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From scroll to sale: how social media triggers and age shape digital consumer decisions through interaction

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This study examines how digital stimuli social media trends (SMT), quality of information (QTI), and influencer cues (ICR) shape consumer buying behavior (CBB) through the mediating role of social media interaction (SMI). Drawing on the Stimulus–Organism–Response (S-O-R) model, Uses and Gratifications Theory (UGT), and the Theory of Planned Behavior (TPB), data were collected from 359 Saudi social media users and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Findings indicate that SMT and QTI significantly enhance SMI, which in turn predicts CBB. However, ICR showed no significant influence, highlighting possible trust erosion or influencer fatigue. Mediation analysis confirmed SMI's central role between SMT/QTI and CBB, while moderation analysis revealed no significant age-based differences. The adjusted R^2 for CBB was 0.276, indicating modest explanatory power. PLS-Predict results showed predictive relevance with limited accuracy. This research repositions social media interaction as a cognitive-emotional mechanism that bridges exposure and behavior. Practically, marketers are encouraged to prioritize credible, engaging content over influencer-centric strategies, particularly in digitally mature markets.

KEYWORDS

social media interaction, consumer buying behavior, digital stimuli, PLS-SEM, influencer fatigue

1 Introduction

Social media has fundamentally reshaped how people communicate and shop, fueling the rapid growth of social commerce form of online retail enriched by user-generated content, peer reviews, and real-time interaction. Unlike traditional e-commerce, social commerce thrives on digital engagement dynamics that shape consumer decisions (Alhumud and Elshaer, 2024; Attar et al., 2022; Lin and Wang, 2023). However, much of the existing research treats these elements branding, usability, or influencer tactics as standalone variables, lacking a unified theoretical structure. This fragmentation obscures how different digital cues combine to influence consumer behavior. This study investigates how three key digital stimuli social media trends (SMT), quality of information (QTI), and influencer cues (ICR) impact consumer behavior in Saudi Arabia. It focuses on the mediating role of social media interaction (SMI) and examines whether age moderates these relationships. By integrating the S-O-R model with UGT and TPB, this research contributes to filling the theoretical gap in understanding how diverse digital cues translate into consumer action, especially in digitally mature environments.

The Saudi market provides a valuable context for examining these trends. With over 90% internet penetration and a predominantly youthful, digitally active population, Saudi Arabia has experienced a fast transition from traditional to digital media platforms (Almuammar et al., 2021; Wahabi et al., 2023), with internet penetration over 95% and widespread adoption of platforms like Instagram, Snapchat, and TikTok (Sanam et al., 2024). The Kingdom's youthful demographic where nearly 70% are under 35 makes it a strategic context for examining digital interactions (Katooa, 2024). Notably, Saudi females demonstrate higher engagement levels on visual platforms, making them a vital segment for consumer-centric marketing studies (Aldhahery et al., 2018). These cultural, technological, and demographic conditions justify the country's selection for investigating social media-driven consumer behavior.

As digital platforms become more integrated into everyday routines, consumer decisions are shaped not just by functional goals, but also emotional and social needs (Alatawy, 2021). Viral trends and peer-generated content increasingly influence purchasing intentions, often more than conventional advertising. Yet, concerns about credibility, such as fake reviews and influencer cues transparency, remain salient particularly in contexts like Saudi Arabia where trust and community values strongly affect decision-making (Onofrei et al., 2022; Palalic et al., 2020; Shahbaznezhad et al., 2021).

While SMT and QTI are widely accepted as core drivers of interaction, influencer cues (ICR) represent a more context-sensitive factor, with their influence potentially shaped by issues such as trust erosion, saturation, and regional norms. This integrated framework offers both theoretical insight and actionable value for digital marketers, particularly those targeting socially driven, mobile-first consumers in the MENA region.

2 Theoretical background

This study extends the Stimulus–Organism–Response (S-O-R) model by integrating insights from the Uses and Gratifications Theory (UGT) and the Theory of Planned Behavior (TPB), framing social media interaction as both a behavioral and epistemic response to digital stimuli.

2.1 Stimulus–organism–response (S-O-R) framework

The S-O-R model explains how environmental cues (stimuli) influence internal evaluations (organism), which then lead to behavioral responses (Russell and Mehrabian, 1974). In digital commerce, stimulus includes viral content, reviews, and influencer posts that shape users' cognitive and emotional states (Kimiagari and Asadi Malafe, 2021; Sultan et al., 2021).

However, this study reconceptualizes stimuli like social media Trends (SMT) and Influencer Cues (ICR) as *knowledge signals* not just marketing messages triggering engagement, opinion formation, and consumer learning in online spaces (Croes and Bartels, 2021; Lina et al., 2022). Trending content includes viral hashtags, influencer challenges, meme-based content, real-time news reactions, and promotional campaigns boosted by algorithmic amplification. The model is operationalized as follows:

- *Stimuli*: Social media trends (SMT), quality of information (QTI), and influencer cues (ICR).
- *Organism*: Social media interaction (SMI).
- *Response*: Consumer buying behavior (CBB).

This layered structure allows mapping of how digital signals influence consumer decisions.

2.1.1 Stimuli as knowledge signals

- *Social Media Trends (SMT)* represent emerging digital cues that encode social proof and ephemeral market insights. These stimuli capture user attention and promote collective engagement behavior through visual content, trends, and virality (Mahoney and Tang, 2024).
- *Quality of Information (QTI)* acts as a cognitive scaffold enabling trust, perceived control, and confidence in decision-making (Jiang et al., 2021; Wang and Yan, 2022).
- *Influencer Cues (ICR)* reflect distributed authority and serve as socio-cognitive heuristics. However, their effectiveness may diminish in oversaturated digital environments (Kim et al., 2025; Vrontis et al., 2021).

2.1.2 Organism: digital cognition and emotion

Social Media Interaction (SMI) is conceptualized as a cognitive-emotional interface through which users process stimuli, form judgments, and co-create meaning. It includes both cognitive (e.g., browsing, evaluation) and emotional (e.g., reassurance, identity alignment) dimensions (Lai Cheung et al., 2021; Munaro et al., 2021).

This includes:

- *Cognitive functions*: browsing, content analysis, and heuristic judgments (Onofrei et al., 2022; Shahbaznezhad et al., 2021).
- *Emotional resonance*: reassurance, identity alignment, and social bonding (Palalic et al., 2020).

These mechanisms enable users to engage with digital stimuli in a meaning-driven and emotionally invested manner.

