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Navigating the Mobile E-Commerce Consumer Journey: An Empirical Investigation of the Sequential ISMAS Behavioral Mechanism in Visual Marketing Contexts

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Abstract

Visual marketing, a strategy that leverages visual elements to convey brand and marketing information, is vital for enhancing mobile e-commerce competitiveness. Despite its importance, research on this topic remains limited and homogeneous. Drawing on the ISMAS model (Interest, Search, Word-of-Mouth, Action, and Sharing) and the Stimulus-Organism-Response (S-O-R) framework, this study explores the sequential behavioral mechanism by which mobile e-commerce visual marketing contexts influence consumers' purchase intentions. Mediation and moderation effect analyses were conducted using SPSS 20.0 and the Hayes PROCESS 3.5 plugin (Model 6 for chain mediation; Model 1 for moderation). The findings reveal significant positive relationships among the five ISMAS variables. Search, word of mouth, and Action mediate distinct impact paths in a sequential chain. Age moderates the Search–Word-of-Mouth and Word-of-Mouth–Action relationships, while education level does not exhibit significant moderating effects. This study extends the ISMAS model by embedding it within the S-O-R framework and introducing Customer Journey Theory, offering new insights for future research. Furthermore, it provides visual marketing recommendations for mobile e-commerce platforms and merchants to optimize strategies, enhance the user experience, and boost conversion rates, thereby supporting sustainable industry development.

1 Introduction

The rapid development of mobile e-commerce has elevated visual marketing—a strategy leveraging visual elements to convey brand information—from a traditional marketing method to a critical component of digital competitiveness. As a primary medium for user-merchant interaction, the visual sensory experience on mobile platforms profoundly affects the quality of online marketing (Wang et al., 2021). With rising consumer aesthetic standards, visual design has become a key differentiator. iResearch statistics indicate that 85% of consumers conduct online comparative research, focusing on visual elements such as product images, and approximately 40% are inclined to purchase products they experience through Augmented Reality (AR). These findings underscore the crucial role of visual marketing. While scholars have established its necessity and provided strategic frameworks (Wang et al., 2022; Wang et al., 2021), recent international evidence confirms that interactive and immersive visual cues are highly effective in mitigating perceived purchase risks and stimulating immediate conversion (Uddin et al., 2026; Huo et al., 2026). Furthermore, visual richness and aesthetic quality significantly enhance perceived value and purchase intention across diverse product categories (Kim & Lennon, 2023; Park et al., 2024).

Despite increasing scholarly attention, the visual design of most mobile e-commerce platforms has become homogenized, resulting in suboptimal user experiences. A vital challenge remains: leveraging page design to transition users from visual resonance to perceptual recognition and, ultimately, to consumption behavior. This challenge is compounded by insufficient corporate attention, lagging application technology, and a mismatch between visual marketing and product quality. Consequently, scholars call for a dynamic integration of multidimensional visual stimuli with sequential consumer

behavior pathways to overcome the static limitations of traditional stimulus-response models (Huo et al., 2026). While existing research has focused on categories such as apparel and cosmetics, studies on mobile e-commerce visual marketing remain scarce and largely homogeneous. Therefore, theoretical research in this area carries significant practical value.

Based on the Interest, Search, Word-of-Mouth, Action, and Sharing (ISMAS) model, this study examines the influence of visual marketing on mobile e-commerce platforms on consumers' purchase intentions. It addresses two core research questions:

(1) How do mobile e-commerce visual elements systematically trigger a chain-mediating sequence (Interest→Search→Word-of-Mouth→Action→Sharing)?

(2) How do individual demographic variables (e.g., age and education) moderate these cognitive-behavioral pathways?

This study aims to optimize platform design and advertising placement to enhance purchase willingness and sales conversion. Effective visual marketing can create a unique brand image, guide purchasing decisions, and improve user loyalty, fostering repeat purchases and word-of-mouth communication. It also helps businesses overcome geographical constraints and expand their market scope. By investigating the impact of visual marketing on consumer purchase intentions, enterprises can promptly adjust their strategies to meet consumer needs better, thereby improving profitability and satisfaction.

In summary, this study offers three unique contributions to the literature:

Theoretical Contribution 1 (Structural Extension)

Unlike prior studies treating the ISMAS model as a static sequence, we embed it within the Stimulus-Organism-Response (S-O-R) framework and integrate Customer Journey Theory. This reconceptualizes the five ISMAS stages as a closed-loop, cyclical system where Sharing feeds back as a secondary Stimulus, transforming the ISMAS from a descriptive sequence into a dynamic, self-reinforcing mechanism.

Theoretical Contribution 2 (Granular Mediation Mechanism)

We move beyond the binary "stimulus → response" paradigm by empirically decomposing the Organism stage into three distinct, sequentially ordered micro-processes (Search→WOM→Action). This multistage chain mediation reveals which specific behavioral transitions carry the strongest indirect effects, providing mechanistic granularity that prior ISMAS applications have not achieved.

Theoretical Contribution 3 (Boundary Conditions)

We identify critical demographic boundary conditions by demonstrating how age differentially moderates specific pathway segments. This specifies for whom and at which stage the visual marketing

mechanism operates most effectively, addressing the homogeneity assumption prevalent in existing research.

2 Literature Review

2.1 Theoretical Framework and Construct Rationale

To systematically capture how mobile e-commerce visual marketing translates into consumer sharing dynamics, this study adopts the Stimulus-Organism-Response (S-O-R) model as its overarching psychological framework. The S-O-R model posits that external environmental stimuli (S) elicit internal cognitive and emotional evaluations within the organism (O), which in turn drive behavioral responses (R).

Within the Information Systems (IS) and digital marketing paradigm, the S-O-R framework is the primary model for explaining how environmental cues shape customer states and behavioral reactions (Wang et al., 2021). However, given the fragmented and hyper-interactive nature of modern mobile commerce, this study enriches the S-O-R framework by integrating Customer Journey Theory via the ISMAS (Interest–Search–Mouth–Action–Share) model. This cross-disciplinary synthesis addresses the critique of theoretical redundancy and provides a highly contextualized model. The integration operates along a structural continuum:

Stimulus (S)

The sensory and environmental triggers provided by high-density mobile visual marketing, acting as the initial entry touchpoint in the consumer journey.

Organism (O)

While standard S-O-R literature often treats the internal state as a single emotion or attitude, Customer Journey Theory suggests cognitive appraisal is a multistage evolution. We utilize the Interest → Search → Word-of-Mouth sequence of the ISMAS model to unpack the "black box" of this internal journey, explaining how initial affective Interest transitions into active, risk-mitigating exploration of digital information and social validation (Uddin et al., 2026).

Response (R)

The ultimate behavioral outputs, translated into immediate Purchase Action and subsequent Social Sharing, which capture the cyclical, loop-closing nature of modern social networks (Huo et al., 2026).

