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FROM SCROLLING TO PURCHASING: THE IMPACT OF SOCIAL MEDIA MARKETING ON THE PURCHASE BEHAVIOUR OF SKINCARE PRODUCTS AMONG YOUNG ADULTS IN LAHORE, PAKISTAN

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Abstract

Social media has become a channel for skincare discovery, yet online engagement does not always translate into purchasing, particularly where consumers question authenticity and quality. Guided by the Stimulus–Organism–Response (S–O–R) framework, this study investigates how Visual Appeal, Information Quality, and Influencer Credibility influence skincare purchase behavior among young adults in Lahore, Pakistan, testing Brand Trust as a mediator. A cross-sectional survey used 20 five-point Likert items and purposive sampling. Of 400 responses collected, 394 valid responses (98.5%) were analyzed using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4, with 5,000 bootstrap subsamples. The model met validity criteria, with composite reliability values of 0.806–0.866 and average variance extracted values of 0.510–0.618. The model explained 54.3% of the variance in Brand Trust and 50.4% in Purchase Behavior, with predictive relevance (Q^2predict = 0.458).

All three social media marketing dimensions significantly predicted Brand Trust: Information Quality (β = 0.301), Visual Appeal (β = 0.297), and Influencer Credibility (β = 0.253; all $p < .001$). Visual Appeal (β = 0.319, $p < .001$), Influencer Credibility (β = 0.131, $p = .028$), and Brand Trust (β = 0.271, $p < .001$) had significant direct effects on Purchase Behavior, whereas the direct effect of Information Quality was not significant (β = 0.108, $p = .064$). Brand Trust significantly mediated all three relationships, with indirect effects for Visual Appeal (β = 0.080, $p < .001$), Information Quality (β = 0.082, $p = .002$), and Influencer Credibility (β = 0.068, $p = .005$). The findings indicate complementary mediation for Visual Appeal and Influencer Credibility, and indirect-only mediation for Information Quality. Thus, product information appears to influence purchasing when supported by brand trust, while visual content has the strongest direct association with purchase behavior. It extends S–O–R research to Pakistan's skincare market and suggests that brands combine attractive content, credible endorsements, transparent information, and

trust-building practices. Cross-sectional, purposive sampling in Lahore limits causal inference and wider generalization.

1. INTRODUCTION

Personal grooming, appearance, and well-being have become everyday concerns for young consumers, and the skincare industry has grown into one of the fastest-expanding consumer sectors as a result. E-commerce and digitalization have changed how people discover, evaluate, and buy skincare products, moving the decision away from the tactile in-store encounter and onto the screen [1]. The shift is most visible among young adults, who use Instagram, TikTok, and Facebook not only for social interaction but also as a search engine for lifestyle consumption [2]. For a skincare brand, the feed has therefore become the shop window, the sales assistant, and the review wall at the same time.

Pakistan is a demographically young country in which 79% of the population is under 40 years of age, and a large share of these consumers use smartphones and social media actively. At the start of 2025 the country counted 66.9 million social media user identities, equivalent to 26.4% of the population, and 116 million internet users [3]. Lahore in particular has a dense youth population with growing beauty consciousness and rising online shopping practice, which makes it a suitable setting for studying how online engagement turns into buying. Existing work on skincare consumers in Pakistan has largely examined satisfaction among female undergraduates [4], and much less is known about what moves a young consumer from watching a skincare post to paying for the product.

A persistent gap remains between the two. Despite heavy engagement with skincare content, many young Pakistani consumers hesitate to buy online. The hesitation reflects a lack of trust in the online marketplace, where consumers doubt brand authenticity, product quality, possible side effects, and delivery. Evidence from Pakistani university students shows that perceived risk lowers online purchase intention and that trust dampens this negative link [5]. The concern about skincare content is not imaginary either: a study published in Pediatrics found that popular skincare-routine videos on TikTok promote multi-product regimens that include ingredients carrying a high risk of skin irritation [6]. Comparative evidence from Pakistan and the United Kingdom points the same way, since influencers raised the visibility of a cosmetics brand but perceived authenticity was the factor that decided trust and purchase [7].

Fig. 1 summarizes this problem as a pathway that begins with scrolling and ends with purchasing, and shows where the 3 social media stimuli examined in this paper act and where the trust barriers interrupt the journey.

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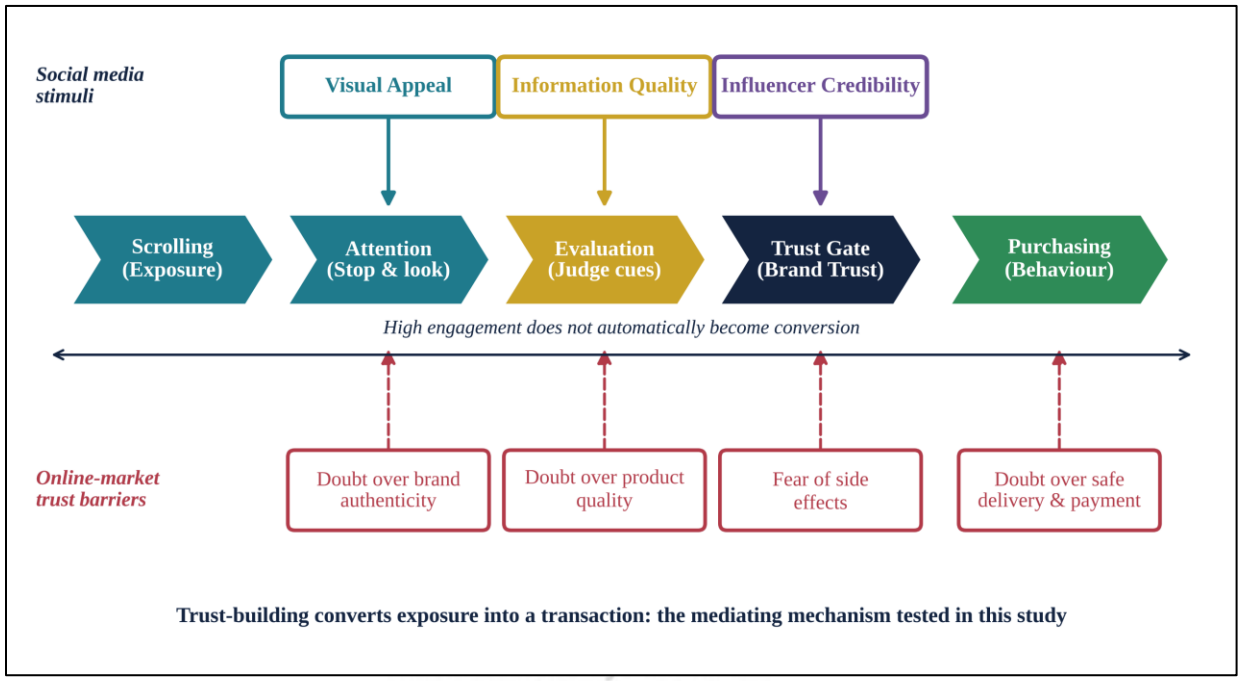


Fig. 1. Conceptual overview of the scrolling-to-purchasing pathway and the trust barriers that interrupt it.

The figure shows 5 stages that a young consumer passes through: exposure while scrolling, attention when a post stops the thumb, evaluation of the cues in the post, a trust gate, and finally the purchase. The 3 stimuli at the top, Visual Appeal, Information Quality, and Influencer Credibility, feed into the first 4 stages, because a post is first noticed for how it looks, then judged for what it says and who says it. The stimuli therefore act early in the journey, and they are the part of the journey that brands control most directly through content design.

The 4 red boxes at the bottom mark the doubts that sit between engagement and transaction: doubt about brand authenticity, doubt about product quality, fear of side effects, and doubt about safe delivery and payment. They push upward against the trust gate rather than against the stimuli themselves, which is the core argument of this paper. A visually strong or well-informed post can raise engagement, but a consumer who still doubts the brand will not pass the gate. The remainder of the paper tests this argument empirically by treating Brand Trust as the mechanism that converts exposure into a transaction.

The literature on digital marketing and consumer behavior is limited in 3 ways. First, most studies treat social media marketing (SMM) as a single entity rather than examining its separate aspects, such as visual appeal, information quality, and influencer credibility, which may affect consumers differently [8]. Second, regional studies have addressed repurchase intention and brand quality rather than initial purchase behavior, which leaves the scrolling-to-purchasing stage unexamined [9], [10]. Third, although Brand Trust is widely regarded as important, few studies model it as the mechanism that converts social media exposure into transactions in the Pakistani skincare context [4].

This study addresses these gaps by examining the effects of Visual Appeal, Information Quality, and Influencer Credibility on the purchase behavior of young skincare consumers in Lahore, and by testing Brand Trust as a mediator of these relationships. The central research question is how the 3 social media marketing components influence the purchase behavior of young

skincare consumers in Lahore, and whether Brand Trust explains the way in which they do so. The objectives are: (1) to evaluate how Visual Appeal, Information Quality, and Influencer Credibility affect the purchase behavior of young adult skincare consumers in Lahore, Pakistan; (2) to examine how Brand Trust bridges the gap between digital marketing efforts and the final purchase decision by reducing consumer doubts; and (3) to propose data-driven strategies for cosmetic brands in Lahore that convert passive social media engagement into actual sales.

Theoretically, the study applies the Stimulus–Organism–Response framework to skincare marketing in a developing country and tests how Brand Trust relates to social media marketing and purchase behavior, which shows whether marketing theories developed in Western countries hold in the Pakistani context. Practically, it guides skincare brands and marketers toward trust-building content that drives purchases rather than vanity metrics. The paper proceeds as follows. Section 2 reviews the literature and derives 10 hypotheses. Section 3 describes the research methodology. Section 4 presents and discusses the results. Sections 5 and 6 give the conclusion, the implications, the limitations, and directions for future work.

2. Literature Review

2.1 Social Media Marketing and Consumer Behavior in Beauty and Skincare

Research on social media marketing has moved from asking whether brand activity on social platforms matters to asking through which psychological routes it works. In a multi-analytic study of UAE consumers, SMM had a direct effect on consumer-based brand equity, on inspiration, and on purchase intention, and the 2 mediators transmitted part of the effect, which the authors describe as partial complementary mediation [11]. Work on fashion retail brands reached a similar conclusion for impulse buying: brand social media marketing activities raised brand resonance, emotional responses, and online impulse-buying intention [12]. These studies establish that the effect of SMM travels through an internal state rather than operating on behavior alone.

