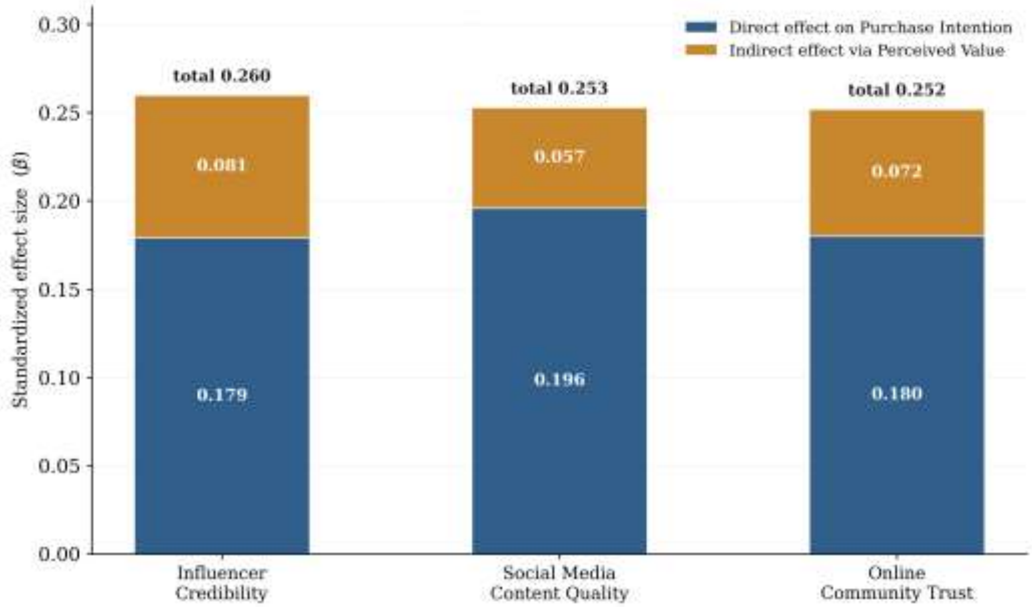
Indirect effects through perceived value (bias-corrected 95% CI, n = 386)

Hyp.	Mediated path (via Perceived Value)	β indirect	CI lower	CI upper	Decision
H5a	Influencer Credibility → PV → Purchase Intention	0.081	0.049	0.123	Supported (partial)
H5b	Social Media Content Quality → PV → Purchase Intention	0.057	0.028	0.100	Supported (partial)
H5c	Online Community Trust → PV → Purchase Intention	0.072	0.039	0.116	Supported (partial)

Note. Confidence intervals from 5,000 bootstrap resamples. No interval includes zero, confirming significant indirect effects.

Figure 3

Decomposition of each stimulus's total effect on purchase intention



Note. Each bar shows the direct effect on purchase intention and the indirect effect transmitted through perceived value, which sum to the total effect. The comparable share carried by the indirect component across all three stimuli illustrates the complementary partial mediation.

Table 7 consolidates the outcome of all seven hypotheses. Every hypothesis was supported, and the three mediation effects were complementary and partial.

Table 7

Summary of hypothesis testing

Hyp.	Relationship	Key result	Decision
H1	IC → PV (+)	β = 0.296, t = 6.36, p < 0.001	Supported
H2	CQ → PV (+)	β = 0.207, t = 4.15, p < 0.001	Supported
H3	OCT → PV (+)	β = 0.261, t = 5.43, p < 0.001	Supported
H4	PV → PI (+)	β = 0.275, t = 5.60, p < 0.001	Supported
H5a	IC → PV → PI	Indirect 0.081, CI [0.049, 0.123]	Supported (partial)
H5b	CQ → PV → PI	Indirect 0.057, CI [0.028, 0.100]	Supported (partial)
H5c	OCT → PV → PI	Indirect 0.072, CI [0.039, 0.116]	Supported (partial)

Note. IC = influencer credibility; CQ = content quality; OCT = online community trust; PV = perceived value; PI = purchase intention.

5. Discussion

5.1 Discussion of Findings

The results support all seven hypotheses and, taken together, tell a coherent story about how social exposure becomes buying intention in community e-commerce. The three social stimuli each raise perceived value, perceived value in turn raises purchase intention, and perceived value carries a meaningful share of each stimulus's influence toward the decision to buy while a direct channel also remains open.