Therefore, the choice of ISMAS is explicitly justified not as an alternative to S-O-R but as a crucial extension of theoretical granularity necessary to map the dynamic customer journey within contemporary mobile marketing interfaces.

2.1.1 Why ISMAS Rather Than AISAS or AIDMA: Addressing Conceptual Redundancy

A critical question arises: given that the AISAS model (Attention→Interest→Search→Action→Share) already captures a sequential consumer pathway, what does the ISMAS model add? We argue that the distinction is theoretically substantive rather than merely nominal:

(1) The elimination of "Attention" as a standalone stage. In the mobile e-commerce context, visual marketing stimuli (e.g., high-definition product imagery, AR overlays, short-video thumbnails) are designed to capture attention simultaneously with generating Interest. The ISMAS model, proposed by Liu Dehuan (Liu & Chen, 2013), explicitly merges these two stages into a unified "Interest" construct. This reflects the empirical reality that in algorithmically curated mobile feeds, attention and Interest are cognitively co-activated rather than sequentially processed (Huo et al., 2026), consistent with processing fluency theory (Reber et al., 2004).

(2) The explicit insertion of "Word-of-Mouth" as a distinct behavioral stage between Search and Action. The AISAS model treats the interval between Search and Action as a cognitive "black box." The ISMAS model, by contrast, theorizes that in social commerce environments, the search phase does not lead directly to purchase; rather, consumers actively seek and evaluate peer-generated word-of-mouth (reviews, ratings, social media recommendations) as a critical risk-mitigation step before committing to a transaction (Uddin et al., 2026). This is consistent with platform economics literature, which demonstrates that user-generated content and algorithmic personalization create information asymmetries that consumers resolve through social proof mechanisms (Boudreau & Hagiu, 2009; Tiwana, 2014).

(3) The reconceptualization of "Sharing" as a cyclical feedback mechanism. While AISAS treats "Share" as a terminal output, the ISMAS framework—and our extension of it—positions Sharing as a generative input that re-enters the system as a new Stimulus for other consumers, creating a closed-loop ecosystem. This aligns with recent Customer Journey Theory, which emphasizes the non-linear, recursive nature of digital consumer experiences (Lemon & Verhoef, 2016; Voorhees et al., 2017).

2.1.2 Micro-Level Theoretical Links Between Visual Marketing and Each ISMAS Stage

To address the need for stage-specific theoretical justification, we articulate the micro-level mechanism linking visual marketing stimuli to each ISMAS stage:

Visual Marketing→Interest ($S \rightarrow O_1$)

Grounded in aesthetic response theory (Bloch, 1995) and visual attention theory (Pieters & Wedel, 2004), high-quality visual elements (color harmony, image clarity, layout balance) trigger involuntary attentional capture and positive affective arousal, manifesting as consumer Interest.

Interest→Search ($O_1 \rightarrow O_2$)

Drawing on information search theory (Punj & Staelin, 1983) and the elaboration likelihood model (Petty & Cacioppo, 1986), once visual stimuli generate sufficient Interest, consumers transition from peripheral processing to central-route information seeking, actively searching for product specifications, comparisons, and detailed reviews.

Search→Word-of-Mouth ($O_2 \rightarrow O_3$)

Consistent with uncertainty reduction theory (Berger & Calabrese, 1975) and social proof theory (Cialdini, 2001), the information gathered during Search is often insufficient to resolve perceived purchase risk in online contexts. Consumers therefore seek peer-generated word-of-mouth as a trust-calibration mechanism before proceeding to Action.

Word-of-Mouth→Action ($O_3 \rightarrow R_1$)

Supported by the theory of planned behavior (Ajzen, 1991) and trust transfer theory (Gefen et al., 2003), positive word-of-mouth consolidates perceived behavioral control and subjective norms, converting intention into concrete purchase Action.

Action→Sharing ($R_1 \rightarrow$ R/Feedback)

Grounded in self-determination theory (Deci & Ryan, 2000) and social exchange theory (Blau, 1964), post-purchase satisfaction generates intrinsic motivation to share experiences, which re-enters the system as a new visual/social stimulus for other consumers.

2.1.3 Integration with IS and Platform Literature

Beyond traditional marketing theory, this study engages with recent IS scholarship on platform ecosystems and algorithmic personalization. Platform economics research demonstrates that digital platforms function as multi-sided markets where visual interface design serves as a critical coordination mechanism between buyers and sellers (Boudreau & Hagiu, 2009; Tiwana, 2014). Algorithmic personalization—the curation of visual content based on user behavioral data—amplifies the Stimulus component of our model by ensuring that visual marketing reaches consumers at their most receptive point (Huang & Benyoucef, 2013). Furthermore, recent work on algorithmic recommendation systems shows that personalized visual displays significantly increase the probability of Interest-to-Search transitions by reducing information overload (Zhou et al., 2022). These IS perspectives complement our S-O-R/ISMAS framework by specifying the platform-level mechanisms through which visual stimuli are delivered and amplified.

Through this cross-disciplinary synthesis, we address the critique of theoretical redundancy and provide a highly contextualized model that is structurally distinct from both AISAS and AIDMA.

2.2 Review of Extant Literature and Identification of the Research Gap

The intersection of digital interface design and consumer behavior has been extensively documented. Traditional e-commerce studies established that page layout, color harmony, and text visibility significantly affect platform trust and static purchase intentions (Wang et al., 2021). As platforms evolved, researchers shifted toward examining dynamic visual components. For instance, Wang et al. (2022) underscored the strategic necessity of mobile-specific visual designs, while subsequent works provided methodologies for optimizing user interface elements to maximize click-through rates. More recently, scholarship has recognized that modern mobile shoppers demand highly immersive environments; interactive visual stimuli, such as augmented reality (AR) and short videos, have been proven to alleviate transaction anxiety and boost immediate buying impulses (Huo et al., 2026; Uddin et al., 2026).

Despite these valuable contributions, a comprehensive review of the current literature reveals three critical research gaps:

Gap 1: The Limitation of Static Endpoint Models. The vast majority of existing visual marketing studies treat purchase intention or immediate impulse buying as the ultimate behavioral endpoint (e.g., Huo et al., 2026). This linear approach fails to account for the cyclical nature of contemporary mobile commerce, in which post-purchase social sharing loops back to serve as secondary marketing stimuli for new consumers.

Gap 2: Lack of Granular, Multistage Sequential Mediation. While the literature widely confirms that visual cues influence consumer attitudes, there is a distinct shortage of research that maps these stimuli onto a highly granular, multistage behavioral pathway. The precise psychological mechanism that tracks how visual resonance transitions sequentially through distinct behavioral phases—from Interest to Search, Word-of-Mouth validation, Action, and eventual Sharing—remains an unexamined "black box."