2.1.3 Response: knowledge-driven behavioral intent

Consumer buying behavior (CBB) is treated as a knowledge-based action, arising from emotionally invested engagement, validated content, and learned digital cues (Alatawy, 2021; Hassan and Sohail, 2021; Majeed et al., 2021).

2.2 Supplementary theoretical lens: UGT and TPB

UGT explains motivations for interaction (e.g., entertainment, information), while TPB captures attitudes, subjective norms, and control over behavior. These lenses offer a blended mechanism to understand why and how digital stimuli influences decision-making (Ajzen, 1991; Alqutub, 2023).

UGT and TPB are embedded into the S-O-R model:

UGT anchors this model by framing stimuli in terms of user motivation:

- SMT and QTI fulfill cognitive and social gratifications (Wang et al., 2021; Zolkepli et al., 2018).
- ICR supports affiliative and identity-related needs (Croes and Bartels, 2021).

TPB supports the organism and response layers by linking attitude, subjective norms, and perceived control to the intention.

2.3 Moderating role of age as a knowledge filter

Age is conceptualized not merely as a demographic variable but as a cognitive moderator that shapes individuals' digital fluency, motivational orientation, and processing capacity in online environments. This perspective is grounded in Socioemotional Selectivity Theory (Carstensen et al., 1999), which posits that age-related motivational goals shift over time where younger individuals tend to prioritize knowledge acquisition and novelty, while older individuals focus on emotionally meaningful interactions. These motivational dynamics may influence how digital stimuli such as social media trends or influencer cues are perceived and internalized.

Furthermore, Digital Literacy Theory (Ng, 2012) suggests that younger users possess higher digital fluency and are more adept at navigating rapidly changing digital landscapes, whereas older cohorts may rely on more deliberate and cognitively conservative strategies. This distinction aligns with prior findings that age differences shape cognitive elaboration and trust mechanisms in digital contexts (Cain and Coldwell-Neilson, 2024; Caton et al., 2022).

From a cognitive processing standpoint, age influences attention allocation, heuristic reliance, and content validation strategies. Younger users, for instance, are more responsive to algorithm-driven and peer-validated cues, whereas older users may favor content aligned with established expertise or values (Karawya, 2025; Mohammed, 2021). This moderating role of age thus acts as a knowledge filter that nuances the relationship between digital stimuli and interaction behaviors, introducing heterogeneity in how users engage with and respond to persuasive digital content.

3 Hypotheses development

While numerous studies have explored how social media content and influencer cues shape consumer behavior, this study fills a key gap by examining how multiple digital cues interact through social media interaction (SMI) as a unified cognitive-emotional process. Most prior studies focus on isolated effects or test direct paths, such as content quality directly affecting purchase intention (Onofrei et al., 2022) or influencer trust influencing decisions (Coutinho et al., 2023). However, few have modeled the mediating role of interaction across diverse stimuli types or explored how user characteristics like age moderate these effects within a structured theoretical framework.

This research integrates the Stimulus–Organism–Response (S-O-R) model with the Uses and Gratifications Theory (UGT) and Theory of Planned Behavior (TPB). UGT helps identify why users are drawn to certain stimuli (to fulfill social, cognitive, or emotional gratifications). S-O-R models how these stimuli are processed, and TPB explains how internal states translate into purchase behavior. Each hypothesis is grounded in this theoretical synthesis.

Social media interaction (SMI) is treated as a digital organismic response that reflects user-level engagement and emotional-cognitive processing. SMI encompasses both active behaviors (e.g., commenting, sharing, participating in challenges or polls) and passive behaviors (e.g., viewing, liking, browsing), all of which contribute to engagement intensity. Although treated as a unified construct in this study, these forms differ in depth and motivation suggesting a potential avenue for future research to explore their discrete effects on consumer behavior.

Understanding the distinction between active and passive engagement is critical for conceptualizing Social Media Interaction (SMI) within digital consumer behavior. Active engagement refers to participatory actions such as commenting, sharing, or contributing user-generated content, which signal higher levels of cognitive and emotional investment (Lai Cheung et al., 2021). These behaviors reflect a user's willingness to engage with content beyond consumption, often indicating deeper processing, stronger attitudinal alignment, and a higher likelihood of behavioral outcomes (Palalic et al., 2020).

Conversely, passive engagement encompasses less participatory but still meaningful behaviors, including browsing, liking, or silently consuming content. Although passive users do not overtly contribute, their behaviors can be indicative of interest, exploratory intent, or cognitive resonance (Onofrei et al., 2022). Research shows that passive engagement may still reflect affective responses and can be a precursor to more active behaviors under the right contextual stimuli (Mahoney and Tang, 2024). However, the psychological depth and conversion potential of passive engagement are typically lower, making the distinction theoretically and practically relevant.

This distinction matters because the cognitive-emotional processing involved in active engagement often strengthens the mediation effect of SMI on behavioral outcomes, such as consumer buying behavior. By integrating both engagement modes under a unified construct, the current study reflects the blended nature of digital interaction, while acknowledging that underlying motivational dynamics may differ (Lina et al., 2022; Rather and Hollebeek, 2021). Recognizing this duality allows for a more nuanced understanding of how stimuli like social media trends and influencer cues shape consumer decision-making across varied user types and contexts.

3.1 The relation between social media trends (SMT) and social media interaction (SMI)

Social media trends serve as digital signals that indicate popularity and social proof. UGT suggests that users are motivated to interact with such content to fulfill social identity or entertainment needs (Wang et al., 2021). Trending content includes viral challenges, memes, or topical discussions, which foster active user involvement like commenting and sharing. According to Mahoney and Tang (2024), engagement with socially validated content enhances emotional resonance (Lina et al., 2022), thus facilitating cognitive scaffolding for deeper interactions. Consequently, SMT is hypothesized to significantly predict SMI through both gratifications sought and perceived digital relevance.

> *H1*: Social media trends (SMT) positively influence social media interaction (SMI).

3.2 The relation between quality information (QTI) and social media interaction (SMI)

Information quality enhances trust, reduces uncertainty, and increases evaluative engagement central aspects of cognitive processing in S-O-R's "Organism" layer (Jiang et al., 2021). UGT posits that accurate and helpful content fulfills users' need for knowledge and control (Wang et al., 2023). Consumers are more likely to interact with content perceived as reliable and clear (Alatawy, 2021), making QTI a vital cognitive trigger

> *H2*: Quality information (QTI) positively influences social media interaction (SMI).