The skincare and cosmetics literature adds a trust-related twist. A study of Indonesian young adults found that social media marketing shaped the purchase intention of skincare products [2]. Studies of a local skincare brand and of a men's skincare brand in Indonesia report that SMM raises brand image and brand trust, that trust raises purchase intention, and that trust carries the effect of SMM on purchase intention [13], [14]. In Pakistan, work on brand loyalty has examined how social media marketing builds loyalty when brand reputation conditions the relationship [15], which suggests that reputation and trust matter in this market. Taken together, the evidence says that social media marketing works, but that how well it works depends on what consumers come to believe about the brand.

2.2 The Stimulus–Organism–Response Framework

The S–O–R framework, which originates in environmental psychology, explains behavior as a sequence in which an external stimulus triggers an internal state of the individual, and this internal state in turn produces an observable response. Marketing scholars have adopted it widely for social media settings. It has been applied to social media marketing and purchase intention [11], to online impulse buying [12], and to the way social media triggers, information quality, and influencer cues shape buying behavior through interaction [16]. A Pakistani study applied it to influencer marketing, electronic word of mouth, and purchase decisions, with brand awareness as the organism [17], and a study of Indonesian beauty followers used it to examine how influencer credibility cues translate into parasocial bonds and purchase intention [18].

The framework suits the present research question for 2 reasons. It separates what the brand controls, the stimulus, from what the consumer experiences, the organism, and so it can explain why identical content produces different outcomes. It also naturally

accommodates mediation, which is exactly the claim made here: that Visual Appeal, Information Quality, and Influencer Credibility work on purchase behavior at least partly through the trust they build. In this study the 3 marketing components are the stimuli, Brand Trust is the organism, and Purchase Behavior is the response.

2.3 Visual Appeal

Visual appeal refers to the aesthetic attractiveness of the images, videos, packaging, and overall presentation of marketing content. The platforms that young consumers use for skincare discovery are visual by design. Instagram's emphasis on images and profiles is considered particularly relevant for cosmetics, because cosmetics are used to enhance appearance [19]. In a survey of 208 participants in India and the Middle East, visual quality, especially color harmony and premium design, significantly influenced consumer trust and emotional engagement towards beauty brands on Instagram [20]. Visual appeal is thus expected to work on 2 fronts: it attracts attention and gives the consumer a quick signal of professionalism and care, which supports trust, and it may also move the consumer directly towards action.

2.4 Information Quality

Information quality captures how useful, relevant, and accurate the product information shown to the consumer is. For skincare, where claims about ingredients and results are hard for a layperson to verify, this dimension is central. A study of social networking sites in India reported that information quality, expertise, and trustworthiness had significant effects on credibility and brand image, and through them an indirect effect on online purchase intention [21]. Research on electronic word of mouth for cosmetics on Instagram identified information quality, source credibility, information usefulness, and information adoption as key antecedents of purchase intention [19]. A study of TikTok users found that information quality had a positive and significant effect on trust, and that trust in turn affected purchase intention [22].

The direct link between information and purchase is less secure. Research on skincare repurchase in Vietnam found that the clarity of product descriptions was not a significant predictor of repurchase intention when attitude and credibility dominated the model [10]. In the Saudi study of digital stimuli, the quality of information was one of the cues that enhanced social media interaction and, through it, buying behavior [16]. These findings suggest that information may influence behavior mainly after it has been accepted as credible, which points to a mediating role for trust.

2.5 Influencer Credibility

Influencer credibility refers to the perceived expertise, trustworthiness, and often attractiveness of the person endorsing a product. It has been studied intensively in influencer marketing. Research on the credibility of social media influencers links it to purchase intention [23], and an analysis of the persuasive power of influencers connects their credibility to brand credibility and purchase intention [24]. In the beauty field, a study of beauty vloggers found that trustworthiness, expertise, and attractiveness build consumers' trust in the vlogger, and that this trust partially mediates the effect of credible attributes on purchase intention [25]. A study of doctor beauty influencers on TikTok found that trustworthiness, attractiveness, expertise, and parasocial interaction each contributed to skincare purchase intention, although to different degrees [26].

Evidence for skincare specifically points in the same direction. Credibility and self-congruence were reported to influence skincare and body care purchase intention among Millennials and Generation Z in Indonesia, both directly and through trust and parasocial bonds [27]. Beauty influencer credibility affected skincare purchase intention directly, and its effect was strengthened when influencer effectiveness mediated it [28]. In Pakistan, influencer marketing was linked to the purchase intention of organic skincare products

through brand awareness and brand reputation [29]. Findings on expertise and attractiveness are not uniform, however: attractiveness did not predict parasocial relationship in one study of Indonesian beauty followers but remained positively related to purchase intention [18], and influencer cues showed no significant influence in the Saudi study, which the authors attributed to possible trust erosion or influencer fatigue [16]. Credibility therefore appears to matter, but its effect is conditional on how consumers experience and trust the endorser.

2.6 Brand Trust and Purchase Behavior

Brand trust is the consumer's willingness to rely on a brand to deliver what it promises. In online skincare, where the product cannot be touched, tested, or returned easily, trust substitutes for direct inspection. Studies of skincare brands show that brand trust significantly predicts purchase intention and that it mediates the effect of social media marketing on purchase intention [13], [14]. Research on cosmetics repurchase reported that brand trust and product quality significantly affected repurchase intention while price and social media marketing alone did not [9]. Evidence from Pakistani university students shows that trust dampens the negative effect of perceived risk on online purchase intention [5]. A further study of brand loyalty places brand reputation as a condition of the effect of social media marketing [15]. The common thread is that trust sits between what the brand shows and what the consumer does.

2.7 PLS-SEM in Consumer Marketing Research

Partial least squares structural equation modelling (PLS-SEM) has become a standard tool in consumer and marketing research, particularly for prediction-oriented models with several constructs and mediation paths [30]. A review of business marketing studies concluded that PLS-SEM is widely used but that researchers' assessment and reporting of measurement and structural models are often insufficient, and it offered guidelines and checklists for better practice [31]. Guidance on mediation and conditional mediation within PLS-SEM has also matured [32]. These developments support a transparent, step-by-step evaluation of reliability, validity, path significance, and mediation, which is the approach adopted in this study.

2.8 Research Gaps and Hypotheses

Synthesizing these studies reveals 3 gaps. Most research treats SMM as a single construct, which hides the possibility that visual, informational, and credibility cues operate through different routes. Much regional work targets repurchase intention and loyalty rather than the initial purchase. And few studies position Brand Trust as the organism that transmits the effects of several distinct stimuli onto purchase behavior in a Pakistani skincare setting. Table 1 summarizes the studies that most directly inform the hypotheses.

Table 1: Summary of selected prior studies informing the conceptual model.

Ref.	Context	Key finding
[11]	UAE consumers; S–O–R; PLS-SEM and ANN	SMM directly affects brand equity, inspiration, and purchase intention; partial complementary mediation.
[16]	Saudi social media users; S–O–R, UGT, TPB	Trends and information quality enhance interaction and buying; influencer cues were not significant.
[13]	Local skincare brand, Surabaya	SMM raises brand image and brand trust; trust carries SMM effect to purchase intention.

Ref.	Context	Key finding
[14]	Men's skincare brand, Indonesia	SMM affects image, trust, and perceived risk; brand trust mediates SMM and purchase intention.
[25]	Beauty vloggers; users aged 16–45	Credible attributes raise trust; trust partially mediates the effect on purchase intention.
[27]	Skincare and bodycare; Millennials and Gen Z	Credibility and similarity affect purchase intention directly and via trust and parasocial bonds.
[21]	Social networking sites, India	Information quality, expertise, and trustworthiness act on intention indirectly via credibility and brand image.
[22]	TikTok users, Padang	Information quality positively affects trust; trust positively affects purchase intention.
[20]	Instagram beauty advertising; n = 208	Visual quality significantly influences consumer trust and emotional engagement.
[5]	Pakistani university students	Perceived risk lowers online purchase intention; trust dampens the link.
[10]	Skincare repurchases, Vietnam	Clarity of product description was not significant when attitude and credibility dominated.

Table 1 shows that trust appears repeatedly as the explanatory link between marketing cues and purchase intention, yet the studies differ in context, in the cues they examine, and in whether the trust effect is full or partial. This variation motivates a model in which the 3 cues are examined separately and trust is tested as a common mediator. Fig. 2 presents the resulting S–O–R framework with its 10 hypotheses.

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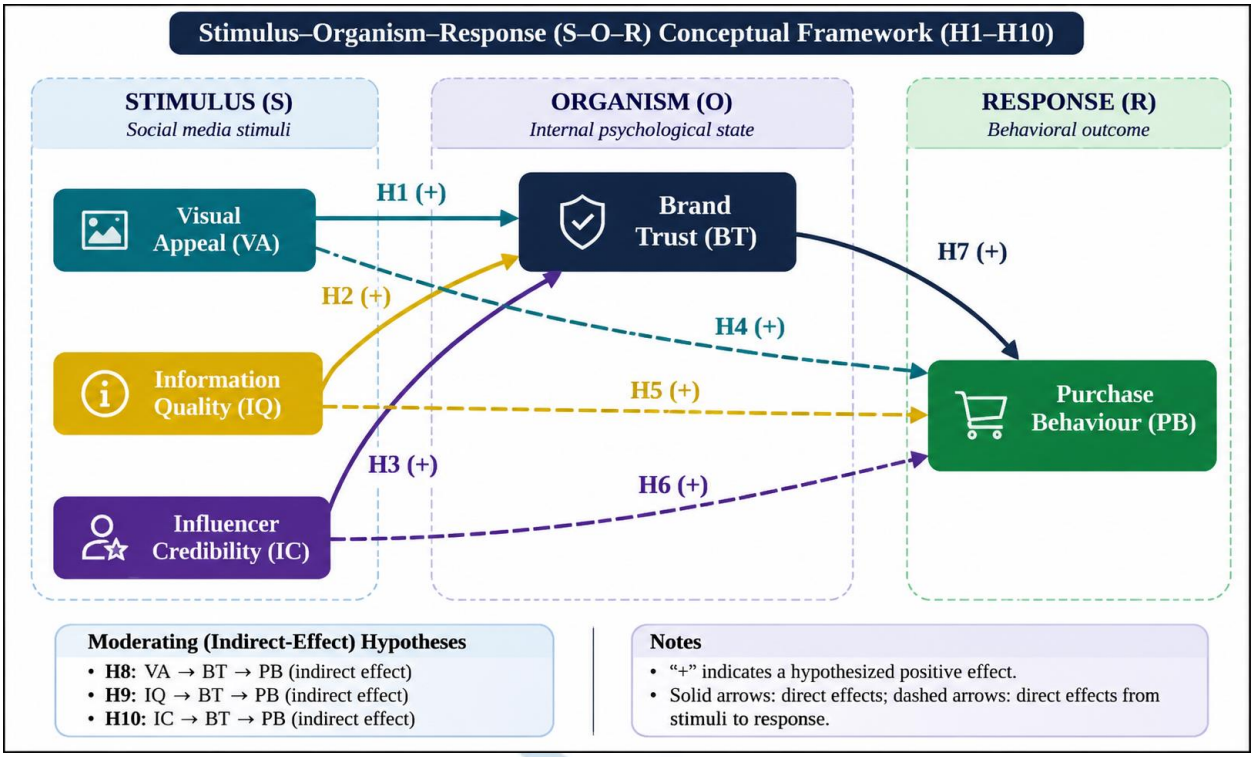


Fig. 2. Stimulus–Organism–Response conceptual framework with hypotheses H1–H10.