Gap 3: Neglect of Demographic Boundary Conditions. Extant studies often assume a homogenous consumer response to digital interfaces. There is an empirical deficit regarding how structural paths within behavioral models are constrained or amplified by demographic boundary conditions, such as generational age gaps and variations in educational background, which shape how digital information is processed. To bridge these gaps, this study introduces a comprehensive, multistage sequential mediation framework utilizing the ISMAS model, providing a clearer blueprint of the digital-to-physical consumer journey.

A comparative analysis of the extant literature reveals a structural pattern: the majority of studies (approximately 72% of the 47 articles reviewed) adopt a single-stage or dual-stage analytical lens, examining either the Stimulus→Response link (e.g., visual design→purchase intention) or a single mediating mechanism (e.g., perceived value as mediator). Only three studies (Wang et al., 2022; Huo et

al., 2026; Uddin et al., 2026) attempt multistage modeling, and even these do not extend beyond a three-stage sequence. None of the reviewed studies simultaneously model all five ISMAS stages as a sequential chain while testing demographic boundary conditions at each transition point.

Furthermore, a critical limitation of the existing body of work is its geographic and methodological concentration: approximately 68% of the reviewed studies are based on Chinese domestic samples and employ convenience sampling without reporting nonresponse bias checks. International replication studies remain virtually absent. The present study addresses this gap by explicitly incorporating international theoretical frameworks (S-O-R, Customer Journey Theory, platform economics) while acknowledging the geographic limitation of our own sample (see Section 5.4).

2.3 ISMAS Model

The ISMAS model is a consumer behavior model for the mobile internet era, improved by Professor Liu Dehuan, based on the attention, interest, desire, memory, Action (AIDMA) and attention, Interest, Search, Action, share (AISAS) models (Liu & Chen, 2013; Zhao & Liu, 2025). Related studies include Li & Liu (2022), who developed a new media marketing model for tourist attractions. Fan and Zhu (2017) analyzed the communication case of the marine-themed app "Yi Yu" (□□). In the food industry, Yang and Hong (2023) examined the "product + story" marketing transformation strategy employed by Holiland (□□□). These studies demonstrate the application value of the ISMAS model in various industries.

(1) Interest

In the ISMAS model, "Interest" is the key starting point. In the era of mobile Internet, the information explosion has fragmented consumer attention, and companies must provide content that engages their audience. Li et al. (2023) constructed user interest portraits using Taobao cosmetics reviews. Zheng and Jiang (2022) studied the marketing strategy of Douyin clothing brands. Musafa et al. (2022) believed in the excellent development potential of e-commerce. However, some studies have shown that Interest has a limited impact on tourist satisfaction (Andayani et al., 2021). Choi et al. (2022) noted that the pandemic would alter consumer preferences for skincare products and cosmetics.

(2) Search

In the ISMAS model, consumers engage in active search behavior once their interests are stimulated. In the mobile internet environment, this precise Search makes marketing more effective. Feng et al. (2022) found that information overload promoted discontinuous searches. Ma and Pu (2022) analyzed cross-border e-commerce market segmentation using keyword searches. Zhou et al. (2022) explored the impact of recommendation systems on brand competition and search behavior. Jamil et al. (2022) confirmed that consumer confidence affected consumer willingness to search for and share information.

(3) Word-of-mouth

In the ISMAS model, word-of-mouth is a key link that directly affects consumer decision-making and brand image. In the era of the mobile Internet, consumers trust real user reviews over corporate propaganda, which fuels the exponential spread of word-of-mouth. Xiong and Shu (2023) used quantitative research to explore the impact of negative word-of-mouth on new energy vehicles. Xu et al. (2022) studied the additional comment function using data from "Autohome." Yin and Huang (2023) employed a combination of qualitative and quantitative methods to develop a word-of-mouth communication model for celebrity internet tourists. Traditional word-of-mouth research confirms that sales staff interaction positively affects willingness to engage in word-of-mouth (Ma & Kim, 2022). Chen and Zhang (2022) explored the impact of the emotional intensity of negative word-of-mouth on consumers' perceived usefulness in electronic word-of-mouth. Rajeh (2021) found that corporate social responsibility and social media marketing significantly improved word-of-mouth.

(4) Action

Consumer actions can be divided into two categories: narrow (purchasing behavior) and broad (online browsing, offline experiences, etc.). Zhang et al. (2022) investigated the relationship between female consumers' consumption tendencies, purchase satisfaction, and purchase actions. Zhou et al. (2021) investigated the effects of a purchase button's position and distance on willingness to click it. Tian et al. (2021) clarified the impact of different picture content on consumers' desire to click pictures when shopping online.

(5) Share

Consumers' sharing behavior is a key link between the closed marketing loop and the starting point of a new consumption cycle. Hou et al. (2020) proposed that the material and social needs of social e-commerce users are the main factors affecting users' post-purchase sharing. Wang (2022) employed the SOR model as a framework and applied social exchange theory to investigate how the quality of online customer experience affects users' sharing behavior in the group-purchase model. Shi et al. (2023) investigated the impact of short video platform characteristics on users' willingness to share marketing information, and explored the mediating role of users' flow experience. Luo et al. (2022) investigated the interaction between limited-time and limited-quantity promotions, and how these promotions, in the form of discounts or gifts, influence consumers' willingness to share.

Critical Assessment of ISMAS Literature

A review of the ISMAS-related literature reveals three patterns. First, the majority of applications (Li, 2021; Fan & Zhu, 2017; Yang & Hong, 2023) are descriptive case studies that apply the ISMAS framework to a specific industry context without empirically testing the sequential relationships. Second, the few quantitative studies that exist (Andayani et al., 2021; Jamil et al., 2022) examine individual ISMAS stages in isolation rather than as an integrated chain. Third, no existing study has tested the full five-stage sequential chain using chain-mediated analysis while simultaneously examining demographic moderators at each transition point. The present study addresses all three gaps.

2.4 Mobile e-commerce visual marketing

While early digital marketing studies were often region-specific, contemporary research demonstrates that the dynamics of visual marketing—particularly the impact of immersive interfaces on consumer psychology—are increasingly global in scope. International scholarship reinforces the view that visual stimuli function as a universal language for consumer engagement. For instance, research in North American e-commerce contexts indicates that product image quality and page layout aesthetics significantly influence perceived trust and purchase intention across diverse consumer segments (Kim & Lennon, 2023; Park et al., 2024). Similarly, European studies have shown that visual richness in mobile interfaces enhances processing fluency, thereby reducing cognitive effort and accelerating purchase decisions (Reber et al., 2004; Orth & Malkewitz, 2008).

These international findings corroborate observations in Asian markets (Wang et al., 2021), suggesting that while cultural preferences for design aesthetics may vary, the underlying cognitive mechanism remains consistent: high-definition visual resonance triggers immediate affective arousal, which serves as a critical antecedent to consumer engagement in the global digital commerce landscape (Huo et al., 2026).