3.3 The relation between influencer cues (ICR) and social media interaction (SMI)

Influencers are often positioned as socio-emotional stimuli that build trust, enhance relatability, and satisfy affiliative or identity-driven gratifications (Coutinho et al., 2023; Croes and Bartels, 2021). Their content can stimulate user engagement through perceived authenticity and emotional resonance (Vrontis et al., 2021). However, recent research points to increasing signs of influencer fatigue, declining credibility, and audience skepticism in oversaturated digital environments (Mabkhot and Piaralal, 2023). These challenges raise questions about the sustained efficacy of influencers as stimuli in all contexts. Accordingly, while ICR may still serve as stimuli in the S-O-R model, their effect may be conditional, weakened, or mediated by platform and audience maturity.

> *H3*: Influencer cues (ICR) are expected to positively influence social media interaction (SMI), though this effect may be attenuated in saturated or skeptical digital contexts.

3.4 The relation between social media interaction (SMI) and consumer buying behavior (CBB)

SMI reflects the active cognitive and emotional involvement of users with digital content. According to S-O-R, this organism-level processing leads to behavioral responses like purchase intentions (Attar et al., 2022). Previous studies confirm that user interaction enhances intention by deepening product understanding and affective connection (Hassan and Sohail, 2021; Kimiagari and Asadi Malafe, 2021).

> *H4*: Social media interaction (SMI) positively influences consumer buying behavior (CBB).

3.5 The relation between social media trends (SMT), quality information (QTI), & influencer cues (ICR), effect on consumer buying behavior (CBB) via social media interaction (SMI)

When users engage with trending content, they develop emotional involvement and shared identification, which enhances the likelihood of action (Kim et al., 2025). Trends act as attention funnels that, when interacted with, shape brand awareness and trigger behavioral intention (Mahoney and Tang, 2024). Prior work also supports that cultural resonance and visibility boost consumer engagement and purchase behavior (Shahbaznezhad et al., 2021).

> *H5a*: Social media trends (SMT) positively influence consumer buying behavior (CBB) via social media interaction (SMI).

Trust in content quality encourages deeper interaction, which in turn affects decision confidence and behavioral outcomes (Jiang et al., 2021). QTI enables the formation of evaluative judgments, which translate into purchase behavior when mediated by interactive engagement (Alatawy, 2021; Wang et al., 2023).

> *H5b*: Quality information (QTI) positively influences consumer buying behavior (CBB) via social media interaction (SMI).

Although direct persuasion by influencers may be declining, their content can still prompt user interaction particularly when signaling authenticity or niche relevance (Coutinho et al., 2023). Prior studies link influencer engagement to behavior via mechanisms such as liking, commenting, or sharing (Lina et al., 2022; Majeed et al., 2021). However, this influence appears increasingly moderated by factors like trust erosion, skepticism, or overexposure, especially in digitally mature markets. Thus, the mediating effect of social media interaction on consumer behavior via ICR may not be universally robust, but rather context-sensitive.

> *H5c*: Influencer cues (ICR) positively influence consumer buying behavior (CBB) via social media interaction (SMI).

3.6 The moderating role of age between social media trends (SMT), quality information (QTI), & influencer cues (ICR), and social media interaction (SMI)

Age shapes users' digital fluency, preferences, and trust levels. Younger users are more likely to engage with symbolic stimuli (e.g., trends), while older users prefer credibility and depth (Rather and Hollebeek, 2021; Zhang et al., 2024). These moderation effects highlight how cognitive and emotional gratifications differ by age (Figure 1).

> *H6a*: Age moderates the relationship between social media trends (SMT) and social media interaction (SMI).
>
> *H6b*: Age moderates the relationship between quality information (QTI) and social media interaction (SMI).

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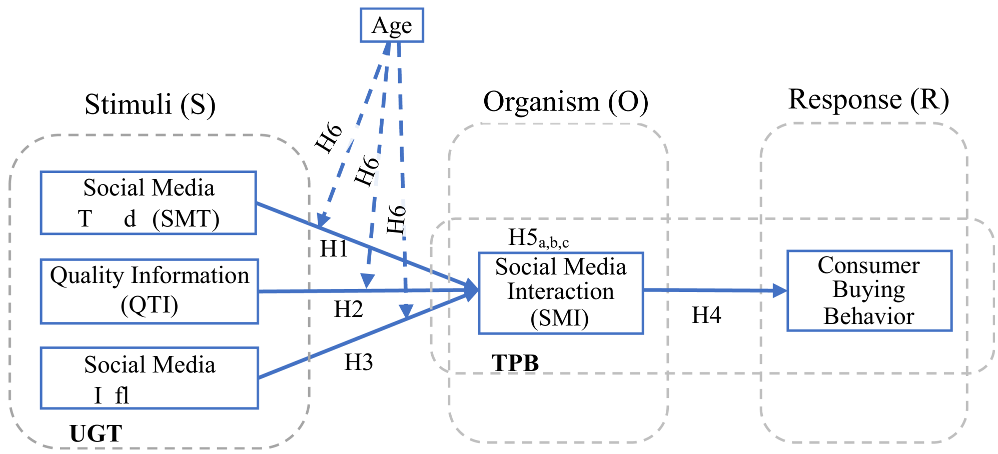

FIGURE 1
Research model.

> *H6c*: Age moderates the relationship between influencer cues (ICR) and social media interaction (SMI).

4 Research methodology

4.1 Measurement strategy

To ensure alignment with our integrated S-O-R, UGT, and TPB framework, we operationalized each construct with validated 5-point likert scales adapted from prior empirical studies. Emphasis was placed on cultural sensitivity, item clarity, and construct validity.

4.2 Questionnaire development

- *Social Media Trends (SMT)*: Measured using 3 items adapted from Shahbaznezhad et al. (2021), which captured respondents' perceptions of content virality, social proof, and trending topics' relevance. Sample item: "I often notice what content is trending on social media before making decisions."
- *Quality of Information (QTI)*: Measured with 3 items derived from Shahbaznezhad et al. (2021), focused on content clarity, accuracy, and trustworthiness. Sample item: "The content I see on social media is helpful and accurate for making purchase decisions."
- *Influencer Cues (ICR)*: Since this study focused specifically on cosmetics influencers, categorization by content type (e.g., fashion, health) was not relevant. Instead, the cues measured included perceived expertise, attractiveness, and credibility, consistent with prior literature, Items adapted from Shahbaznezhad et al. (2021), These 4 items assessed perceived credibility, attractiveness, and expertise of influencers. Sample item: "I trust product recommendations from influencer cues I follow."
- *Social Media Interaction (SMI)*: Items adapted from Wang et al. (2023), 4 items assessed active behaviors such as commenting, comparing, or sharing. Sample item: "I often compare opinions or reviews on social media before making decisions."
- *Consumer Buying Behavior (CBB)*: Purchase intention was measured using 4 items adapted from Mabkhot and Piaralal (2023). These items reflected impulsive intent, loyalty, and likelihood to buy after interacting online. Sample item: "After engaging with content on social media, I am more likely to purchase."