The framework places the 3 stimuli on the left, Brand Trust as the organism in the middle, and Purchase Behaviour as the response on the right. Solid arrows from the stimuli to Brand Trust carry H1, H2, and H3, which propose that Visual Appeal, Information Quality, and Influencer Credibility each increase Brand Trust. Dashed arrows from the stimuli to Purchase Behaviour carry H4, H5, and H6, which propose direct positive effects on purchase behaviour. The arrow from Brand Trust to Purchase Behaviour carries H7, and the box at the top denotes H8, H9, and H10, the indirect effects of the 3 stimuli on purchase behaviour through Brand Trust.

The layout also makes the logic of the mediation test visible. If a stimulus affects Purchase Behaviour only through the solid path and the Brand Trust arrow, the mediation is full. If the dashed direct path remains significant alongside the indirect path, the mediation is partial. Because the review above suggests that visual cues and influencer cues may move behaviour directly, while information may need to be trusted first, the model is built to detect these different patterns instead of assuming a single uniform one.

Accordingly, the following hypotheses are proposed. H1, H2, and H3: Visual Appeal, Information Quality, and Influencer Credibility each have a positive effect on Brand Trust. H4, H5, and H6: Visual Appeal, Information Quality, and Influencer Credibility each have a positive direct effect on Purchase Behaviour. H7: Brand Trust has a positive effect on Purchase Behaviour. H8, H9, and H10: Brand Trust mediates the relationships between Visual Appeal, Information Quality, and Influencer Credibility, respectively, and Purchase Behaviour.

3. Materials and Methods

3.1 Research Design and Rationale

The study follows a quantitative, cross-sectional, explanatory design. The research question asks how 3 marketing components relate to purchase behaviour and whether Brand Trust transmits their effects, and a question of this kind calls for

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measurement of latent perceptions across a sizeable sample and for the simultaneous estimation of direct and indirect paths. A self-administered online survey was therefore chosen as the data collection strategy, because the phenomenon under study occurs on social media and the target respondents are already active there. The Stimulus–Organism–Response logic provided the structure of the model: Visual Appeal, Information Quality, and Influencer Credibility were specified as stimuli, Brand Trust as the organism, and Purchase Behaviour as the response.

Fig. 3 gives the overall process of the investigation, from the definition of the problem to the interpretation of the findings.

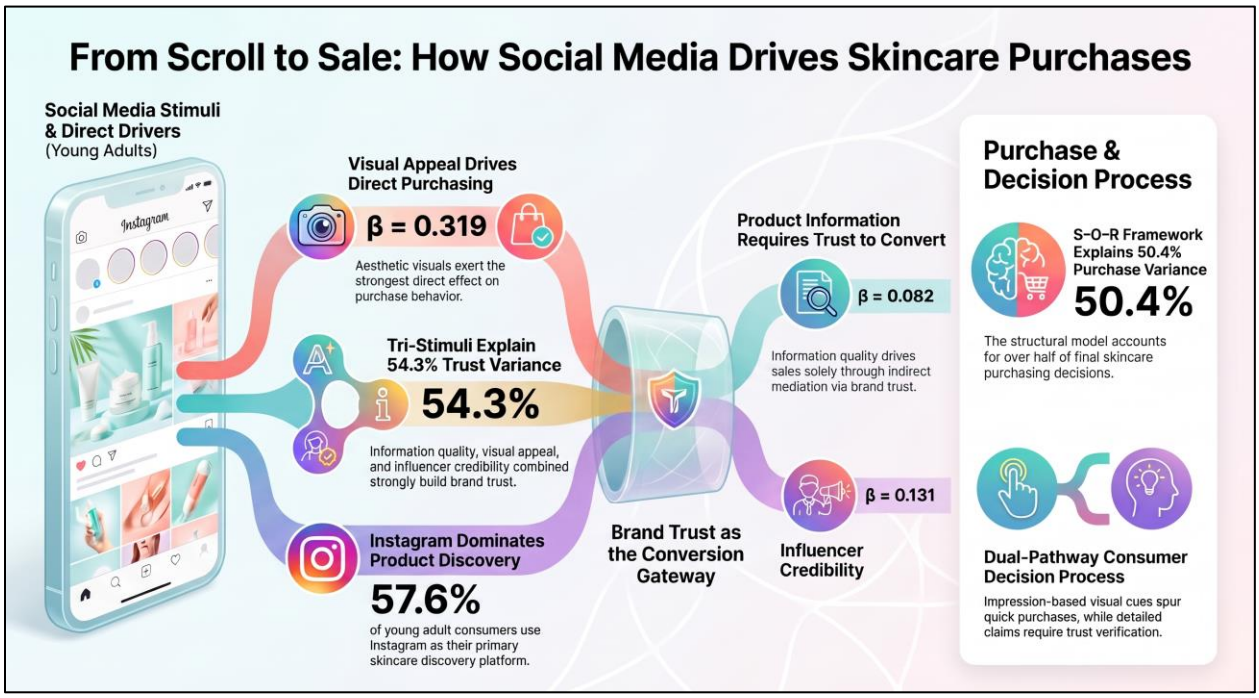


Fig. 3. Overall research process flow from problem definition to interpretation.

The flow chart is organised in 3 bands. The design band (steps 1 to 4) covers the problem definition, the specification of the S–O–R model with its 10 hypotheses, the construction of the 20-item instrument, and the purposive sampling of young adults in Lahore aged 18 to 40. The data band (steps 5 to 8) begins with the online survey, passes through a screening decision in which 394 of 400 responses were retained, and then checks common method bias with Harman's single-factor test before evaluating the measurement model. The decision diamond is the only branching point in the process, and it is placed before any statistical modelling so that no model is estimated on incomplete or duplicate responses.

The analysis band (steps 9 to 12) follows the sequence in which PLS-SEM results must be read. The structural model is estimated with 5,000 bootstrap subsamples, the mediation effects are then tested through the indirect paths and their confidence intervals, and the explanatory and predictive power of the model is summarised through R^2, f^2, and Q^2predict. Only after these steps is the evidence interpreted for theory and practice. The ordering reflects a deliberate rationale: a structural coefficient is meaningful only when the measures behind it are reliable and distinct, so the structural stage never precedes the measurement stage.

3.2 Population, Sampling, and Procedure

The study targeted young adults aged 18 to 40 years living in Lahore, Pakistan, who actively use at least 1 social media platform (Instagram, Facebook, TikTok, or YouTube) and who have purchased or considered purchasing skincare products after seeing them on social media. The products included face wash, cleanser, serum, skin-brightening cream, sunscreen, and moisturizer. This population was selected because young adults are the most active social media users in Pakistan and are the explicit target of skincare marketing campaigns, which makes their purchase behaviour central to the S–O–R dynamics investigated here.

A non-probability purposive sampling technique was used, because the population of interest cannot be listed exactly. Purposive sampling deliberately selects respondents who have directly experienced skincare-related social media content, which ensures relevance and depth in the data. Respondents were reached through university communities, WhatsApp networks, and online social media groups. Individuals below 18 or above 40 years of age, those who were not active social media users, and those without experience of purchasing skincare products through social media were excluded through the screening questions. Because non-probability sampling limits statistical generalisability, the findings apply to social-media-active young adult skincare consumers in Lahore rather than to all consumers in Pakistan.

3.3 Sample Size Adequacy

The required sample size was first calculated with the standard formula for infinite populations, which gives a minimum of 384 respondents at a 95% confidence level and a 5% margin of error. The figure of 384 also satisfies the inverse square root criterion for PLS-SEM, under which the minimum sample needed to detect the smallest expected path coefficient at the 5% significance level is well below 384 for the present model. A target of 400 to 450 responses was set to compensate for duplicate entries and incomplete submissions. A total of 400 responses were collected, of which 394 were retained as valid after screening. Because 394 exceeds the calculated minimum, the sample provides adequate statistical power for PLS-SEM estimation.

3.4 Instrument and Measurement of Variables

Data were collected with a structured questionnaire distributed through a Google Forms link. It began with screening and demographic questions and then presented 20 measurement items on a five-point Likert scale, where 1 meant Strongly Disagree and 5 meant Strongly Agree. All items were drawn from previously validated measurement scales and adapted to the context of skincare advertisements on social media. Table 2 presents the 5 constructs, the number of items per construct, and the role each plays in the model.

Table 2: Constructs, items, and roles in the S–O–R model.

Construct	Items	Role in model	Operational focus
Visual Appeal (VA)	4	Stimulus	Aesthetic appearance and attractiveness of skincare content (VA4 reverse-worded).
Information Quality (IQ)	4	Stimulus	Usefulness, relevance, and accuracy of product information (IQ3 reverse-worded).

Construct	Items	Role in model	Operational focus
Influencer Credibility (IC)	4	Stimulus	Perceived expertise and trustworthiness of endorsing influencers (IC3 reverse-worded).
Brand Trust (BT)	4	Organism (mediator)	Willingness to rely on the brand to meet expectations.
Purchase Behaviour (PB)	4	Response	Extent to which consumers act on skincare purchase decisions after exposure.

Table 2 shows a balanced design with 4 items per construct. Reverse-worded items (VA4, IQ3, and IC3) were included to detect careless responding and were reverse-coded before analysis. The full wording of the screening questions and of all 20 items is provided in Appendix A.

3.5 Analytical Strategy

Data were analysed with Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4. PLS-SEM was preferred over covariance-based SEM for 3 reasons. First, the study aims at the prediction and explanation of 2 key target constructs, Brand Trust and Purchase Behaviour, which matches the prediction-oriented logic of PLS-SEM. Second, PLS-SEM is well suited to models with mediation and reflective indicators. Third, it handles complex models efficiently and does not require distributional assumptions. Descriptive statistics, including demographic frequencies and percentages, were calculated in SPSS.