2.5 Consumer purchase intention

The antecedents of consumer purchase intention have been extensively examined across various digital contexts. In the realm of e-commerce and software applications, visual marketing elements have been shown to influence consumer decisions significantly. For instance, Yu and Mu (2021) explored the direct impact of visual marketing on purchase intentions, while Li et al. (2020) revealed the mediating role of perceived value in this relationship. Further studies have analyzed specific visual elements, such as those in live broadcasts (Ma & Qu, 2022), fast fashion brand channels (Li & Zhang, 2021), and mobile app interfaces (Patel et al., 2020), all confirming their significant influence on purchase intention. Research has also extended to the impact of virtual touch in software (Guo et al., 2019) and visual display mechanisms in live travel broadcasts (Wang & Li, 2022).

Beyond pure e-commerce, the principles of visual influence extend to other domains. Kim et al. (2023) examined factors affecting consumers' purchase intentions on e-commerce platforms and proposed competitive strategies rooted in visual and experiential differentiation. In offline channels, research on packaging design has demonstrated its significant impact on brand image and subsequent purchase intentions (Zheng & Cho, 2022). Even in the food industry, studies have shown that environmental factors such as light-source parameters can significantly influence food evaluation and consumer choice (Chen et al., 2022). Collectively, this body of literature confirms that visual cues are a primary driver of consumer intention, operating through both direct affective pathways and indirect cognitive evaluations across a wide range of commercial contexts.

2.6 Summary

The current research identified a homogenization phenomenon in the study of the ISMAS model, with limited relevant literature available. Although there are abundant studies on visual marketing (630 articles in the China National Knowledge Infrastructure [CNKI]), most are concentrated in the fields of clothing and beauty. Research on mobile e-commerce is limited, and the conclusions are broad. Research on consumer purchase intention is relatively mature; however, most studies employ the S-O-R model, and research based on the ISMAS model is underrepresented. This study innovatively combines the five dimensions of Interest, Search, word-of-mouth, Action, and sharing (ISMAS), expands the SOR model chain, and explores the impact of mobile e-commerce visual marketing on purchase intention through quantitative methods.

3 Research Design

3.1 Theoretical Basis

Consumer behavior is a dynamic process involving perception, cognition, and environmental interaction (Kollat et al., 1970). Modern theory posits that purchase decisions are shaped by both internal factors (e.g., perception, memory) and external factors (e.g., culture, family). In mobile e-commerce, these choices reflect distinct consumption concepts influenced by this interplay. Research should therefore focus on the decision-making process and actual consumption behavior, which form the core of marketing activities.

Schmitt (1999, 2000) proposed that experiential marketing challenges the traditional "rational person" hypothesis by emphasizing that both rational and emotional experiences drive consumer decisions. In the experience economy, enterprises must create value by optimizing experience strategies to enhance purchase intentions and foster brand loyalty. Furthermore, Latane's social influence theory posits that the actions and opinions of others significantly shape individual attitudes and behaviors. Mobile e-commerce visual marketing leverages this principle by showcasing social proof—such as others' purchase scenes—on social media to evoke empathy. By employing visual elements like color and imagery to strengthen the product image, this approach influences consumer preferences and drives purchase decisions.

3.2 Research hypothesis

3.2.1 Direct Effect: Interest and Sharing (H1)

Consumer interest significantly impacts the willingness to share. When consumers develop a strong interest in a product, they experience a powerful urge to communicate it with others. This psychological Interest drives them to share interesting products and unique designs, expressing personal preferences and brand recognition. Xiang & Zheng (2022) noted that consumer interest has a significant positive impact on sharing. In the context of contemporary digital media, highly engaging visual stimuli provoke emotional resonance, creating an affective drive that compels users to self-disclose and participate in

online social circles (Huo et al., 2026). Thus, visual resonance directly translates into a willingness to communicate. Based on this, we propose the following hypothesis:

H1: Interest has a significant positive impact on sharing.

3.2.2 Sequential Chain-Mediating Effect (H2)

In mobile e-commerce visual marketing, a visual presentation that stimulates consumer interest prompts them to search for product information (Deng, 2022). This search behavior deepens product understanding, and satisfactory results can lead to positive emotions and active sharing (Xiang & Zheng, 2022). Concurrently, after visual content stimulates Interest, consumers refer to other users' word-of-mouth (WOM) to form product cognition (Liljander et al., 2015). Positive WOM can enhance purchase intentions and promote positive sharing (Li & Liu, 2022). Visual marketing attracts Interest and encourages purchases (Xue & Zhao, 2023), and the resulting satisfaction motivates sharing.

Structurally, consumer interest triggers WOM references (Liu & Chen, 2013; Zhao & Liu, 2025). Positive WOM drives purchase behavior, and a satisfactory experience leads to positive sharing (Hou et al., 2020). Empirically, active information search amid risk awareness naturally directs consumers toward social proof, such as peer reviews, thereby solidifying trust and accelerating concrete transaction behavior (Uddin et al., 2026). In summary, visual marketing stimulates Interest, guides product search, leverages WOM for informed decisions, and, ultimately, drives consumers to share.

In summary, we propose the following hypothesis:

H2: Search, word-of-mouth, and Action play a chain-mediating role between Interest and sharing.

The research model was constructed based on H1 and H2, as shown in Fig. 1.

3.2.3 Moderating Boundary Conditions (H3–H5)

Research in consumer information processing suggests that demographic characteristics may moderate the strength of sequential behavioral pathways.

Gender. Prior research indicates that men and women may differ in their information processing styles during online shopping (Darley et al., 2010; Gefen & Straub, 2004). Some studies suggest that male consumers tend to adopt a more task-oriented search strategy, while female consumers may place greater emphasis on social cues such as peer reviews (Fisher et al., 2018). Rather than assuming fixed patterns, this study empirically tests whether gender moderates the strength of each ISMAS pathway transition.

Age. Generational differences in digital literacy may influence how consumers navigate sequential behaviors. Younger consumers, as digital natives, may transition more rapidly between Interest and Search due to greater familiarity with digital interfaces (Prensky, 2001). Older consumers may require additional verification steps and exhibit different patterns of reliance on WOM (Huo et al., 2026).

Education Level. Educational attainment is associated with information processing capability (Cacioppo et al., 1996). Individuals with higher education may engage in more systematic evaluation of WOM content before committing to a purchase, while those with lower education may rely more on heuristic cues (Petty & Cacioppo, 1986). However, the direction and magnitude of these effects in mobile e-commerce contexts remain empirically undetermined.

Modern consumer behavior literature emphasizes that demographic heterogeneity alters the cognitive weight assigned to digital cues, thereby affecting the operational efficiency of S-O-R behavioral pathways (Huo et al., 2026; Uddin et al., 2026). In summary, we propose Hypotheses 3 to 5 as exploratory tests of boundary conditions:

H3: Gender moderates the relationships between Interest and Search, Search and Word-of-Mouth, Word-of-Mouth and Action, and Action and Sharing.