All constructs used a 5-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree."

4.3 Pretesting and modification

To ensure contextual validity, the questionnaire was reviewed by academic experts and pretested with marketing professionals familiar with Saudi digital behavior. Based on feedback, terminology was localized (e.g., replacing "viral" with "popular"), and items were revised to reflect regional content consumption norms and behavioral patterns.

4.4 Data collection

Data was collected over a six-week period from January to February 2023. The survey targeted active users of Instagram, TikTok, and Twitter residing in Saudi Arabia. Demographic representation included users aged 18–50+, with a gender distribution of 58% female and 42% male. Participants were also asked about their familiarity with influencers, categorized as macro (over 100,000 followers) or micro (under 100,000). This granularity allowed a richer understanding of how user-influencer dynamics differ by context.

4.5 Sampling

A structured online survey was deployed using non-probabilistic convenience sampling across major platforms including Twitter, Instagram, LinkedIn, and WhatsApp groups. Efforts were made to ensure demographic balance, with targeted outreach across regions and gender. The final sample included 359 complete responses (response rate: 89%).

4.6 Sample size and power

Using G*Power, the minimum required sample was calculated to be 89 (effect size = 0.15; power = 0.95; two predictors) (Harris, 2001). The final sample exceeded this with 359 responses, providing strong statistical power for PLS-SEM analysis.

4.7 Challenges during data collection

One of the key challenges faced was ensuring balanced participation across age groups and genders. To mitigate this, the survey was distributed during both weekdays and weekends, and reminders were sent at staggered intervals. While younger audiences responded more readily, targeted outreach helped capture broader demographic representation.

5 Data analysis and results

Data analysis utilized SmartPLS 4 software applying the partial least squares (PLS) approach for structural equation modeling (SEM). PLS was preferred over traditional SEM due to its focus on maximizing variance explained by independent variables. It has minimal sample size requirements while delivering reliable results for both measurement and structural models, aligning well with the study's goals (Hair and Alamer, 2022). Additionally, SmartPLS 4's PLS-SEM is ideal for exploratory research and complex models, especially when assumptions of normality are not met (Chin, 1998; Hair et al., 2011).

5.1 Common method bias

As the data from a single source necessitated an assessment for Standard method bias (Fuchs, 2012). Recent studies have identified notable limitations of Harman's Single-Factor Test in accurately detecting common method bias (CMB) in survey-based research. A recent analysis by Aguirre-Urreta and Hu (2019) and Howard and Henderson (2023) indicated that this widely used method has limited effectiveness in identifying CMB, prompting the selection of the Full Collinearity method as a more efficient alternative to address CMB issues. This suggests that researchers may be incorrectly led to believe that their findings are reliable when they may not be. A variance inflation factor (VIF) value of ≤ 3.3 indicates the absence of bias (Kock, 2015; Kock and Lynn, 2012). The evaluation revealed that the VIF was less than 3.3, as shown in Table 1, confirming the absence of bias (See Table 1).

5.2 Model assessment

The assessment of the PLS-SEM model followed the two-step approach suggested by Anderson and Gerbing (1988) and Hair et al. (2019a), which includes examining both the measurement model first

TABLE 1 Full collinearity testing.

Construct	CBB	ICR	QTI	SMI	SMT
VIF	2.418	2.218	2.07	1.264	1.646

to confirm that the model is accurate and consistent (Sarstedt et al., 2022; Ramayah et al., 2018) followed by the second step of the analysis of the structural model.

5.2.1 Step 1: measurement model

In evaluating the measurement model, it is essential to analyze four specific types of validity. The inter- item reliability of the indicators is assessed via their loadings (Hair et al., 2019b), whereas the convergence validity is determined through the Average Variance Extracted (AVE), and the internal consistency reliability can be ascertained using Composite Reliability (CR) (Darsono et al., 2019; Henseler et al., 2015).

According to the standards established by Sarstedt et al. (2022), these values are expected to meet or exceed specific thresholds: 0.708 for loadings, 0.5 for AVE, and 0.7 for CR. Presented in Table 2, the outer loading of each indicator surpassed the minimum requirement of 0.708, thereby affirming the convergent validity at the indicator level. Additionally, our analysis demonstrated that all constructs recorded AVE values above 0.5, further confirming the convergent validity at the construct level. Importantly, each indicator within the measurement models complied with the prescribed benchmarks for composite reliability. These results collectively affirm that all constructs maintained a high degree of internal consistency and reliability.

Following this, we conducted an analysis of discriminant validity to evaluate the extent to which a construct is distinctly differentiated from other constructs within the model framework. The assessment of discriminant validity was executed in accordance with the methodology proposed by Fornell and Larker (1981), which stipulates that the Average Variance Extracted (AVE) for a construct must exceed the highest squared correlation with any other construct in the model. This assessment is detailed in Table 3.

The two tests confirmed that the measurement model is both valid and reliable.

5.2.2 Step 2: structural model

5.2.2.1 Path coefficient

After successfully validating the reliability and validity of our measurement model, we analyzed the structural model to test our hypotheses (Hair et al., 2019a). Path coefficients, standard errors, t-values, and p-values according to Becker et al. (2023) and Sarstedt et al. (2022), we paired p-values with confidence intervals and effect sizes for evaluating the significance of the hypothesis as recommended (Hahn and Ang, 2017). 10,000 bootstrapping samples was carried out as recommended by Becker et al. (2023) and Sarstedt et al. (2022), Bootstrapping improved the stability and accuracy of estimates, resulting in more reliable confidence intervals for path coefficients. Hypothesis testing results, both direct and indirect effects, are in Tables 4, 5.

5.2.2.1.1 Direct effects. Hypothesis 1 (H1) received empirical support ($\beta = 0.302$, $t = 4.411$, $p < 0.001$) with PCI = [0.171, 0.444], and an

TABLE 2 Construct reliability and validity.