Influencer credibility was the strongest driver of perceived value, which is consistent with signaling theory and with prior work placing the credibility-to-value path at the centre of influencer effectiveness (Spence, 1973; Erdem & Swait, 2004; Lou & Yuan, 2019; Lim et al., 2017). In a market where formal quality assurance is comparatively weak, a trusted endorsement reduces information asymmetry and lowers perceived risk, and so it lifts the net benefit the consumer expects to receive. A striking nuance strengthens this reading. Credibility items attracted the lowest average agreement in the sample, yet credibility carried the greatest structural weight. Consumers appear sceptical of influencers as a group, but when an influencer is judged credible, that judgment does more to shape perceived worth than any other cue. The finding is encouraging for brands working with modest budgets, since it points toward smaller, trusted, authentic voices rather than expensive reach, and toward durable partnerships rather than one-off transactions (Casalo et al., 2020).

Content quality also raised perceived value, in line with dual-route persuasion and with earlier findings that value carries much of the effect of content on intention (Petty & Cacioppo, 1986; Tafesse & Wood, 2021; Zhang et al., 2022). One expectation going in was that in a maturing digital market content quality might overtake credibility, as some Western studies suggest. It did not. Credibility led, community trust followed, and content quality came third. This ordering does not make content unimportant. In a crowded feed, quality is often the price of entry that earns the first moments of attention before credibility and trust can take effect, and weak content can blunt even a trusted voice. The result is about emphasis rather than exclusion: where resources are scarce, credibility has the first claim, but content remains the vehicle through which credibility and trust are expressed.

Online community trust likewise raised perceived value, consistent with trust theory and with prior evidence (Gefen et al., 2003; McKnight et al., 2002; Wang & Yu, 2020; Lu et al., 2016). Its effect sat between those of credibility and content, which suggests that trust often works as an enabling condition. Trust needs something to act on: when a trusted community discusses thin or uninformative content, there is little for that trust to amplify. Read alongside the other two results, this points to a system rather than a set of independent levers. Credibility, content, and trust reinforce one another and are jointly expressed in perceived value, so treating any one in isolation, whether in strategy or in research, risks missing the interplay among them.

Perceived value was the strongest single predictor of purchase intention, which places it at the centre of the model exactly as the SOR framework anticipates (Zeithaml, 1988; Ajzen, 1991; Lin & Shen, 2023). The explained variance in intention, at 41.6 percent, is substantial for a parsimonious model, while the unexplained portion is a reminder that price promotions, urgency, habit, and convenience also shape buying and remain open for future work. The mediation results complete the picture. Each indirect effect through perceived value was significant, and because each direct effect survived, the mediation is complementary and partial rather than full (Zhao et al., 2010; Nitzl et al., 2016). Contemporary guidance cautions against reading a surviving direct effect as weak mediation and instead emphasises the significance and size of the indirect effect itself (Rucker, Preacher, Tormala, & Petty, 2011). On that basis, perceived value is best understood as a real and transferable channel between social cues and intention, though not the only one.

5.2 Theoretical Implications

The study makes three theoretical contributions. First, it extends and empirically validates an SOR-based model of community e-commerce in a Muslim-majority, collectivist, developing market in South Asia, a context largely absent from a literature dominated by Western and East Asian evidence. In doing so it offers a first test of whether the framework's stimulus-organism-response logic holds where trust norms, uncertainty avoidance, and family-centred decision making differ markedly from the settings in which the model was built.

Second, by routing three distinct stimuli through a single mediator it provides convergent evidence for the perceived-value mechanism that no single-stimulus study can supply. That all three indirect paths were significant indicates that perceived value is not an artefact of one particular cue but a genuine psychological process that translates varied social inputs into buying motivation. This strengthens the case for treating value as the organism variable of choice in social-commerce applications of the SOR model.

Third, the study offers a culturally specific account of which cues matter most. The primacy of influencer credibility over content quality, against the expectation that a maturing market would favour production polish, points to the salience of source-based interpersonal cues in a collectivist setting. This invites a comparative and longitudinal agenda that asks whether the relative weight of source, message, and community cues shifts as a market matures and as institutional guarantees strengthen. A quieter methodological contribution accompanies these points: the analysis shows that a rich mediation model can be estimated with PLS-SEM in a developing-market sample that is moderate in size, non-normal, and marked by high inter-construct correlation, conditions under which covariance-based estimation would struggle, which lowers a practical barrier to theory testing in markets where large, clean samples are hard to obtain.