H4: Age moderates the relationships between Interest and Search, Search and Word-of-Mouth, Word-of-Mouth and Action, and Action and Sharing.

H5: Education level moderates the relationships between Interest and Search, Search and Word-of-Mouth, Word-of-Mouth and Action, and Action and Sharing.

3.3 Participants and Sampling Technique

All methods were performed in accordance with the relevant guidelines and regulations. This study employed a non-probability sampling design that combined convenience and snowball sampling to reach a targeted consumer group. Initial participants, who were active users of prominent mobile e-commerce and social commerce platforms, were recruited via convenience sampling. Subsequently, snowball sampling was used by encouraging these respondents to share the online questionnaire link with their social networks, thereby expanding the sample's diversity.

To ensure sample relevance, two strict screening questions were placed at the beginning of the questionnaire:

"Have you browsed, searched for, or purchased products on mobile e-commerce platforms in the past three months?"

"Have you ever been attracted to make a purchase or share product information due to visual marketing elements (e.g., live streams, short videos, or high-definition graphics)?"

Only respondents who answered "Yes" to both questions were permitted to proceed. Incomplete questionnaires or those completed in an unrealistically short duration (less than 120 seconds) were excluded as invalid. To minimize potential nonresponse bias and common method bias (CMB), participation was voluntary, anonymous, and incentivized with a small monetary reward. A post hoc analysis comparing early and late respondents confirmed that nonresponse bias did not pose a significant threat to the validity of the findings.

Generalizability Considerations. We acknowledge that the use of non-probability sampling limits the statistical generalizability of our findings. The sample may over-represent younger, more digitally literate, and socially connected individuals. Consequently, the estimated pathway coefficients may not fully represent the behavioral patterns of older or less digitally engaged consumer segments. We address this limitation in two ways: (1) by including age and education as moderating variables to capture within-sample heterogeneity, and (2) by explicitly flagging this constraint in the Limitations section (Section 5.4) and recommending future replication using stratified probability sampling.

3.4 Measurement of variables

This study defines Interest as the psychological tendency of users to understand and explore a product or brand, measured along two dimensions: breadth and intensity (Lin & Tsai, 2021). Search is defined as the behavior of using search functions, keywords, or filters to locate specific products or information, measured through product and platform searches (Zhang & Chen, 2022; Li et al., 2023). Word-of-mouth (WOM) refers to the collection of consumer evaluations and opinions, measured by the quantity and quality of WOM information (Luo et al., 2019; Xu et al., 2020; Su & Song, 2020). Action refers to behaviors related to products or brands, such as purchases and repurchases (Yang & Hong, 2023). Finally, Sharing is defined as the behavior of sharing content or links about merchants or products with others via mobile devices, measured across four dimensions: frequency, channels, content, and target (Hou et al., 2020). To enhance content validity, an expert brainstorming session was conducted on December 26, 2023, with six experts (three scholars and three government officers with e-commerce experience). After multiple rounds of discussion, the final 34-item measurement scale was established, as detailed in Table 1.

Visual marketing is conceptualized not as a separately measured independent variable but as the contextual stimulus environment (i.e., the "S" component in the S-O-R framework) within which the five ISMAS behavioral stages unfold. This operationalization is grounded in three considerations. First, in the mobile e-commerce ecosystem, visual marketing is omnipresent and multimodal—encompassing product imagery, short-form video thumbnails, AR overlays, and algorithmically curated feeds—making it impractical to isolate a single set of visual attributes without sacrificing ecological validity (Kim & Lennon, 2023; Park et al., 2024). Second, the primary objective is to map the sequential behavioral mechanism, rather than quantify the marginal contribution of individual visual elements. Third, all 34 measurement items are explicitly anchored in visual marketing contexts (e.g., "After seeing attractive product images/videos on the platform, I became interested in…"), ensuring that respondents evaluate their behavioral responses specifically within visually rich mobile commerce environments. We acknowledge that this design does not permit the isolation of specific visual attributes (e.g., color harmony, layout aesthetics) as discrete predictors, and we identify this as the most consequential limitation of the present study (see Section 5.5, Limitation 1). Future research should incorporate validated visual marketing scales to decompose the stimulus component of our model.

This study employed a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) to collect data via the Wenjuxing platform. The survey was conducted from February 14 to 28, 2024, and was disseminated

through WeChat, QQ, and Weibo to high-frequency mobile e-commerce users aged 18–40. Stratified random sampling was used to control for variables such as gender, age, and education.

To mitigate the inherent biases of online surveys, this study employed rigorous procedural and statistical controls. To reduce Common Method Bias (CMB), the survey instrument was designed to create psychological separation between the independent and dependent variables, ensuring that participants could not easily discern the hypothesized relationships (Podsakoff et al., 2003). Additionally, the survey platform required anonymous participation to reduce social desirability bias. Post-data collection, we conducted Harman's single-factor test to assess the variance explained by a single construct. The result (below 40%) indicated that CMB was not a substantial threat to our findings. We also performed a wave analysis (comparing early vs. late respondents) to identify significant differences. No significant disparities were found in demographic profiles or behavioral patterns, confirming the representativeness of the sample (Armstrong & Overton, 1977).

Table 1
Measurement Scale

Variable	Dimension	Number	Item	Source
Interest	Breadth	A1	I am interested in the visual marketing content of multiple mobile e-commerce platforms.	Su & Song (2020). Sun (2023)
		A2	I am interested in different styles of mobile e-commerce visual marketing.	
		A3	I am interested in mobile e-commerce visual marketing content across various fields.	
	Intensity	A4	I am very interested in mobile e-commerce visual marketing.	
		A5	I am very interested in this product in mobile e-commerce visual marketing.	
		A6	I am very interested in this brand in mobile e-commerce visual marketing.	
Search	Product search	B1	I will actively search for products or brands in mobile e-commerce visual marketing.	Yuan et al. (2021); Yang & Hong (2023)
		B2	I will search for discount information on products in mobile e-commerce visual marketing.	
		B3	I will research product specifications in mobile e-commerce visual marketing.	
		B4	I will conduct comparative product searches in mobile e-commerce visual marketing.	
	Platform search	B5	I will search for products in mobile e-commerce visual marketing on different platforms.	
		B6	I tend to use the platform's filtering function to search for products in mobile e-commerce visual marketing.	
Word of mouth	Quantity	C1	The products in mobile e-commerce visual marketing have enough reviews to refer to.	Fei & Wang (2020). Liu (2015); Deng (2022)
		C2	Products or brands in mobile e-commerce visual marketing receive many supportive replies or comments.	
		C3	The products in mobile e-commerce visual marketing share similar word-of-mouth information across platforms.	
	Quality	C4	Word-of-mouth information about products in mobile e-commerce visual marketing is generally accurate.	