The analysis followed a two-stage procedure. In the first stage the measurement (outer) model was assessed for reliability and validity. Internal consistency was judged through Cronbach's alpha, rho_a, and composite reliability against the 0.70 benchmark. Convergent validity was judged through outer loadings and Average Variance Extracted (AVE) against the 0.50 benchmark, and discriminant validity through the Heterotrait-Monotrait (HTMT) ratio, with 0.90 as the strict and 0.95 as the liberal threshold. Collinearity was checked through inner variance inflation factors against a threshold of 3.3, overall model fit through the standardised root mean square residual (SRMR), and common method bias through Harman's single-factor test against a 50% threshold.

In the second stage the structural (inner) model was assessed. Path coefficients and their significance were obtained through bootstrapping with 5,000 subsamples, and a path was judged significant when its p-value fell below .05 and its 95% confidence interval excluded zero. Mediation was classified from the combined pattern of direct and indirect effects: when both were significant the mediation was complementary (partial), and when only the indirect effect was significant it was full (indirect-only). Explanatory power was evaluated through R^2, effect sizes through f^2 with thresholds of 0.02 for small, 0.15 for medium, and 0.35 for large, and predictive relevance through Q^2predict, where values above 0 indicate predictive relevance.

4. Results and Discussion

4.1 Sample Profile and Data Screening

A total of 400 responses were collected and screened for incomplete submissions and duplicate entries, and 394 were retained as valid, a retention rate of 98.5%. Table 3 presents the characteristics of the valid sample that were

reported from the survey, together with the complementary shares that follow from them.

Table 3: Sample characteristics and data screening summary.

Characteristic	Category	Value	Basis
Responses	Collected / valid	400 / 394 (98.5% valid)	Reported counts
Gender	Female	55.6%	Reported
	Male	44.4%	Complement of female share
Age group	18–29 years	92.7%	Reported
	30–40 years	7.3%	Complement of 18–29 share
Platform used most for skincare discovery	Instagram	57.6%	Reported
	TikTok	19.5%	Reported
	Facebook, YouTube, and other	22.9%	Complement of Instagram and TikTok
Common method bias	Harman first factor	40.21% of variance (threshold 50%)	Reported

Fig. 4 visualises the same information so that the relative weight of each group can be compared at a glance.

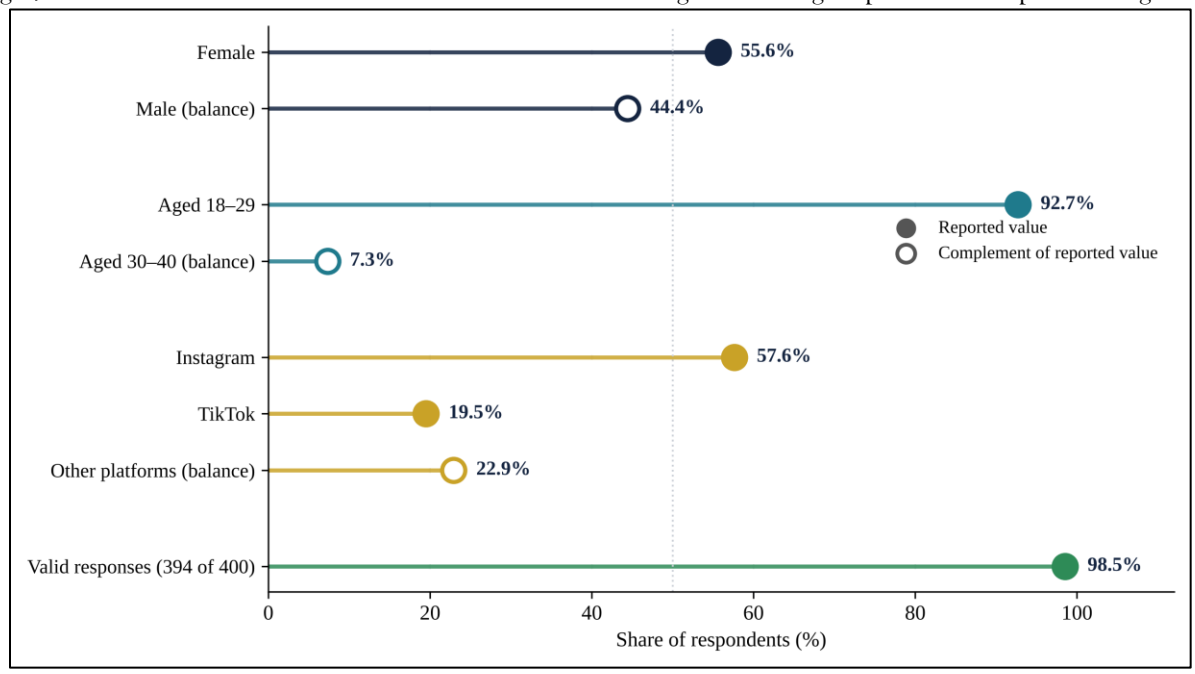


Fig. 4. Composition of the valid sample by gender, age, platform, and data retention.

The sample is female-dominant, with 55.6% female and 44.4% male respondents, which reflects the female-dominant composition of the skincare consumer segment. The age distribution

is strongly concentrated in the youngest part of the target range: 92.7% of respondents were aged 18–29 and only 7.3% were aged 30–40. This concentration confirms that the sample represents the young adult demographic that the study set out to examine, but it also means that conclusions about the 30–40 group rest on a very small subsample of roughly 29 respondents, so they should be treated with caution.

Instagram was the most frequently used platform for skincare discovery, at 57.6%, followed by TikTok at 19.5%, while Facebook, YouTube, and other platforms together accounted for 22.9%. Instagram alone therefore accounts for more than half of the discovery behaviour in the sample, and the first 2 platforms together cover 77.1%. This matters for interpretation, because Visual Appeal behaves differently on image- and video-led platforms than it would on text-led ones, and the strong visual effect reported below should be read in that light. Common method bias was not a concern: the first factor in Harman's test explained 40.21% of the total variance, below the 50% threshold.

4.2 Measurement Model: Loadings, Reliability, and Convergent Validity

The measurement model was evaluated through outer loadings, composite reliability, and Average Variance Extracted. Table 4 reports the results for all 20 items and 5 constructs.

Table 4: Outer loadings, reliability, and convergent validity of the constructs.

Construct	Item	Loading	α	rho_a	CR	AVE
Visual Appeal	VA1	0.689	0.677	0.677	0.806	0.510
	VA2	0.775				
	VA3	0.728				
	VA4	0.658				
Information Quality	IQ1	0.810	0.756	0.765	0.846	0.580
	IQ2	0.782				
	IQ3	0.657				
	IQ4	0.787				
Influencer Credibility	IC1	0.793	0.794	0.795	0.866	0.618
	IC2	0.795				
	IC3	0.791				
	IC4	0.765				
Brand Trust	BT1	0.809	0.787	0.788	0.863	0.613
	BT2	0.835				
	BT3	0.706				
	BT4	0.774				
Purchase Behaviour	PB1	0.662	0.753	0.763	0.844	0.576
	PB2	0.772				
	PB3	0.809				

Construct	Item	Loading	α	rho_a	CR	AVE
	PB4	0.783				

Source: SmartPLS 4 output. All outer loadings are significant at $p < .001$. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Composite reliability ranges from 0.806 to 0.866 and therefore exceeds the 0.70 threshold for all 5 constructs. The Cronbach's alpha of Visual Appeal (0.677) is marginally below 0.70, but this is acceptable because the composite reliability (0.806) and AVE (0.510) of that construct exceed their respective benchmarks. AVE values range from 0.510 to 0.618 and exceed the 0.50 cut-off, which establishes convergent validity. All outer loadings exceed 0.65, and 16 of the 20 items load at 0.70 or above. Fig. 5 shows the individual loadings against these benchmarks.

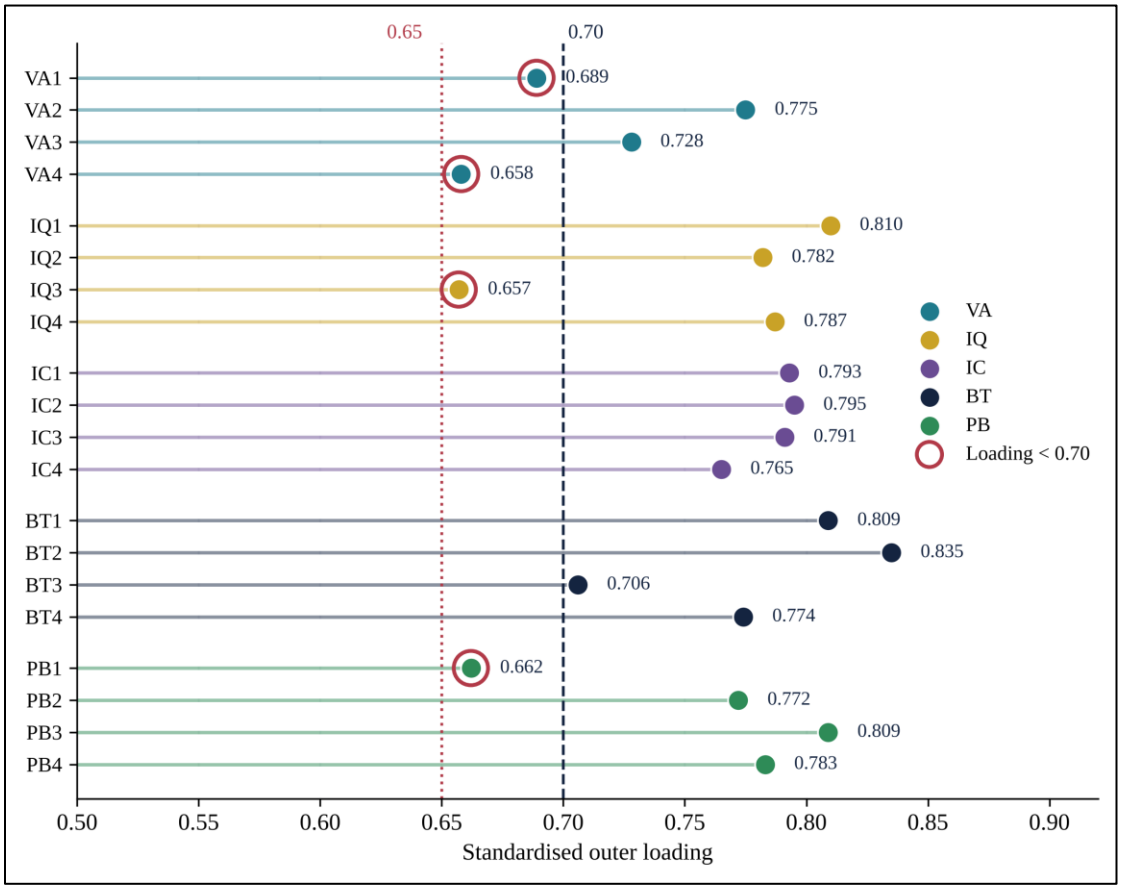


Fig. 5. Standardised outer loadings of the 20 measurement items.