Constructs	λ	CR	AVE
Consumer buying behavior		0.86	0.61
CBB1: You intend to use Social Media while making a purchase decision toward cosmetic brands	0.801		
CBB2: It is easy to deliver your opinion on cosmetic brands by looking at their social media sites	0.743		
CBB3: Social Media influences your choice of cosmetic products	0.785		
CBB4: Social Media has played an important role in changing your attitude toward cosmetic brands	0.791		
Influencer cues		0.9	0.68
ICR1: You refer to the opinion of influencers on Social Media while considering any cosmetic product	0.824		
ICR2: You would intend to seek information from social media influencers if your decision making for purchase is important	0.822		
ICR3: You would like to consider all alternatives advised by the influencer before making the final purchase decision	0.823		
ICR4: You give preference to the products that have been suggested by notable influencers rather than any other	0.834		
Quality information		0.83	0.62
QTI1: You refer to Social Media whenever you need information on cosmetic brands or products	0.788		
QTI2: You intend to make a purchase after searching product information on Social Media	0.809		
QTI3: You give careful consideration to the information which you look up on Social Media	0.766		
Social Media Interaction		0.82	0.61
SMI2: Online consumer reviews are beneficial to you while making a purchase decision	0.731		
SMI3: Social Media advertising is more interactive than traditional advertising	0.802		
SMI4: Social Media reviews and comments enables you to make comparison of cosmetic products	0.799		
Social Media trends		0.87	0.68
SMT1: You are interested in knowing about trendy cosmetic products through social media	0.798		
SMT2: You follow latest news and events of cosmetic brands from social media	0.822		
SMT4: You would use social media to keep up with the trend about different cosmetic brands available	0.857		

TABLE 3 Discriminant validity.

Construct	AGE	CBB	ICR	QTI	SMI	SMT
AGE	1					
CBB	0.077	0.78				
ICR	0.078	0.76	0.83			
QTI	0.073	0.61	0.62	0.79		
SMI	0.113	0.53	0.47	0.56	0.78	
SMT	0.071	0.72	0.68	0.63	0.55	0.83

effect size of $f^2 = 0.077$. This confirms that social media trends significantly trigger user interaction, aligning with established concepts of media richness and user engagement as elaborated by Zolkepli et al. (2018). In the same way, Hypothesis 2 (H2), which states that better information (QTI) improves social media interaction (SMI), was also supported ($\beta = 0.308$, $t = 3.834$, $p < 0.001$). This suggests that high-quality information fosters user engagement through cognitive gratification, corroborating the insights provided by Wang et al. (2023). In contrast, Hypothesis 3 (H3), which examines the impact of influencer cues (ICR) on social media interaction (SMI), did not receive support ($\beta = 0.075$, $t = 0.919$, $p = 0.358$). suggesting influencer cues do not significantly impact user engagement in this context. Lastly, Hypothesis 4 (H4) received robust support ($\beta = 0.533$, $t = 7.867$, $p < 0.001$) for linking social media interaction (SMI) to consumer buying behavior (CBB). This confirmation underscores the notable effect that interaction has on purchasing intentions, which is consistent with prevailing findings in the social commerce domain (Shahbaznezhad et al., 2021).

5.2.2.1.2 Mediation effect. The mediating role of SMI was tested for SMT, QTI, and ICR on CBB:

> *H5a*: SMT → SMI → CBB was supported ($\beta = 0.162$, $t = 3.561$, $p < 0.001$; PCI = [0.079, 0.252]).
>
> *H5b*: QTI → SMI → CBB was supported ($\beta = 0.167$, $t = 2.918$, $p = 0.004$; PCI = [0.039, 0.272]).
>
> *H5c*: ICR → SMI → CBB was not supported ($\beta = 0.04$, $p = 0.378$; PCI = [−0.043, 0.117]).

These findings reinforce that while SMT and QTI exert indirect influence via SMI, ICR does not follow the same pattern possibly due to diminished trust or relevance of influencers in this cultural setting. Although age was proposed as a moderator due to its link with cognitive processing and digital literacy (Zhang et al., 2024), the lack of statistical significance suggests that generational differences may be attenuated in highly digitized environments like Saudi Arabia. Younger users often exhibit exploratory behaviors regardless of digital fluency, while older users may adapt through social learning. This

TABLE 4 Structural model assessment: hypotheses testing (direct relationships).

Hypothesis	Direct relationships	STd. Beta	Std Dev.	*t*-value	*p*- values	PCI LL	f^2
H1	SMT - > SMI	0.302	0.068	4.411	$p < 0.001$	[0.171, 0.44]	0.07
H2	QTI - > SMI	0.308	0.08	3.834	$p < 0.001$	[0.146, 0.459]	0.079
H3	ICR - > SMI	0.075	0.074	0.919	0.358	[−0.082, 0.208]	0.003
H4	SMI - > CBB	0.533	0.067	7.867	$p < 0.001$	[0.369, 0.636]	0.381
H6a	AGE x SMT - > SMI	−0.067	0.071	0.935	0.35	[−0.21, 0.069]	0.002
H6b	AGE x QTI - > SMI	−0.036	0.07	0.803	0.422	[−0.182, 0.08]	0.003
H6c	AGE x ICR - > SMI	0.045	0.075	0.791	0.429	[−0.095, 0.192]	0.002

TABLE 5 Structural model assessment: hypotheses testing (Indirect relationships).

Hypothesis	Direct relationships	STd. Beta	Std Dev.	*t*-value	*p*- values	PCI LL
H5a	SMT - > SMI - > CBB	0.162	0.045	3.561	p < 0.001	[0.079, 0.252]
H5b	QTI - > SMI - > CBB	0.167	0.055	2.918	0.004	[0.059, 0.272]
H5c	ICR - > SMI - > CBB	0.04	0.04	0.881	0.378	[−0.043, 0.117]

finding aligns with emerging evidence that digital age gaps are narrowing in platform-native societies (Hassan and Sohail, 2021). Thus, while theoretically plausible, age-based segmentation may require deeper psychographic profiling rather than demographic classification.

5.2.2.1.3 Moderation analysis: age as a moderator. To test the moderating role of age, interaction terms between age and the three independent variables (SMT, QTI, and ICR) were analyzed. None of the interactions yielded statistically significant results:

> *H6a*: Age × SMT → SMI ($\beta = -0.067$, $p = 0.35$; PCI = [−0.201, 0.068]).
>
> *H6b*: Age × QTI → SMI ($\beta = -0.066$, $p = 0.422$; PCI = [−0.181, 0.081]).
>
> *H6c*: Age × ICR → SMI ($\beta = 0.045$, $p = 0.429$; PCI = [−0.095, 0.192]).

As none of the confidence intervals excluded zero, these moderation effects are statistically non-significant and should not be interpreted as evidence of generational differences in digital engagement. Although slope graphs visually suggested that younger users might respond more to trends and information than older users, none of the interaction terms were statistically significant, and all confidence intervals included zero. Therefore, these visual trends are exploratory and should not be interpreted as evidence of moderation (Figures 2, 3).