Variable	Dimension	Number	Item	Source
		C5	Word-of-mouth information about products in mobile e-commerce visual marketing is generally objective.	
		C6	Word-of-mouth information about products in mobile e-commerce visual marketing is clearly conveyed.	
		C7	I think the word-of-mouth information about the products in mobile e-commerce visual marketing is easy to understand	
		C8	Word-of-mouth information about the product in mobile e-commerce visual marketing is relevant.	
Action	Purchase	D1	I am ready to purchase products in mobile e-commerce visual marketing.	Zeng (2021); Wang & Chen (2021); Fan & Zhu (2017); Tian et al. (2021)
		D2	I am very likely to buy products in mobile e-commerce visual marketing.	
		D3	The products in mobile e-commerce visual marketing are worth buying.	
	Repurchase	D4	I will repeatedly purchase products through mobile e-commerce visual marketing.	
		D5	I will become a frequent or loyal customer of the merchant or brand in mobile e-commerce visual marketing.	
		D6	Every time I need to buy this type of product, I first think of this product in mobile e-commerce visual marketing.	
Sharing	Frequency	E1	I often share products in mobile e-commerce visual marketing Channel.	Wang (2022)
	Channel	E2	I tend to share products in mobile e-commerce visual marketing through online platforms.	
		E3	I like to share products in mobile e-commerce visual marketing in real-life communication occasions.	
	Content	E4	When I promote products in mobile e-commerce visual marketing, I will share product images.	
		E5	When I share products in mobile e-commerce visual marketing, I will share my shopping experience.	

Variable	Dimension	Number	Item	Source
		E6	When I share products in mobile e-commerce visual marketing, I will share my experience using them.	
	Target	E7	I tend to share my experiences buying products on mobile e-commerce platforms with friends and family through visual marketing.	
		E8	I am happy to share my experience of buying products in mobile e-commerce visual marketing with a broader audience (such as netizens, fans, etc.).	

4 Empirical analysis

4.1 Descriptive statistical analysis

This study was conducted from 15/02/2024 to 28/02/2024. In total, 539 questionnaires were collected. Invalid questionnaires with unreasonable, incomplete, or false information were deleted, and 516 valid responses were obtained, yielding an efficiency of 95.73%. The effective ratio of the sample and items was 15.18:1, which is better than the 5:1 criterion suggested by Dai et al. (2022) and Chu and Dai (2021). The results of the descriptive statistical analyses are presented in Table 2.

Table 2
Basic information of survey samples (n = 516)

Variable	Sample characteristics	Frequency	Proportion
Gender	Male	210	40.7
	Female	306	59.3
Age	Under 18	18	3.5
	19–25	193	37.4
	26–35	156	30.2
	36–45	87	16.9
	46–55	35	6.8
	56 and above	27	5.2
Education level	High school and below	36	7.0
	Associate degree	129	25.0
	Undergraduate degree	274	53.1
	Master's degree and above	77	14.9
Most commonly used mobile e-commerce platforms	Taobao	231	44.8
	JD.com	99	19.2
	Pinduoduo	65	12.6
	Vipshop	64	12.4
	WeChat Mini Programs	36	7.0
	Others	21	4.1
Average monthly spending on mobile e-commerce platforms (Unit: RMB)	Less than 500 yuan	192	37.2
	501–1000 yuan	167	32.4
	1001–3000 yuan	83	16.1
	3001-5000yuan	50	9.7
	5001 yuan and above	24	4.7

The skewness of the items ranged from − 0.718 to -0.125, with absolute values less than 3.0 (Matthes & Ball, 2019). The kurtosis of each item ranged from − 0.815 to -0.156, whereas the absolute values were less than 10 (Matthes & Ball, 2019). These results showed that the sample had a normal distribution (Table 3). Thus, we used maximum-likelihood estimation to fit the structural equation model.

Table 3
Results of normally test (n = 516)

Variables	items	mean	S.D.	Kurtosis (S.E.)	Skewness (S.E.)	Factor loading	Standard Factor loading
Interest	A1	3.78	1.179	− .791 (.108)	− .216 (.215)	.873	.940
	A2	3.82	1.206	− .808 (.108)	− .330 (.215)	.770	.774
	A3	3.82	1.232	− .815 (.108)	− .394 (.215)	.750	.781
	A4	3.76	1.213	− .697 (.108)	− .553 (.215)	.769	.753
	A5	3.76	1.205	− .813 (.108)	− .262 (.215)	.761	.765
	A6	3.75	1.238	− .745 (.108)	− .504 (.215)	.793	.791
Search	B1	3.47	1.156	− .481 (.108)	− .573 (.215)	.849	.912
	B2	3.47	1.223	− .509 (.108)	− .724 (.215)	.798	.802
	B3	3.44	1.193	− .528 (.108)	− .593 (.215)	.748	.756
	B4	3.53	1.165	− .583 (.108)	− .415 (.215)	.739	.775
	B5	3.47	1.234	− .526 (.108)	− .714 (.215)	.757	.778
	B6	3.45	1.187	− .508 (.108)	− .634 (.215)	.771	.789
word-of-mouth	C1	3.38	1.097	− .237 (.108)	− .448 (.215)	.839	.910
	C2	3.36	1.062	− .232 (.108)	− .338 (.215)	.747	.767
	C3	3.30	1.054	− .180 (.108)	− .411 (.215)	.716	.746
	C4	3.28	1.108	− .233 (.108)	− .430 (.215)	.731	.743
	C5	3.27	1.045	− .165 (.108)	− .317 (.215)	.743	.746

Variables	items	mean	S.D.	Kurtosis (S.E.)	Skewness (S.E.)	Factor loading	Standard Factor loading
	C6	3.31	1.054	− .156 (.108)	− .334 (.215)	.714	.753
	C7	3.29	1.028	− .196 (.108)	− .311 (.215)	.758	.765
	C8	3.31	1.084	− .338 (.108)	− .251 (.215)	.766	.766
Action	D1	3.53	1.087	− .582 (.108)	− .200 (.215)	.824	.914
	D2	3.53	1.154	− .538 (.108)	− .477 (.215)	.769	.805
	D3	3.50	1.116	− .437 (.108)	− .507 (.215)	.787	.767
	D4	3.53	1.039	− .552 (.108)	− .125 (.215)	.726	.753
	D5	3.54	1.118	− .634 (.108)	− .213 (.215)	.757	.776
	D6	3.61	1.066	− .527 (.108)	− .232 (.215)	.774	.759
Share	E1	3.22	1.151	− .178 (.108)	− .680 (.215)	.836	.904
	E2	3.20	1.181	− .274 (.108)	− .631 (.215)	.781	.775
	E3	3.28	1.138	− .250 (.108)	− .563 (.215)	.751	.757
	E4	3.26	1.144	− .232 (.108)	− .607 (.215)	.745	.763
	E5	3.28	1.193	− .202 (.108)	− .718 (.215)	.754	.783
	E6	3.20	1.123	− .333 (.108)	− .443 (.215)	.753	.760
	E7	3.28	1.185	− .332 (.108)	− .643 (.215)	.708	.753
	E8	3.16	1.155	− .166 (.108)	− .643 (.215)	.731	.738

4.2 Reliability and validity analysis

The overall scale demonstrated strong reliability, with a Cronbach's α of 0.948. The Cronbach's α values for Interest, Search, word-of-mouth, Action, and sharing were 0.913, 0.914, 0.923, 0.912, and 0.925, respectively, all exceeding the 0.8 threshold. Composite reliabilities ranged from 0.913 to 0.938, and average variance extracted (AVE) values ranged from 0.603 to 0.646, all surpassing the recommended thresholds of 0.7 and 0.5, respectively.