The dot plot shows that loadings span a narrow, healthy range from 0.657 (IQ3) to 0.835 (BT2). Influencer Credibility is the most homogeneous construct, with all 4 loadings between 0.765 and 0.795 and a mean of 0.786, followed by Brand Trust (mean 0.781), Information Quality (mean 0.759), Purchase Behaviour (mean 0.757), and Visual Appeal (mean 0.713). The 4 items that fall below 0.70 are VA1 (0.689), VA4 (0.658), IQ3 (0.657), and PB1 (0.662), and each is ringed in red. None of them drops below the 0.65 line, and each belongs to a construct whose AVE remains above 0.50, which is why they were retained.

The pattern among the weaker items is informative. VA4 and IQ3 are 2 of the 3 reverse-worded items, and they are among the 3 lowest loadings in the model, while the third reverse-worded item, IC3, loads strongly at 0.791. Negatively worded items often load lower because some respondents read them less carefully, which suggests that the weaker loadings of VA4 and IQ3 reflect wording effects rather than a conceptual flaw. PB1, which refers to impulse purchasing immediately after seeing an advertisement, is the weakest purchase indicator, which indicates that impulsive buying is only one facet of a purchase behaviour construct that also includes saving posts for later, actual purchase, and recommendation to others.

Fig. 6 summarises the 4 construct-level quality indices for each construct on one set of axes.

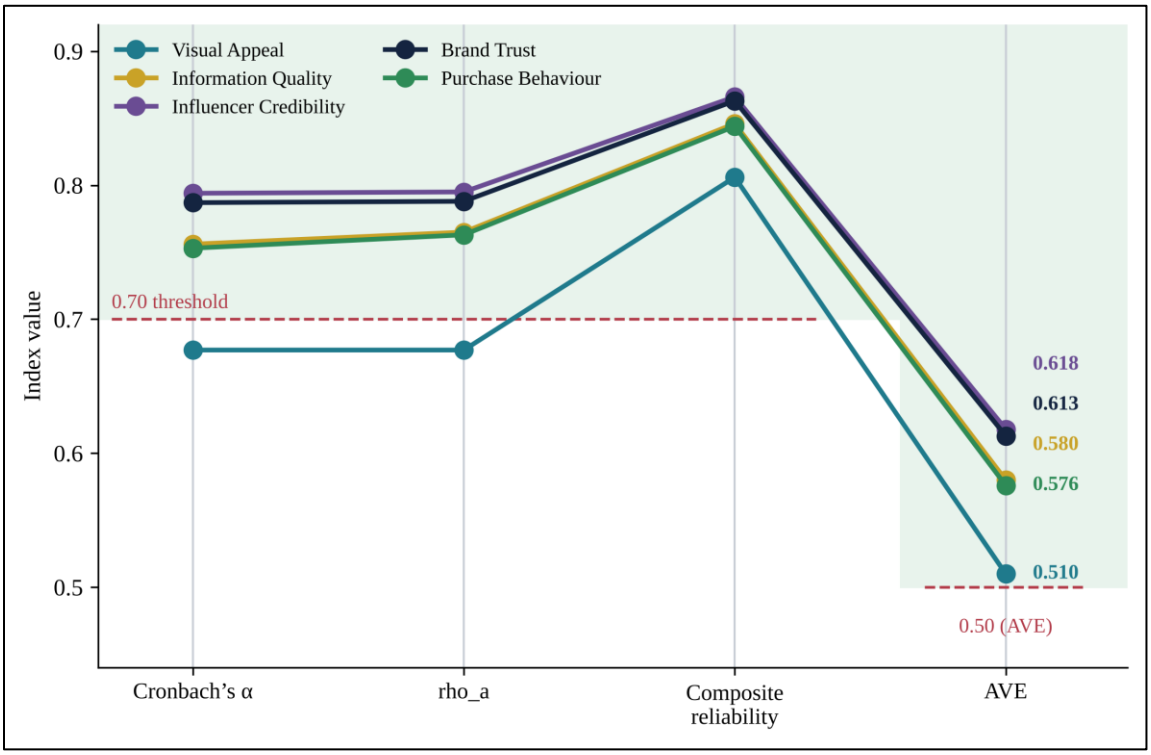


Fig. 6. Reliability and convergent validity indices by construct.

The parallel-coordinates plot shows that the 5 constructs follow the same profile: indices rise from Cronbach's alpha and rho_a to composite reliability and then fall to AVE, which is a typical pattern because AVE is a stricter measure of shared variance. Influencer Credibility (0.866 composite reliability, 0.618 AVE) and Brand Trust (0.863, 0.613) occupy the top of the plot, whereas Visual Appeal sits at the bottom on every index, with 0.677 for alpha and rho_a, 0.806 for composite reliability, and 0.510 for AVE. Visual Appeal is thus the least precisely measured construct but still meets every benchmark except alpha.

Two details deserve attention. First, rho_a values (0.677 to 0.795) are almost identical to the corresponding alpha values, so the borderline reliability of Visual Appeal is not an artefact of the choice of reliability coefficient. Second, the AVE of Visual Appeal (0.510) sits only 0.010 above the 0.50 benchmark, which leaves little margin. Any future use of this 4-item scale should therefore consider strengthening the 2 weakest items, VA1 and VA4, before relying on it in other samples.

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Volume 3 • Issue 7 • November 2026

4.3 Discriminant Validity, Collinearity, and Model Fit

Discriminant validity was assessed through the Heterotrait-Monotrait ratio, which is reported in Table 5.

Table 5: Heterotrait-Monotrait (HTMT) discriminant validity matrix.

	VA	IQ	IC	BT	PB
VA	–				
IQ	0.830	–			
IC	0.776	0.917	–		
BT	0.850	0.848	0.802	–	
PB	0.883	0.733	0.713	0.798	–

Note. The IQ–IC HTMT of 0.917 marginally exceeds the strict 0.90 threshold but remains below the liberal 0.95 criterion applied to conceptually related constructs.

Of the 10 construct pairs, 9 fall below the conservative 0.90 threshold. The IQ–IC pair yields 0.917, which marginally exceeds the strict criterion but remains below the liberal 0.95 threshold used for conceptually related constructs. The SRMR value of 0.080 sits at the commonly used 0.08 cut-off and indicates acceptable model fit, and all inner VIF values range from 1.660 to 2.470, well below 3.3, which confirms the absence of problematic multicollinearity. Fig. 7 displays the full HTMT matrix as a heat map.

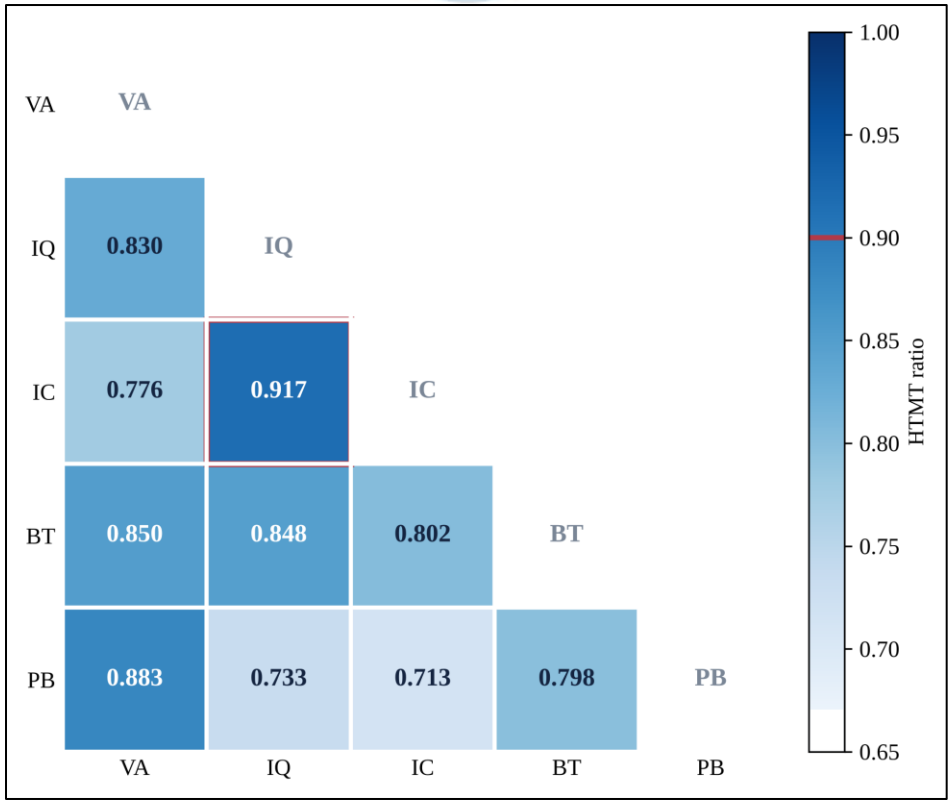


Fig. 7. HTMT discriminant validity matrix.

The heat map shows where the constructs are closest to each other. The darkest cell is IQ–IC (0.917), outlined in red, followed by PB–VA (0.883), BT–VA (0.850), BT–IQ (0.848), and IQ–VA (0.830). The lightest cells involve Purchase Behaviour and the 2 non-visual stimuli: PB–IC (0.713) and PB–IQ (0.733). The response construct is therefore most distinct from Influencer Credibility and Information Quality, and closest to Visual Appeal, which is consistent with the finding below that Visual Appeal has the strongest direct effect on purchase behaviour.

The single flagged cell has a plausible conceptual explanation. Followers often judge a skincare influencer by the quality of the information given, and judge information by the credibility of the person giving it, so the 2 constructs overlap in practice. The overlap is within the liberal tolerance, so the 2 constructs were retained as separate, but it signals that the 2 scales are not fully independent and that the IQ and IC results should be read together. This point is taken up again in the limitations.

4.4 Structural Model: Direct Effects

The structural model was tested with 5,000 bootstrap subsamples, and the hypothesis results are reported in Table 6.