5.2.2.2 Testing coefficient of determination, effect sizes, and predictive performance

Following Sarstedt et al. (2022), both in-sample and out-of-sample prediction quality were assessed to evaluate the explanatory and predictive capabilities of the model. This section outlines the evaluation of the coefficient of determination (R^2), effect size (f^2), and predictive performance using the PLS-Predict algorithm.

5.2.2.2.1 Coefficient of determination (R^2). The coefficient of determination (R^2) assesses the extent to which the model's exogenous constructs explain the variance in the endogenous variable, Consumer Buying Behavior (CBB). According to Hair et al. (2019a), R^2 values of 0.25, 0.50, and 0.75 represent weak, moderate, and substantial explanatory power, respectively. In this study, the adjusted R^2 for CBB was 0.276, indicating a weak level of explained variance (Table 6).

This suggests that the combined influence of Social Media Interaction (SMI), Social Media Trends (SMT), Quality of Information (QTI), and Influencer Cues (ICR) accounts for approximately 27.6% of the variance in CBB. This moderate explanatory power suggests the model captures a partial but meaningful share of variance in consumer behavior.

5.2.2.2.2 Effect size (f^2). To evaluate the specific impact of each exogenous construct within the model, we calculated effect sizes (f^2). According to Daly and Cohen (1987), these f^2 values are categorized as small (0.02), medium (0.15), and large (0.35). The results show that Social Media Trends (SMT) had a small but meaningful effect on Social Media Interaction (SMI) ($f^2 = 0.077$), indicating that exposure to trending content moderately increases user engagement. Quality of Information (QTI) demonstrated a similar small effect size ($f^2 = 0.079$), supporting its role in fostering interactive evaluation and trust-building behaviors. In contrast, Influencer Cues (ICR) exhibited a negligible effect size ($f^2 = 0.003$), suggesting that the presence of influencer endorsements alone contributes minimally to driving social media interaction in this context. Finally, SMI exerted a substantial effect on Consumer Buying Behavior (CBB) ($f^2 = 0.381$), reinforcing its critical mediating role between digital stimuli and purchase intention. These findings align with the broader conclusion that interaction with content and information rather than influencer cues is the primary driver of consumer behavioral response in Saudi Arabia.

5.2.2.2.3 Predictive performance (PLS-Predict). In assessing the predictive relevance of the model, the PLS-Predict methodology was employed, utilizing a 10-fold cross-validation approach as advocated by Shmueli et al. (2019). The model demonstrated limited scope of

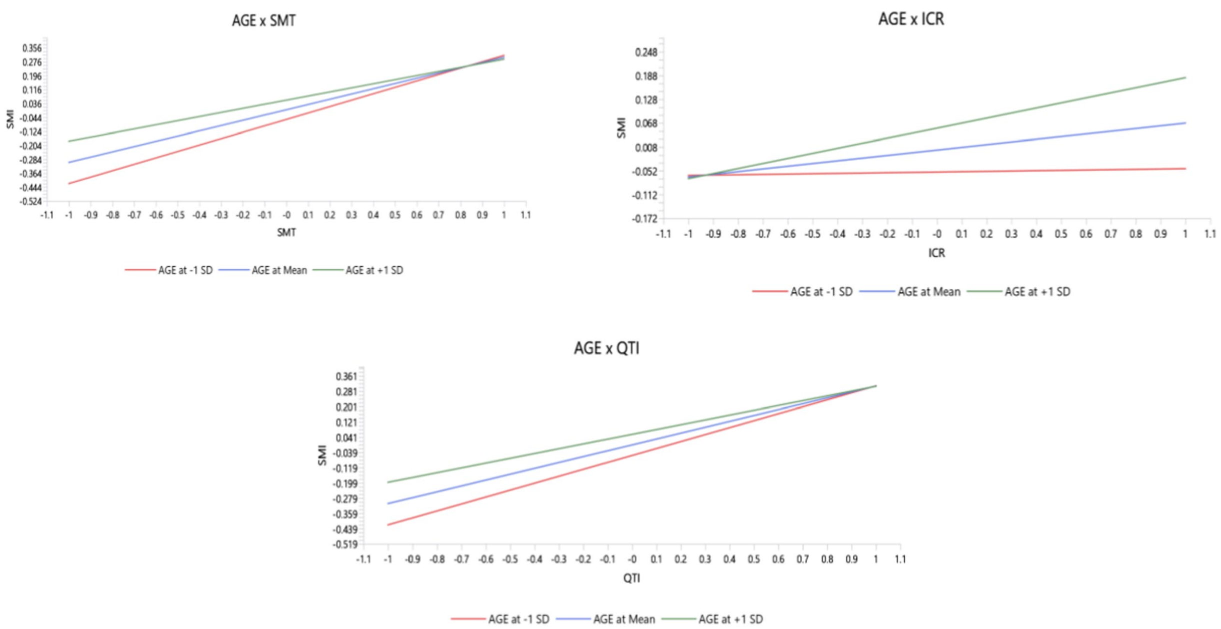

FIGURE 2
Simple slope analysis on the moderating effect. (No moderation effects were statistically significant; visual trends are exploratory only).