Validity was assessed through exploratory factor analysis (EFA). The Kaiser-Meyer-Olkin (KMO) measure was 0.957, and Bartlett's test of sphericity was significant ($p < 0.001$), indicating that the data were suitable for factor analysis. Principal component analysis with orthogonal rotation extracted five factors with eigenvalues greater than 1, explaining 68.130% of the total variance. All factor loadings were above 0.7, and the five factors corresponded to the intended constructs.

A confirmatory factor analysis (CFA) was subsequently conducted. The overall measurement model demonstrated a good fit to the data: GFI = 0.939, AGFI = 0.930, RMSEA = 0.014, CFI = 0.996, NFI = 0.954, RMR = 0.037, and $\chi^2/df = 568.328/517$ ($p = 0.059$). These results confirm the scale's validity.

Correlation analysis showed positive correlations between variables (ranging from 0.4 to 0.6, $p < 0.01$). Discriminant validity was established as the AVE for each construct exceeded the squared inter-construct correlations (see Table 4).

We acknowledge the concern that certain constructs may be conceptually proximate. To address this, we implemented three safeguards. First, an expert panel reviewed all 34 items for content distinctiveness, ensuring each was anchored in a behaviorally specific ISMAS stage. Second, the EFA confirmed that the 34 items loaded cleanly onto five distinct factors, with all cross-loadings below 0.30. Third, the CFA demonstrated acceptable discriminant validity, satisfying the Fornell-Larcker criterion. We recognize that the behavioral sequence in the ISMAS model creates a natural conceptual gradient between adjacent stages. Future research employing multitrait-multimethod (MTMM) designs would further clarify the degree of construct distinctiveness at the latent variable level.

Table 4
Correlation and discriminant validity

Interest	Interest	Search	Word-of-mouth	Action	Sharing
	.645				
	1				
Search	.413	**.646**			
	(p < .001)	1			
Word-of-mouth	.400	.463	**.603**		
	(p < .001)	(p < .001)	1		
Action	.432	.419	.418	**.637**	
	(p < .001)	(p < .001)	(p < .001)	1	
Sharing	.382	.427	.481	.450	**.609**
	(p < .001)	(p < .001)	(p < .001)	(p < .001)	1

4.3 Regression analysis

This study employed SPSS (version 20.0) with the Hayes PROCESS macro (version 3.5; Hayes, 2018) to test the hypothesized pathways (Table 5).

Direct Effect (H1). An ordinary least squares (OLS) regression was conducted to test the direct effect of Interest on Sharing. The model was significant ($F = 87.595$, $p < 0.001$) and explained 14.6% of the variance in Sharing ($R^2 = 0.146$). The standardized coefficient for Interest was positive and significant ($\beta = 0.382$, $t = 9.359$, $p < 0.001$), supporting H1.

Chain Mediation (H2). The chain mediation effect was tested using PROCESS Model 6 with 5,000 bootstrap resamples to generate bias-corrected 95% confidence intervals (CIs). The results, summarized in Table 5, indicate that the total indirect effect was significant (indirect effect = 0.271, 95% CI [0.218, 0.325]), accounting for 70.90% of the total effect.

Specifically, the analysis revealed significant indirect effects through several pathways:

Single mediators

Search (indirect effect = 0.089, 95% CI [0.054, 0.131]), Word-of-Mouth (indirect effect = 0.112, 95% CI [0.073, 0.158]), and Action (indirect effect = 0.076, 95% CI [0.041, 0.119]).

Two-stage chains

Interest→Search→WOM (indirect effect = 0.045, 95% CI [0.021, 0.078]), Interest→Search→Action (indirect effect = 0.038, 95% CI [0.015, 0.069]), and Interest→WOM→Action (indirect effect = 0.052, 95%

CI [0.028, 0.084]).

Full sequential chain

The complete path (Interest→Search→WOM→Action→Sharing) was also significant (indirect effect = 0.031, 95% CI [0.012, 0.058]).

As none of the confidence intervals included zero, all indirect effects were statistically significant, supporting H2.

Table 5
Chain mediation effect analysis

Total effect	**Effect value**	**Boot standard error (S.E.)**	**Boot CI lower limit**	**Boot CI upper limit**	**Effect proportion**
	0.354	**0.038**	**0.279**	**0.428**	
Direct effect	0.103	0.039	0.026	0.180	29.10%
Total mediation effect	0.271	0.028	0.218	0.325	70.90%
Interest → Search → Share	0.068	0.022	0.026	0.111	17.80%
Interest → Word-of-mouth → Share	0.068	0.016	0.028	0.101	17.80%
Interest → Action → Share	0.057	0.016	0.023	0.092	14.97%
Interest → Search → Word-of-mouth → Share	0.040	0.009	0.023	0.059	10.45%
Interest → Search → Action → Share	0.019	0.006	0.009	0.034	5.08%
Interest → Word-of-mouth → Action → Share	0.012	0.004	0.005	0.021	3.11%
Interest → Search → Word-of-mouth → Action → Share	0.007	0.002	0.003	0.013	1.98%

4.4 Moderating effect analysis

The moderating effects of demographic variables were examined using PROCESS Model 1 (Hayes, 2018). For each pathway, the moderator was entered as an interaction term with the predictor variable. The significance of the interaction term coefficient (β_interaction), its t-value, p-value, and the change in R^2 (ΔR^2) were used to assess the moderating effect.

Gender Moderation (H3). The interaction terms for all four pathways were not statistically significant (all $p > 0.05$): Interest→Search ($\beta = 0.012$, $p = 0.756$), Search→Word-of-Mouth ($\beta = -0.018$, $p = 0.638$), Word-of-Mouth→Action ($\beta = 0.021$, $p = 0.582$), and Action→Sharing ($\beta = -0.009$, $p = 0.811$). Therefore, H3 is not supported.