5.3 Managerial and Policy Implications

For marketers and brand managers, the central lesson is that perception drives conversion. Perceived value was both the strongest direct predictor of intention and the conduit for all three stimuli, so managers should attend not only to the stimulus environment but to the value judgments it produces. This argues for a shift away from input metrics such as follower counts and engagement rates toward outcome metrics such as value-perception scores, conversion, and controlled tests of how value is communicated.

Influencer strategy deserves particular attention. Because credibility, and specifically trustworthiness and authenticity, exerted the strongest effect on value, brands should select and evaluate influencers on these qualities rather than on reach alone (Lou & Yuan, 2019; Casalo et al., 2020). Short, low-authenticity campaigns will convert less well than sustained, genuine partnerships in which the influencer understands and values the brand. Content remains a real but secondary lever. Investment should aim at content that tells a credible, specific, and relevant value story across the informational, visual, entertainment, interactive, and brand dimensions identified by Tafesse and Wood (2021), rather than at polish for its own sake.

For platform operators, community trust converts into perceived value, which makes trust infrastructure a direct commercial investment rather than a cost of doing business. Verified-purchase badges, algorithmic curation that suppresses fake and paid reviews, clear disclosure of influencer and brand affiliations, active moderation, and reputation systems that reward trustworthy members all feed the trust that the model links to value and, through value, to intention.

For policymakers and regulators, the same finding carries a consumer-protection dimension. Because community trust anchors perceived value, the integrity of online communities is not only a commercial matter. Undisclosed paid endorsements, fabricated reviews, and manipulated ratings mislead individual buyers and erode confidence in the channel as a whole. Baseline rules requiring influencers to disclose brand relationships, and standards for how reviews are verified and displayed, would protect consumers while supporting the long-term sustainability of community e-commerce in Pakistan. The results provide an evidence base for such measures rather than a mere assertion of their value.

6. Limitations and Future Research

Several limitations qualify these findings and set an agenda for future work. The design is cross-sectional, so while it establishes the strength and pattern of associations it cannot confirm causal direction.

Longitudinal or real-time designs would better capture how attitudes, value judgments, and intentions develop over time and would allow firmer causal inference.

The sample was confined to consumers aged 25 to 40 with a defined income band in urban Pakistan. This segment is central to community commerce, but the results may not generalise to younger or older consumers, who may weigh social cues differently, or to rural consumers, whose access to devices, digital literacy, and purchasing power differ from those of the urban middle class. Future studies should widen the age range, incorporate rural and small-town respondents, and use probability sampling where feasible to strengthen generalisability.

The model included a single mediator and no moderators. Perceived value is a central mechanism, but other mediators and moderating conditions almost certainly shape these relationships. Perceived risk, price value, brand image, satisfaction, and platform quality are candidate additions, and gender, income, education, product category, and prior experience are plausible moderators that could reveal how effects vary across consumer groups and contexts. The study also relied solely on quantitative survey data, which is well suited to testing theorised relationships but less able to surface the motivations and lived experience behind stated attitudes. Combining surveys with interviews or focus groups would enrich the account. Finally, the dependent variable was purchase intention rather than observed behaviour; although intention predicts behaviour well, the two are not identical, and future work using transaction or behavioural data would sharpen the link to actual buying.

The most consequential limitation concerns measurement. The shortened, adapted scales showed limited psychometric strength: outer loadings below the ideal threshold, Cronbach's alpha and average variance extracted below conventional benchmarks, and several heterotrait-monotrait ratios above 0.85, most notably the near-collinear relationship between perceived value and purchase intention. A supplementary exploratory factor analysis did not recover a clean five-factor structure and accounted for only about 40 percent of the total variance, which reinforces rather than resolves these concerns. The structural results should therefore be read as indicative, and a priority for future research is to refine, lengthen, and re-validate the measures before the model is applied further or extended to new settings.

7. Conclusion

This study set out to explain how social exposure is converted into buying intention on community e-commerce platforms in a collectivist developing market. Building on the Stimulus-Organism-Response framework, it modelled influencer credibility, social media content quality, and online community trust as stimuli, perceived value as the organism, and purchase intention as the response, and tested the model with PLS-SEM on 386 active users in Pakistan. All seven hypotheses were supported. The three stimuli each raised perceived value, with influencer credibility the strongest; perceived value was the strongest single predictor of intention; and perceived value partially, and complementarily, mediated every stimulus-to-intention relationship.