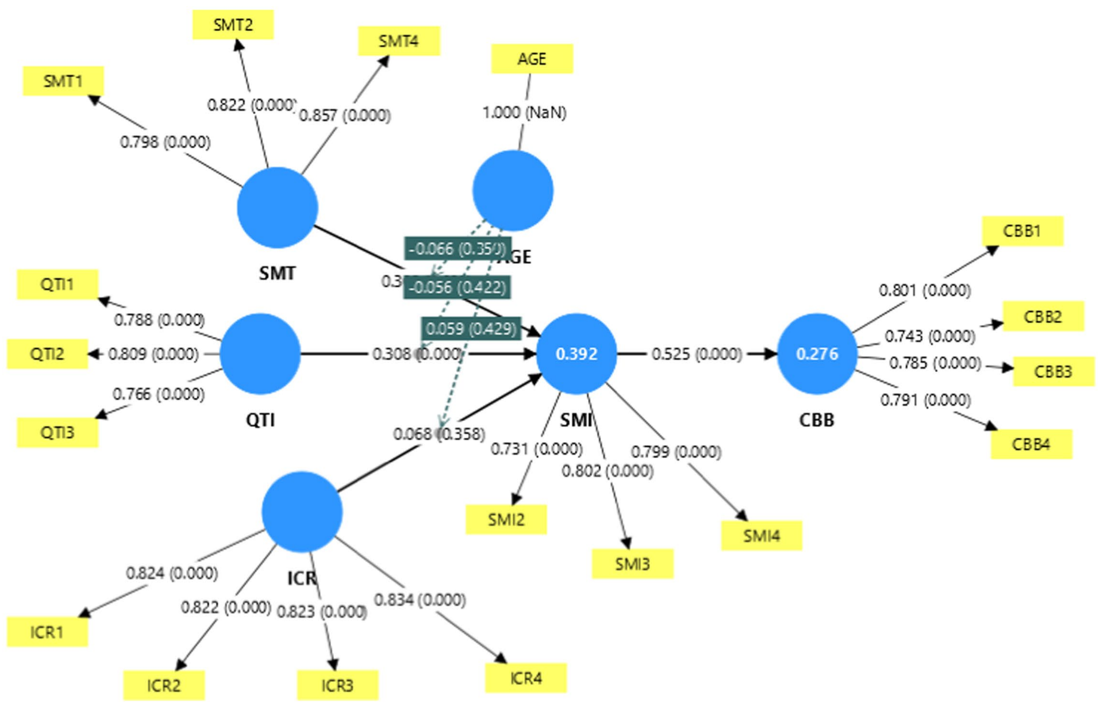

FIGURE 3
Structural model with R^2 values and moderation effects.

TABLE 6 Summary of predictive relevance (Q^2) and coefficient of determination (R^2).

Item	Q^2predict	R^2
CBB	0.63	0.276

predictive capacity performance for the endogenous construct Consumer Buying Behavior (CBB). Specifically, the Q^2predict value for CBB exceeded the threshold of zero across all four items (CBB1–CBB4), indicating that the model has predictive relevance, albeit with weak to moderate accuracy (Hair et al., 2021).

The observed Q^2predict values ranged from 0.178 to 0.267 (Table 7), suggesting weak predictive accuracy depending on the indicator. Moreover, Root Mean Squared Error (RMSE) values obtained from the PLS-Predict analysis were consistently lower than those generated by linear regression benchmarks for most indicators, reinforcing the superior predictive validity of the structural model.

These findings confirm that the model explains a weak-to-moderate explanatory value of variance in consumer behavior ($R^2 = 0.276$) but also predictive relevance with limited accuracy, particularly in relation to social media interaction and its influence on purchasing outcomes. This enhances the model's practical utility for forecasting consumer responses in digital commerce contexts.

6 Discussion

This study contributes to a growing body of literature exploring how digital cues influence consumer decision-making by testing a multi-theoretical model combining the Stimulus–Organism–Response (S-O-R) framework, Uses and Gratifications Theory (UGT), and Theory of Planned Behavior (TPB). It investigated how the triad of Social Media Trends (SMT), Quality of Information (QTI), and Influencer Cues (ICR) affect Social Media Interaction (SMI) and, ultimately, Consumer Buying Behavior (CBB).

The results highlight several critical insights. First, both SMT and QTI had significant and positive effects on SMI, suggesting that exposure to trending content and access to reliable information increase digital engagement. These findings align with prior research indicating that digital media content fulfilling cognitive and emotional gratifications prompts deeper involvement (Mahoney and Tang, 2024; Wang and Yan, 2022; Zolkepli et al., 2018). The effect sizes, although modest ($f^2 = 0.077$ for SMT, $f^2 = 0.079$ for QTI), confirm that these forms of content act as effective stimuli in triggering interaction.

Trending Content was conceptualized as media material that gains rapid visibility within a short timeframe due to high engagement. SMT items captured perceptions of content virality and social proof. Examples include viral hashtags (e.g., #NewDrop), influencer challenges (e.g., dance trends), meme-based content, real-time news reactions, and promotional campaigns amplified by algorithms. These formats were chosen because they embody emotionally appealing, socially validated, and time-sensitive stimuli that trigger spontaneous interaction (Mahoney and Tang, 2024). This clarification supports the construct's grounding in UGT and S-O-R theory as a stimulus with both cognitive and affective triggers.

From a theoretical standpoint, ICR did not significantly influence SMI or CBB, with a negligible effect size for ICR → SMI ($\beta = 0.003$) and a non-significant indirect path to CBB, as confidence intervals crossed zero. This finding diverges from prior assertions in the UGT and TPB literature that position influencers as persuasive cues shaping attitudes and behaviors (Coutinho et al., 2023; Croes and Bartels, 2021). A plausible explanation lies in the evolving phenomenon of "influencer fatigue," where consumers become desensitized to repetitive influencer content or view it as commercially motivated (Kim et al., 2025; Lina et al., 2022). In digitally mature markets like Saudi Arabia, especially among younger users, persuasion may place greater trust in peer-generated content or algorithmically ranked posts than in celebrity endorsements. Yet, this interpretation should be approached with caution, as the study did not capture fine-grained distinctions in influencer types (e.g., micro vs. macro) or message framing, and the generalizability of findings may be constrained by cultural and contextual nuances.

TABLE 7 Predictive relevance (Q^2) and RMSE comparison.

Item	Q^2predict	PLS-SEM_RMSE	LM_RMSE	ΔRMSE
CBB1	0.267	0.558	0.484	0.074
CBB2	0.178	0.61	0.58	0.03
CBB3	0.235	0.645	0.575	0.07
CBB4	0.23	0.59	0.533	0.057

Future studies should consider examining micro-influencers, AI-generated content, or peer-led validation as more culturally aligned alternatives.

The statistical insignificance of ICR in the structural model both directly and through SMI highlights an important theoretical implication: not all stimuli labeled as influential maintain their persuasive capacity across contexts. This aligns with recent studies showing that digital literacy and content discernment have equipped users to critically evaluate promotional content (Zhang et al., 2024). Thus, traditional influencer strategies may need reevaluation, particularly in digitally mature societies where consumer empowerment and authenticity drive decision-making. Future models should consider incorporating micro-influencer dynamics, AI-generated content, and peer-led credibility signals to better capture the evolving nature of online influence.

Social Media Interaction (SMI) itself was shown to be the strongest predictor of Consumer Buying Behavior (CBB) ($\beta = 0.533$, $f^2 = 0.381$), affirming that interactive engagement, rather than passive exposure, drives purchase intent. This supports the view that consumer decision-making is increasingly co-constructed in dynamic, socially embedded digital environments (Attar et al., 2022; Hassan and Sohail, 2021). These findings also validate SMI's mediating role between stimuli and behavior, particularly for SMT and QTI (H5a and H5b supported), reinforcing its theoretical centrality.