Table 6: Hypothesis testing results for direct and indirect effects.

Hyp.	Path	β	SE	t-value	p-value	95% CI	Decision
H1	VA → BT	0.297	0.052	5.695	<.001	[0.198, 0.401]	Supported
H2	IQ → BT	0.301	0.055	5.528	<.001	[0.193, 0.409]	Supported
H3	IC → BT	0.253	0.064	3.937	<.001	[0.129, 0.377]	Supported
H4	VA → PB	0.319	0.061	5.249	<.001	[0.200, 0.439]	Supported
H5	IQ → PB	0.108	0.058	1.856	.064	[−0.005, 0.223]	Not supported
H6	IC → PB	0.131	0.060	2.195	.028	[0.018, 0.252]	Supported
H7	BT → PB	0.271	0.069	3.925	<.001	[0.131, 0.406]	Supported
H8	VA→BT→PB	0.080	0.024	3.298	<.001	[0.037, 0.131]	Supported
H9	IQ→BT→PB	0.082	0.026	3.101	.002	[0.037, 0.140]	Supported
H10	IC→BT→PB	0.068	0.024	2.806	.005	[0.026, 0.122]	Supported

Note. β = standardised path coefficient; SE = standard error; H8–H10 report indirect effects. Significance was obtained through 5,000-subsample bootstrapping.

Six of the 7 direct-effect hypotheses are supported. All 3 social media marketing dimensions significantly predict Brand Trust: Information Quality shows the largest coefficient (β = 0.301, p < .001), followed by Visual Appeal (β = 0.297, p < .001) and Influencer Credibility (β = 0.253, p < .001). For direct effects on Purchase Behaviour, Visual Appeal shows the strongest path (β = 0.319, p < .001), followed by Brand Trust (β = 0.271, p < .001) and Influencer Credibility (β = 0.131, p = .028). Information Quality has no significant direct effect on Purchase Behaviour (β = 0.108, p = .064). Fig. 8 presents the 7 direct paths with their confidence intervals.

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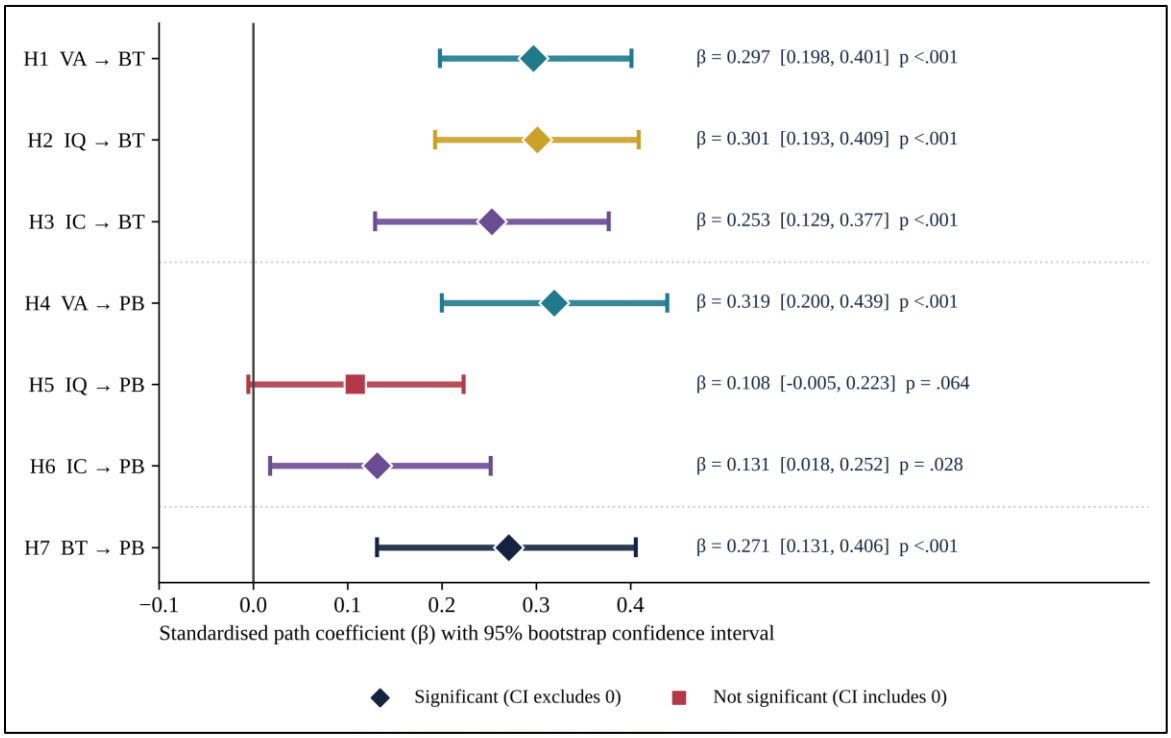


Fig. 8. Direct path coefficients with 95% bootstrap confidence intervals.

The forest plot makes the uncertainty around each coefficient visible. The 3 paths into Brand Trust (H1–H3) have confidence intervals that overlap almost completely, running from 0.198 to 0.401 for Visual Appeal, 0.193 to 0.409 for Information Quality, and 0.129 to 0.377 for Influencer Credibility. The ranking of Information Quality (0.301) above Visual Appeal (0.297) therefore rests on a difference of only 0.004 and should not be interpreted as a real ordering; the more defensible reading is that all 3 stimuli contribute to trust at broadly similar strength, with Influencer Credibility slightly lower.

The picture for Purchase Behaviour is more differentiated. The interval for Visual Appeal (0.200 to 0.439) lies well to the right of zero, and the interval for Brand Trust (0.131 to 0.406) is similarly clear. The interval for Influencer Credibility (0.018 to 0.252) excludes zero but only just, which fits the modest coefficient of 0.131. The interval for Information Quality (−0.005 to 0.223) includes zero by a margin of 0.005, and its p-value of .064 is close to the .05 boundary. The honest conclusion is that the direct effect of Information Quality is weak and statistically unconfirmed in this sample, not that it is demonstrably absent.

4.5 Mediation Analysis

The 3 mediation hypotheses (H8–H10) are supported. Brand Trust partially mediates the VA→PB relationship (indirect β = 0.080, p < .001) and the IC→PB relationship (indirect β = 0.068, p = .005), because both the direct and the indirect effects are significant, which is complementary mediation. Brand Trust fully mediates the IQ→PB relationship: the direct effect is non-significant (β = 0.108, p = .064) while the indirect effect is significant (β = 0.082, p = .002), and its confidence interval excludes zero. Fig. 9 compares the direct, indirect, and total effects of each stimulus.

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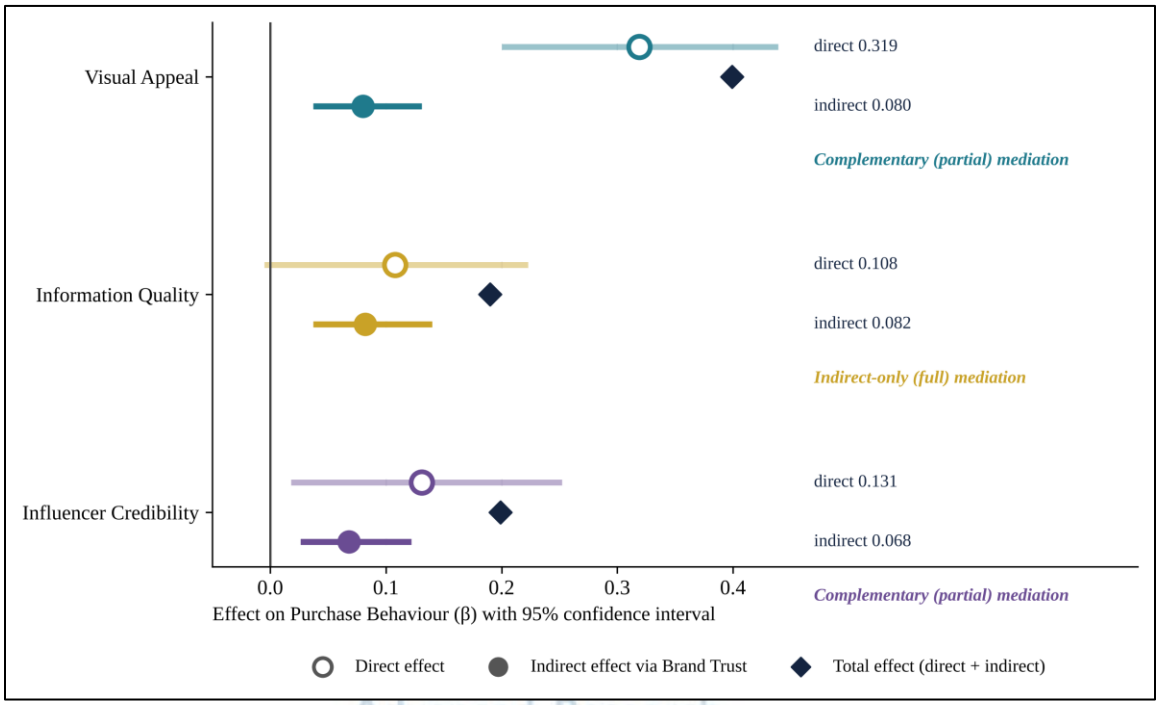


Fig. 9. Direct, indirect, and total effects of each stimulus on Purchase Behaviour.

The dumbbell plot shows that the 3 indirect effects are similar in size, at 0.080, 0.082, and 0.068, and that their confidence intervals overlap (0.037–0.131, 0.037–0.140, and 0.026–0.122). What distinguishes the 3 stimuli is the direct effect. For Visual Appeal the direct effect (0.319) is about 4 times the indirect effect (0.080), so the total effect of 0.399 is mostly direct, and only about 20.1% of it travels through Brand Trust. For Influencer Credibility the direct effect (0.131) is about twice the indirect effect (0.068), giving a total effect of 0.199, of which about 34.2% runs through trust.

Information Quality shows the opposite configuration. Its direct effect (0.108) is not distinguishable from zero, and its indirect effect (0.082) accounts for about 43.2% of a total effect of 0.190. The total-effect shares were computed from the reported coefficients and are descriptive rather than inferential. They nevertheless show a consistent ordering: the more a cue works through direct visual or endorser impressions, the less it depends on trust, and the more a cue works through argument and evidence, the more it depends on trust. This is the central empirical result of the study.

4.6 Explanatory Power, Effect Sizes, and Predictive Relevance

Table 7 reports the coefficient of determination, effect sizes, and predictive relevance of the model.