The contribution is at once theoretical, empirical, and practical. The paper extends an SOR account of community commerce to an under-studied market, provides convergent evidence that perceived value is a genuine channel linking several social cues to intention, and clarifies the relative weight of source, message, and community cues in a collectivist setting. For practice, it points marketers toward credibility and authenticity, platform operators toward trust infrastructure, and regulators toward disclosure and review integrity, always by way of managing the perceived value that ultimately moves consumers to buy. These conclusions are tempered by the measurement limitations noted above, which mark the clearest path for future work. As the digital economy of Pakistan continues to grow, understanding how community platforms build buying motivation will remain central for everyone who depends on them.

References

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211.

Appel, G., Grewal, L., Hadi, R., & Stephen, A. T. (2020). The future of social media in marketing. Journal of the Academy of Marketing Science, 48(1), 79–95.

Ashley, C., & Tuten, T. (2015). Creative strategies in social media marketing: An exploratory study of branded social content and consumer engagement. Psychology and Marketing, 32(1), 15–27.

Casais, B. (2024). Consumer brand engagement fostered by cause-related marketing in emotional and functional brands. Journal of Nonprofit & Public Sector Marketing. Advance online publication.

Casalo, L. V., Flavian, C., & Ibanez-Sanchez, S. (2020). Influencers on Instagram: Antecedents and consequences of opinion leadership. Journal of Business Research, 117, 510–519.

Chan, T. K., Cheung, C. M., & Lee, Z. W. (2017). The state of online impulse-buying research: A literature analysis. Information and Management, 54(2), 204–217.

Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. Decision Support Systems, 54(1), 461–470.

Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications.

Erdem, T., & Swait, J. (2004). Brand credibility, brand consideration, and choice. Journal of Consumer Research, 31(1), 191–198.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51–90.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24.

Hajli, N. (2015). Social commerce constructs and consumer's intention to buy. International Journal of Information Management, 35(2), 183–191.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.

Hovland, C. I., Janis, I. L., & Kelley, H. H. (1953). Communication and persuasion: Psychological studies of opinion change. Yale University Press.

Jacoby, J. (2002). Stimulus-organism-response reconsidered: An evolutionary step in modeling (consumer) behavior. Journal of Consumer Psychology, 12(1), 51–57.

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. Educational and Psychological Measurement, 30(3), 607–610.

Kumar, V., & Gupta, S. (2021). Transformative marketing: The next 20 years. Journal of Marketing, 85(6), 1–12.
Lee, J. E., & Watkins, B. (2016). YouTube vloggers' influence on consumer luxury brand perceptions and intentions. Journal of Business Research, 69(12), 5753–5760.
Lim, X. J., Radzol, A. M., Cheah, J. H., & Wong, M. W. (2017). The impact of social media influencers on purchase intention and the mediation effect of customer attitude. Asian Journal of Business Research, 7(2), 19–36.
Lin, H. C., Bruning, P. F., & Swarna, H. (2019). Using online opinion leaders to promote the hedonic and utilitarian value of products and services. Business Horizons, 62(4), 431–442.
Lin, Z., & Shen, H. (2023). Perceived value in live streaming commerce: The moderating role of streamer credibility. Journal of Retailing and Consumer Services, 73, 103350.
Lou, C., Tan, S. S., & Chen, X. (2019). Investigating consumer engagement with influencer- vs. brand-promoted ads: The roles of source and disclosure. Journal of Interactive Advertising, 19(3), 169–186.
Lou, C., & Yuan, S. (2019). Influencer marketing: How message value and credibility affect consumer trust of branded content on social media. Journal of Interactive Advertising, 19(1), 58–73.
Lu, B., Fan, W., & Zhou, M. (2016). Social presence, trust, and social commerce purchase intention: An empirical research. Computers in Human Behavior, 56, 225–237.
McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. Information Systems Research, 13(3), 334–359.
Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.
Nitzl, C., Roldán, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. Industrial Management & Data Systems, 116(9), 1849–1864.
Pakistan Telecommunication Authority. (2024). Annual report and telecom indicators. Islamabad: Author.
Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. MIS Quarterly, 30(1), 115–143.
Petty, R. E., & Cacioppo, J. T. (1986). Communication and persuasion: Central and peripheral routes to attitude change. Springer-Verlag.
Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903.
Rucker, D. D., Preacher, K. J., Tormala, Z. L., & Petty, R. E. (2011). Mediation analysis in social psychology: Current practices and new recommendations. Social and Personality Psychology Compass, 5(6), 359–371.
Saunders, M., Lewis, P., & Thornhill, A. (2019). Research methods for business students (8th ed.). Pearson Education.
Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research. Journal of Consumer Research, 15(3), 325–343.
Sheth, J. N. (2020). Borderless media: Rethinking international marketing. Journal of International Marketing, 28(1), 3–12.