Similarly, age-based moderation produced no statistically significant interaction effects. While slope graphs visually suggested potential differences in responsiveness between younger and older users, none of the interactions (H6a, H6b, H6c) reached significance thresholds ($p > 0.05$), and all confidence intervals crossed zero. This absence of significant moderation should not be taken as definitive evidence of age convergence in digital engagement behaviors. Rather, it may reflect limitations in the age distribution of the sample, which was not sufficiently detailed to allow for robust segmentation or subgroup comparisons. Future research with more stratified age samples is warranted to uncover potential age-driven differences in digital media processing and consumer behavior.

From a predictive standpoint, the model demonstrated acceptable predictive relevance and moderate explanatory power, with an adjusted R^2 of 0.276 for CBB and Q^2predict values confirming out-of-sample performance.

7 Conclusion

This study advances theoretical and empirical understanding of how digital stimuli influence consumer behavior through interaction. Integrating the S-O-R model with UGT and TPB, it empirically tested the roles of social media trends, quality of information, and influencer cues in shaping interaction and driving consumer purchase intent.

Findings indicate that SMT and QTI significantly enhance SMI, which in turn strongly predicts buying behavior. These results highlight the power of trending content and credible information as key catalysts for engagement. ICR, however, showed neither significant nor substantive effects, suggesting that the influence of online personalities is waning, possibly due to credibility fatigue or the need for more personalized, context-sensitive approaches.

The model's predictive strength and clarity of effect sizes particularly the dominant role of interaction ($f^2 = 0.381$) position it as a meaningful contribution to digital consumer behavior research. Importantly, the study challenges assumptions about influencer supremacy and raises questions about the cultural and generational consistency of digital responsiveness, particularly in digitally evolved societies.

The research reframes the conversation around social media influence from one centered on personalities to one anchored in interactivity, trust, and content relevance. Future research should explore these dynamics across varied cultural contexts, incorporate qualitative insights into trust perceptions, and consider other moderators such as digital literacy or platform-specific norms to deepen understanding of digital consumer intelligence.

8 Empirical implications

8.1 Theoretical implications

This study contributes to digital consumer behavior literature by reconceptualizing social media stimuli not as mere marketing messages, but as knowledge signals that activate user cognition and emotion. By integrating the Stimulus–Organism–Response (S-O-R) model with the Uses and Gratifications Theory (UGT) and the Theory of Planned Behavior (TPB), the research offers a multi-theoretical lens for understanding the mediating role of social media interaction (SMI). Unlike prior studies that treat influencer cues and content trends as independent predictors, this model highlights SMI as a dynamic, cognitive-emotional mechanism that converts digital exposure into purchase behavior.

This study expands the application of the S-O-R model by illustrating how integrated constructs from UGT and TPB complement the stimulus-organism-response sequence in a digital setting. The use of SMT, QTI, and ICR as distinct digital stimuli contributes to more nuanced mapping of how users form cognitive and affective evaluations before acting on purchase intentions. Unlike prior studies where influencer cues were stand-alone triggers, our findings suggest that user interaction and internal processing play a mediating role, challenging simplistic models of persuasion in social media contexts.

Moreover, the negligible influence of influencer cues (ICR) and the non-significant moderation by age suggest that influencer strategies may be losing effectiveness in this context. However, further research is necessary to determine whether this pattern extends to other markets or platforms.

8.2 Practical implications

For marketers and digital strategists, this study provides several measurable and actionable recommendations. First, investing in content virality (e.g., trending topics, visual appeal) and informational clarity (e.g., expert-backed advice, content trustworthiness) as measured by Social Media Trends (SMT) and Quality of Information (QTI) is more effective than relying solely on high-profile influencers. Marketers should design campaigns that incorporate peer reviews, interactive polls, and community Q&A formats, all of which map onto Social Media Interaction (SMI) constructs shown to trigger user engagement.

Second, while the study found that influencer cues (ICR) did not significantly predict engagement outcomes, the findings suggest that content authenticity and trust cues remain influential in shaping user perceptions. Rather than generalizing a decline in influencer effectiveness, marketers are encouraged to consider micro-influencer strategies with domain relevance (e.g., cosmetics) and align messaging with audience trust and relatability preferences. These approaches may better resonate in digitally mature or saturated markets where skepticism toward mainstream influencers is more pronounced.

Third, engagement strategies should emphasize active user participation, using measurable tools like polls, social listening prompts, and comment-based recommendation systems. These align with the SMI construct and foster deeper involvement, promoting co-creation and increased purchase intent.

Finally, despite hypothesized generational effects, age did not significantly moderate digital engagement. Therefore, instead of targeting age segments, marketers should focus on shared digital behaviors and motivations. Strategies grounded in emotional resonance, identity alignment, and platform-specific norms offer stronger predictive relevance across audience groups.

Given the modest explanatory power ($R^2 = 0.276$), marketers are advised to use these insights as directional guidance rather than deterministic rules. The model helps benchmark specific content strategies that are most effective in driving engagement toward purchase intent in cosmetics-focused digital campaigns.

9 Limitations and future research

First, the research was conducted in a single national context Saudi Arabia, which may limit the generalizability of findings to other cultural or digital ecosystems. Future studies should replicate the model in diverse cultural and regulatory environments to test cross-national consistency, especially regarding influencer skepticism and platform usage norms.

Second, while the moderation by age was conceptually justified and graphically explored, the lack of statistical significance suggests a need for more granular moderators such as digital literacy, trust orientation, or platform-specific behaviors. Including qualitative methods such as focus groups or digital ethnographies could also uncover deeper motivations underlying interaction and purchase behavior.

Third, although the study incorporated validated measurement scales, some constructs like ICR may have evolved beyond their original theoretical definitions. Future research should explore new forms of digital influence, including micro-influencers, AI-generated content, and community-driven endorsements.

Lastly, the cross-sectional design restricts causal inference. Longitudinal studies could provide richer insights into how user interaction evolves over time and how digital gratifications shift with market saturation or platform innovation.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

RA: Conceptualization, Formal analysis, Investigation, Software, Supervision, Validation, Visualization, Writing – original draft. SF: Data curation, Methodology, Writing – review & editing. NM: Project administration, Writing – review & editing. AM: Resources, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that Gen AI was used in the creation of this manuscript. During the preparation of this work, the author used several AI-assisted tools to support non-analytical tasks. Specifically, ChatGPT (OpenAI) was used to rephrase sentences and simplify complex findings for clarity; Grammarly was employed for grammar and language refinement; Scite.ai assisted in evaluating citation contexts; and Google Forms was used to design and distribute the survey questionnaire. These tools were applied to enhance writing clarity, citation reliability, and data collection efficiency. After using these services, the author reviewed and edited the content as needed and took full responsibility for the content of the publication.

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