Table 7: R^2, Q^2predict, and f^2 effect sizes.

Construct / Path	R^2	R^2 adj.	Q^2predict	f^2	Assessment
Panel A: Endogenous constructs					
Brand Trust	0.543	0.540	0.531		Moderate
Purchase Behaviour	0.504	0.499	0.458		Moderate

Construct / Path	R^2	R^2 adj.	Q^2predict	f^2	Assessment
Panel B: Effect sizes of paths					
VA → BT				0.116	Small
IQ → BT				0.088	Small
IC → BT				0.064	Small
VA → PB				0.111	Small
BT → PB				0.067	Small
IC → PB				0.015	Negligible
IQ → PB				0.009	Negligible

Source: SmartPLS 4 output. f^2 thresholds: 0.02 = small, 0.15 = medium, 0.35 = large.

The R^2 for Brand Trust (0.543) indicates that the 3 stimuli collectively explain 54.3% of its variance, while the full model explains 50.4% of the variance in Purchase Behaviour (R^2 = 0.504); both indicate moderate explanatory power. The Q^2predict values for Brand Trust (0.531) and Purchase Behaviour (0.458) exceed zero, which confirms predictive relevance. Fig. 10 places these quantities on the estimated model.

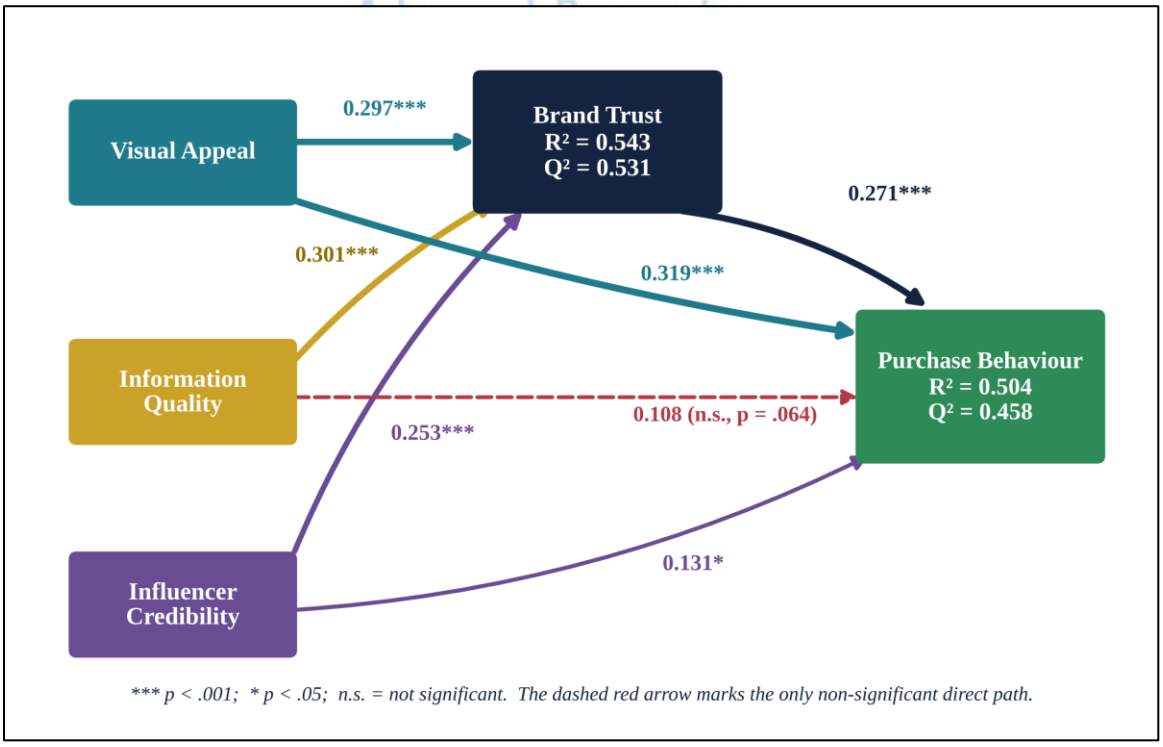


Fig. 10. Estimated structural model with path coefficients, R^2, and Q^2predict.

The estimated model shows that the full set of significant paths forms a dense network around Brand Trust: all 3 stimuli feed into it, and it feeds into Purchase Behaviour with a coefficient of 0.271. Three of the 4 paths that enter Purchase Behaviour directly or through trust are of similar

magnitude (0.319, 0.271, and 0.131 are all clearly positive), and the only broken arrow is the dashed red line for Information Quality. A model with only 7 structural paths therefore accounts for about half of the variance in purchase behaviour, which is a respectable share for a behavioural outcome that depends on price, budget, and skin type as well as on marketing exposure.

The gap between the 2 R^2 values is also informative. Brand Trust (0.543) is explained slightly better than Purchase Behaviour (0.504), which fits the S–O–R logic: stimuli are expected to act more strongly on an internal state than on a behaviour that is subject to additional constraints. The adjusted R^2 values (0.540 and 0.499) differ from the raw values by only 0.003 to 0.005, so the explained variance is not inflated by the number of predictors. The Q^2predict of 0.458 for Purchase Behaviour shows that the model predicts out-of-sample purchase behaviour better than a simple mean benchmark.

Fig. 11 ranks the effect sizes of the individual paths.

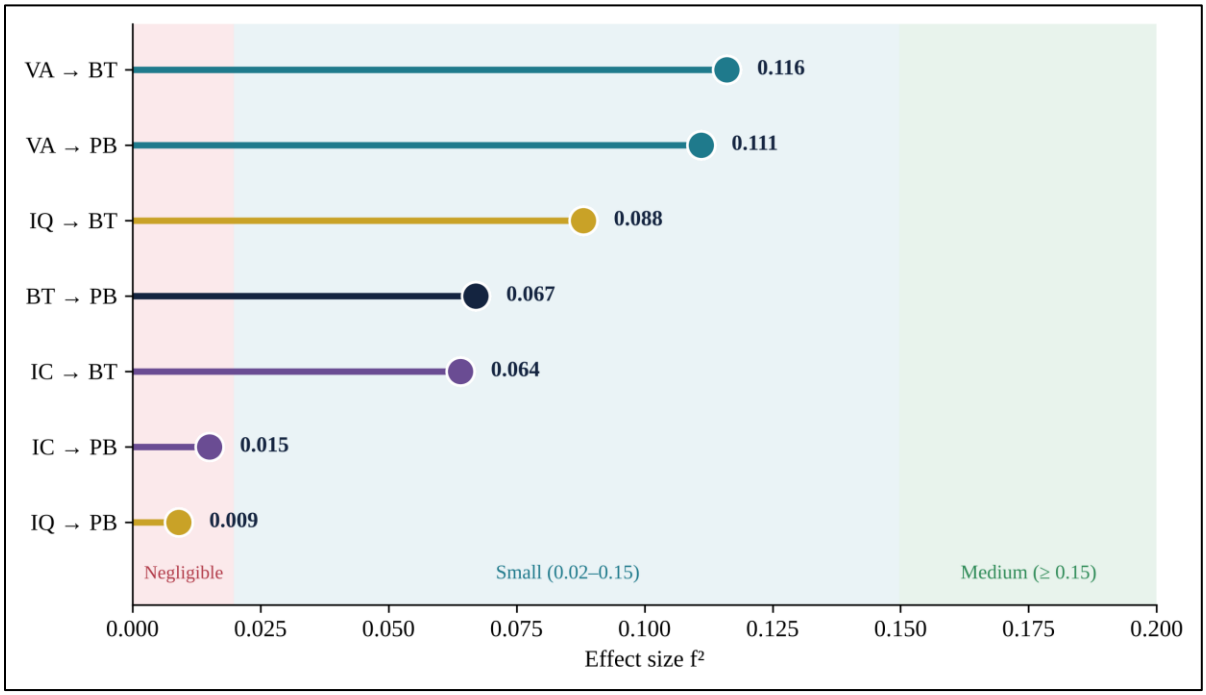


Fig. 11. Effect sizes (f^2) of the structural paths.

None of the 7 paths reaches the medium threshold of 0.15. The largest effect sizes belong to VA→BT (0.116) and VA→PB (0.111), and Visual Appeal is therefore the strongest single driver of both trust and behaviour in terms of explained variance. IQ→BT (0.088), BT→PB (0.067), and IC→BT (0.064) form a middle group of small effects. The 2 lowest values, IC→PB (0.015) and IQ→PB (0.009), fall below 0.02 and are negligible, which confirms that the direct paths of Influencer Credibility and Information Quality contribute minimally to the explained variance.

An important nuance follows. Information Quality has the largest coefficient on Brand Trust (0.301), yet its effect size on trust (0.088) is smaller than that of Visual Appeal (0.116). The 2 statistics answer different questions: a path coefficient describes the expected change in the outcome, whereas f^2 describes how much R^2 would fall if the predictor were removed, which depends on how much a predictor overlaps with the others. Because Information Quality overlaps

strongly with Influencer Credibility (HTMT = 0.917), part of its contribution can be replaced by the other predictor, and its unique contribution is smaller than its coefficient suggests.

4.7 Discussion

This study examined how 3 components of social media marketing, Visual Appeal, Information Quality, and Influencer Credibility, shape the purchase behaviour of young skincare consumers in Lahore, and how Brand Trust mediates these relationships. The results show that the scrolling-to-purchasing mechanism is not uniform. The 3 stimuli operate through distinct pathways, and the difference between them is clearer in the mediation pattern than in the size of their coefficients on trust.

Visual Appeal had the strongest direct effect on purchase behaviour ($\beta = 0.319$) and the largest effect sizes on both Brand Trust ($f^2 = 0.116$) and Purchase Behaviour ($f^2 = 0.111$). For young consumers who discover skincare on image- and video-led platforms, with 77.1% of the sample using Instagram or TikTok as the main discovery platform, the look of the content works as a quick and largely automatic cue. It is plausible that a polished image reduces the effort needed to decide, and that this is why only about 20.1% of its total effect passes through trust. Visual appeal is therefore best understood as a trigger of action as well as a builder of confidence.

Influencer Credibility had a significant but comparatively modest direct effect on purchase behaviour (H6, $\beta = 0.131$) and a significant effect on Brand Trust (H3, $\beta = 0.253$). This pattern agrees with the wider evidence from comparative studies in Pakistan and the United Kingdom, where influencers raised the visibility of a brand but authenticity was the decisive factor for trust and purchase. The modest direct effect suggests that, for these consumers, credible endorsers matter partly because they help build trust rather than because the endorsement alone drives the purchase, and the 34.2% share of the total effect that runs through trust is consistent with that reading.