Spence, M. (1973). Job market signaling. Quarterly Journal of Economics, 87(3), 355–374.
Sweeney, J. C., & Soutar, G. N. (2001). Consumer perceived value: The development of a multiple item scale. Journal of Retailing, 77(2), 203–220.
Tafesse, W., & Wood, B. P. (2021). Followers' engagement with Instagram influencers: The role of influencers' content characterization and posting frequency. Journal of Retailing and Consumer Services, 58, 102303.
Vogel, E. A., Rose, J. P., Roberts, L. R., & Eckles, K. (2014). Social comparison, social media, and self-evaluation. Psychology of Popular Media Culture, 3(4), 206–222.
Wang, X., & Yu, C. (2020). Social media peer communication and impacts on purchase intentions: A consumer socialization framework. Journal of Interactive Marketing, 51, 65–75.
Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. Journal of Marketing, 52(3), 2–22.
Zhang, K. Z., Liu, H., & Chen, Z. (2022). Understanding consumers' cross-buying intentions in online communities: The role of perceived value and social influence. Information and Management, 59(4), 103641.
Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. Journal of Consumer Research, 37(2), 197–206.

Appendix. Measurement Items, Loadings, and Item Descriptives

All items were rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Standardised outer loadings, means, and standard deviations are reported for the full sample (n = 386).

Table A1

Measurement items with standardised loadings and descriptive statistics

Item	Statement	Loading	Mean	SD
Influencer Credibility (IC)				
1	I trust recommendations made by social media influencers.	0.62	2.74	1.120
2	Influencers demonstrate sufficient expertise and knowledge about the products they promote.	0.56	2.68	1.104
3	The influencers I follow appear honest and authentic in their reviews.	0.58	2.82	1.114
4	I believe that influencers provide reliable and accurate product information.	0.59	2.63	1.105
5	Influencer credibility increases my willingness to consider purchasing products.	0.65	2.91	1.228
Social Media Content Quality (CQ)				
6	Product-related content shared on social media is visually appealing.	0.56	3.46	1.049
7	Content provided by influencers is informative and accurate.	0.55	2.78	1.110
8	Social media content helps me clearly understand product features and benefits.	0.55	3.25	1.169
9	High-quality content increases my confidence in making purchase decisions.	0.66	3.58	1.146
10	Well-presented and engaging content positively shapes my perception of products.	0.66	3.59	1.041
Online Community Trust (OCT)				
11	I trust the reviews and opinions shared by members of online communities.	0.57	3.27	1.145
12	Feedback from online communities is generally reliable and unbiased.	0.62	3.16	1.142
13	I feel confident relying on online community information when purchasing products.	0.61	3.29	1.061

Item	Statement	Loading	Mean	SD
14	Participation in online communities helps me make informed purchase decisions.	0.66	3.32	1.077
15	Trust in online communities increases my likelihood of purchasing products.	0.66	3.29	1.076
Perceived Value (PV)				
16	I perceive products promoted by influencers as worth their cost.	0.56	2.97	1.048
17	Products endorsed through social media and online communities offer good value for money.	0.58	3.08	1.016
18	The perceived benefits of products strongly influence my purchasing decisions.	0.60	3.29	1.070
19	Online communities help me evaluate whether a product provides good value.	0.66	3.24	1.015
20	My perception of value significantly affects my purchase intention.	0.56	3.33	0.975
Purchase Intention (PI)				
21	I am likely to purchase products recommended by influencers.	0.58	2.75	1.072
22	Positive reviews in online communities increase my likelihood of purchasing products.	0.59	3.46	1.029
23	High-quality social media content motivates me to purchase products online.	0.67	3.26	1.036
24	Perceived value strongly influences my intention to purchase products.	0.60	3.27	1.111
25	I tend to follow influencer and community recommendations when making online purchase decisions.	0.63	2.80	1.132

Note. Loadings from the PLS-SEM measurement model; means and standard deviations from SPSS 26.