The result for Information Quality is theoretically the most important. It had no significant direct effect on purchase behaviour (H5 not supported), yet its indirect effect through Brand Trust was significant, which indicates full mediation (H9). Detailed and accurate product information alone therefore cannot motivate young consumers to purchase unless they trust the brand. This is consistent with earlier findings that the clarity of product descriptions was not a significant predictor of repurchase intention when attitude and credibility dominated, and with the role of information quality as an antecedent of trust. Information in skincare marketing works as a credibility signal rather than a direct persuasion lever, because consumers do not act on information that they do not yet trust.

Brand Trust significantly predicted purchase behaviour (H7) and mediated all 3 stimulus paths (H8–H10), which confirms its role as the organism in the S–O–R model. This supports evidence that trust and product quality drive purchase in cosmetics markets more than price or unmediated social media marketing, and that social media marketing builds trust that is later consolidated into loyalty. Two features distinguish the present study. First, whereas similar studies often treat brand trust as an independent antecedent of repurchase, this study positions it as a mediator, and the significant indirect effects support that role. Second, the dependent variable is initial purchase behaviour rather than the repurchase intention that dominates the regional literature, so the mediation of Information Quality through trust extends trust-based reasoning from loyalty to the earlier conversion stage.

Taken together, the findings help explain why high engagement often fails to convert in Pakistan's online skincare market. Consumers respond most directly to visual and credible cues, but the informational content that brands frequently emphasise influences behaviour only after it has built trust. The persistent lack of trust in the online marketplace therefore acts as the bottleneck between exposure and transaction, which is exactly the gap that the mediation model

was designed to capture. One caution applies: the full mediation of Information Quality rests on a direct effect with p = .064, and the high overlap between Information Quality and Influencer Credibility (HTMT = 0.917) means that the separate roles of the 2 constructs should be confirmed in further samples.

5. Conclusion

This study examined how social media marketing converts online engagement (scrolling) into skincare purchases (purchasing) among young adults in Lahore. Applying the S–O–R framework with PLS-SEM to 394 valid responses, the results show that Visual Appeal (β = 0.319) and Influencer Credibility (β = 0.131) directly affect purchase behaviour, whereas Information Quality (β = 0.108, p = .064) does not; the effect of Information Quality is fully mediated by Brand Trust (indirect β = 0.082). Brand Trust significantly predicts purchase behaviour (β = 0.271) and mediates all 3 stimulus paths, which clarifies why high engagement does not always lead to actual sales when consumers do not trust the brand. The model explains 54.3% of the variance in Brand Trust and 50.4% in Purchase Behaviour. Overall, the findings suggest that emerging digital skincare markets should focus on credible, trust-building content to turn scrolling into purchasing rather than simply providing more product information.

6. Discussion and Future Work

6.1 Theoretical Implications

The study makes 3 main contributions. First, it extends S–O–R theory by showing that different types of marketing stimuli follow distinct mediation pathways: Information Quality shows full mediation, while Visual Appeal and Influencer Credibility show partial mediation. This challenges the uniform-mediation assumption in many S–O–R applications and suggests that stimulus type should be treated as a differentiating variable. Second, the study contributes to the brand trust literature by showing that trust acts as a necessary processing gateway for information-based stimuli but is less central for visually evaluated stimuli, which connects the S–O–R framework with dual-process reasoning, in which fast, impression-based judgements and slower, evidence-based judgements follow different routes. Third, the study applies the S–O–R framework in a Pakistani consumer context, which extends its applicability to developing economies with their own digital environments and cultural settings.

6.2 Practical Implications

The findings are useful for skincare brands in Pakistan. Because Visual Appeal had the strongest direct effect on purchase behaviour, brands should invest in visually appealing content such as professional product photography, aesthetically consistent social media profiles, and attractive campaign materials. The full mediation of Information Quality indicates that providing product information alone is not enough to convert consumers into buyers; brands should combine information with trust-building content such as third-party certifications, dermatologist endorsements, and transparent ingredient details. The partial mediation results for influencer marketing suggest that brands should select influencers who can build brand trust by sharing authentic content with consumers. Brands should also measure success by conversion and trust indicators rather than by likes and views alone, because the evidence here shows that engagement without trust does not reliably become a sale.

6.3 Limitations

Several limitations should be noted. The cross-sectional design cannot establish causal relationships between variables, and a longitudinal study could better explain them. Because the data were collected only from Lahore through purposive sampling, the findings may not generalise to other cities or populations, and the sample is heavily concentrated in the 18–29 age group (92.7%). There is also a possibility of social desirability bias because the data are self-reported. Moreover, the HTMT value between Information Quality and Influencer Credibility

(0.917) slightly exceeded the strict 0.90 criterion, which indicates some conceptual overlap between the 2 constructs and a need for further scale refinement. Finally, the Visual Appeal scale had a Cronbach's alpha of 0.677 and an AVE of only 0.510, so its measurement precision is the weakest of the 5 constructs.

6.4 Future Research

Future research could extend this study by targeting populations in multiple cities and by using experimental designs to isolate individual marketing dimensions, which would allow causal claims about the effect of visual, informational, and credibility cues. Longitudinal designs could track whether trust built through content leads to repeat purchase and loyalty over time. Other mediators, such as perceived risk and brand attitude, and moderators, such as product involvement and platform type, could also be examined, particularly because the platform in this sample was dominated by Instagram and TikTok. Finally, refining the Visual Appeal and Information Quality scales, and testing whether the Information Quality and Influencer Credibility constructs can be separated more cleanly, would strengthen the measurement base for future S–O–R research in developing markets.

Recent developments in artificial intelligence, predictive analytics, and advanced machine-learning techniques offer promising opportunities for understanding digital consumer behavior and improving social media marketing analysis. Hybrid artificial intelligence frameworks combining machine-learning algorithms with time-series analysis provide methodological opportunities for identifying temporal patterns and predicting changes in consumer preferences and purchasing trends [33]. Advanced deep-learning approaches further demonstrate the potential of predictive modeling for analyzing complex datasets and identifying evolving patterns over time [34]. Machine-learning-based predictive monitoring and regression techniques offer additional analytical approaches for identifying patterns, evaluating behavioral changes, and developing data-driven prediction models [35]. Furthermore, deep neural network-based predictive analytics highlight the potential of intelligent computational systems for extracting meaningful patterns from complex information and supporting data-driven decision-making [36]. Machine-learning approaches for environmental prediction also demonstrate the applicability of predictive algorithms to complex datasets and changing contextual conditions [37]. In addition, context-aware natural language processing provides opportunities to analyze consumer comments, online reviews, and sentiment patterns for understanding brand perceptions and trust formation [38]. Generative artificial intelligence and cybersecurity further highlight the importance of information credibility, digital security, and consumer confidence in online environments [39]. Collectively, these developments provide complementary methodological perspectives for future research integrating social media content analysis, influencer credibility, consumer sentiment, brand trust, and skincare purchasing behavior.

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Appendix A. Survey Instrument

The screening and demographic questions were used to determine eligibility and respondent profile. The 20 measurement items were rated on a five-point Likert scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree.

Table A1: Screening and demographic questions.

No.	Question	Response options
1	Do you currently reside in Lahore, Pakistan?	Yes / No (if No, end survey)
2	What is your age group?	Under 18 (end survey) / 18–24 / 25–29 / 30–35 / 36–40 / Above 40 (end survey)
3	Have you purchased or considered purchasing a specific skincare product (e.g., face washes, cleansers, serums, skin brightening creams/eye creams, sunscreens, or moisturizers) after seeing it on social media (Instagram, TikTok, Facebook) in the last 6 months?	Yes / No (if No, end survey)
4	Gender	Male / Female
5	Which social media platform do you use MOST for skincare discovery?	Instagram (Reels/Posts) / TikTok / Facebook / YouTube / Other
6	What is your primary skin concern? (Select one)	Acne / Blemishes; Skin Brightening / Pigmentation; Anti-Aging / Wrinkles; General Maintenance / Hydration

Table A2. Measurement items (five-point Likert scale).

Code	Item
Variable 1: Visual Appeal (VA)	
VA1	High-quality images and aesthetic videos make me stop scrolling and look at specific skincare items (e.g., face washes, serums, or sunscreens).
VA2	I am more likely to click “Shop Now” if the product packaging looks visually appealing in the post.
VA3	Visual “Before-and-After” transformation videos convince me to try a new skincare product, such as a skin brightening cream or serum.
VA4	Poor video quality or bad lighting in an ad makes me immediately scroll past without buying.
Variable 2: Information Quality (IQ)	

Code	Item
IQ1	I prefer purchasing from posts that clearly explain the ingredients and their specific benefits.
IQ2	I am more likely to buy if the brand replies to comments and questions with helpful information.
IQ3	Vague claims like "instant whitening" without scientific info discourage me from purchasing.
IQ4	Accurate and detailed tutorials on "how to use" the product increase my confidence to buy.
Variable 3: Influencer Credibility (IC)	
IC1	I am more likely to buy a product if the influencer shows their real skin texture (pores/acne) instead of using filters.
IC2	I trust an influencer's recommendation more if they also mention the "cons" (negatives) of the product.
IC3	I perceive an influencer as "Not Credible" if they promote too many different skincare brands at once.
IC4	Niche influencers (skincare experts) influence my buying decision more than famous celebrities.
Variable 4: Brand Trust (BT) – mediating variable	
BT1	Even if an ad is visually beautiful, I will not buy unless I trust the brand's online reputation.
BT2	Seeing positive reviews from real users in the comments section builds my trust in the brand.
BT3	I feel safe sharing my delivery details with local Instagram skincare brands.
BT4	Brand Trust is the main reason I decide to purchase a product after seeing it on social media.
Variable 5: Purchase Behaviour (PB) – dependent variable	
PB1	I often make impulse purchases of daily skincare essentials (like cleansers, sunscreens, or moisturizers) immediately after seeing a compelling ad.
PB2	I save posts about specific skincare products (face washes, serums, etc.) to purchase them later after doing my own research.

Code	Item
PB3	I have actually purchased a targeted skincare product (e.g., sunscreen, eye cream, or moisturizer) in the last 6 months based on a social media recommendation.
PB4	I have recommended specific skincare items (like face washes or serums) to friends/family that I originally discovered on social media.

Note. The age categories in this appendix are aligned with the categories reported in the sample profile. The negatively worded items (VA4, IQ3, and IC3) correspond to the reverse-coding procedure used in the analysis.

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