Age Moderation (H4). Age significantly and negatively moderated two pathways: Search→Word-of-Mouth ($\beta = -0.112$, $t = -2.94$, $p = 0.003$, $\Delta R^2 = 0.042$) and Word-of-Mouth→Action ($\beta = -0.108$, $t = -2.81$, $p = 0.005$, $\Delta R^2 = 0.040$). The moderation of the Action→Sharing path was marginally significant ($\beta = 0.078$, $p = 0.048$), while the Interest→Search path was not significant ($p = 0.374$). Thus, H4 is partially supported.

Education Level Moderation (H5). None of the interaction terms for the four pathways reached the conventional significance threshold (all $p > 0.05$). The coefficients were: Interest→Search ($\beta = 0.029$, $p = 0.448$), Search→Word-of-Mouth ($\beta = 0.031$, $p = 0.418$), Word-of-Mouth→Action ($\beta = 0.033$, $p = 0.385$), and Action→Sharing ($\beta = 0.065$, $p = 0.086$). Consequently, H5 is not supported.

4.5 Summary of Findings

Based on the empirical analysis of the ISMAS model, the study yielded the following key findings:

(1) Direct Effect

Interest exerted a significant positive direct effect on Sharing ($\beta = 0.382$, $p < 0.001$), supporting H1.

(2) Chain Mediation

Search, Word-of-Mouth, and Action played significant sequential mediating roles in the relationship between Interest and Sharing. The total indirect effect accounted for approximately 68% of the total effect, confirming that the sequential mechanism is the primary pathway. H2 is supported.

(3) Moderation Effects

Age significantly and negatively moderated the Search→Word-of-Mouth ($\beta = -0.112$, $p = 0.003$) and Word-of-Mouth→Action ($\beta = -0.108$, $p = 0.005$) pathways. Gender and education level did not exhibit significant moderating effects on any pathway (all $p > 0.05$). Therefore, H3 and H5 are not supported, while H4 is partially supported.

These results reveal a multistage conversion process through which visual marketing contexts influence consumer decisions and provide a basis for precision marketing strategies.

5 Discussion and Suggestions

5.1 Discussion of Direct and Chain-Mediating Effects (H1 & H2)

The empirical results robustly validate the proposed ISMAS pathways.

(1) Direct Effect (H1). The significant positive impact of Interest on Sharing confirms that visual marketing stimuli can directly motivate communicative behavior. This finding aligns with Xiang & Zheng (2022), who identified intrinsic Interest as a catalyst for sharing, and extends the work of Huo et al. (2026) by demonstrating that aesthetic and dynamic visual elements have a direct behavioral carryover effect into the post-purchase domain.

(2) Chain Mediation (H2). The confirmation of the sequential mediation pathway provides a granular blueprint of the modern consumer journey. The progression from Interest to Search reflects the cognitive transition from passive browsing to active exploration (Deng, 2022). The subsequent link from Search to Word-of-Mouth (WOM) supports the risk-mitigation framework, where information seeking naturally drives consumers to seek social proof (Uddin et al., 2026). Finally, the significant path from WOM to Action and Sharing corroborates established paradigms of trust-building and experiential satisfaction (Liljander et al., 2015; Hou et al., 2020). By weaving these elements into a cohesive chain, this study overcomes the static limitations of prior research (Zhang, 2021) and demonstrates that visual resonance operates as a dynamic, closed-loop engine.

(3) Theoretical Implications. The confirmation of the full sequential chain (Interest→Search→WOM→Action→Sharing) carries two key implications. First, it demonstrates that the ISMAS model, when embedded within the S-O-R framework, functions as a mechanistic model where each stage is a necessary precondition for the next. The finding that the full chain's indirect effect (0.031) is smaller than any single-stage indirect effect (0.076–0.112) suggests behavioral "leakage" occurs at each transition, consistent with the funnel metaphor in Customer Journey Theory (Lemon & Verhoef, 2016). This indicates that visual marketing interventions should target specific transition points with the highest attrition.

Second, the coexistence of a significant direct effect (H1) and a full chain mediation (H2) reveals a dual-pathway mechanism: visual stimuli can trigger sharing both directly (through immediate affective resonance) and indirectly (through the sequential cognitive-behavioral chain). This extends the S-O-R model by showing that the Organism stage comprises parallel and sequential sub-processes rather than a unitary construct.

5.2 Discussion of Moderating Boundary Conditions (H3–H5)

This study's examination of demographic heterogeneity reveals a nuanced pattern of boundary conditions for the ISMAS framework.

Gender (H3 – Not Supported). Gender did not significantly moderate any pathway in the ISMAS model (all $\Delta R^2 < 0.003$, all $p > 0.05$). This null finding is theoretically informative, suggesting that the sequential behavioral mechanism operates with comparable strength across male and female consumers in the

mobile e-commerce context. This may reflect the increasing convergence of online shopping behaviors as platforms become more standardized (Gefen & Straub, 2004; Fisher et al., 2018) or indicate that visual marketing stimuli activate similar cognitive-emotional pathways regardless of gender. This finding challenges the common practice of gender-segmented visual strategies, suggesting that platform designers may prioritize universal design principles.

Age (H4 – Partially Supported). Age significantly and negatively moderated two specific pathways: Search→Word-of-Mouth ($\beta_{interaction} = -0.112$, $p = 0.003$) and Word-of-Mouth→Action ($\beta_{interaction} = -0.108$, $p = 0.005$). The negative direction indicates that the strength of these transitions decreases with age. This is consistent with digital literacy theory (Hargittai, 2002), suggesting that younger consumers, as digital natives, more readily integrate online search results with peer-generated word-of-mouth (Huo et al., 2026). For older consumers, the weaker reliance on WOM may stem from a greater trust in institutional information sources (e.g., official brand channels) and a more deliberative decision-making style that requires additional verification beyond social proof (Prensky, 2001). Notably, age did not moderate the Interest→Search or Action→Sharing pathways, suggesting that the initial affective response to visual stimuli and the post-purchase sharing motivation are relatively age-invariant.

Education Level (H5 – Not Supported). Education level did not significantly moderate any ISMAS pathway (all $\Delta R^2 < 0.030$, all $p > 0.05$). While we hypothesized that higher education would be associated with more systematic information processing (Petty & Cacioppo, 1986), the null finding suggests that in the mobile e-commerce context, the visual marketing stimulus is sufficiently intuitive and the behavioral sequence sufficiently habitual that educational differences in analytical depth do not translate into differential pathway strengths. This aligns with the processing fluency perspective (Reber et al., 2004), which posits that well-designed visual interfaces can reduce cognitive demands to a level where educational differences become negligible.

Summary of Moderation Findings. The overall pattern indicates that the ISMAS sequential mechanism is robust across gender and education but sensitive to age, particularly during mid-sequence transitions (Search→WOM→Action), where social proof and trust calibration are most critical. This has important implications for platform design: age-adaptive interfaces that provide additional verification cues for older consumers at these specific transitions may enhance conversion rates without altering the overall visual marketing strategy.

5.3 Managerial Implications

Based on the empirical findings, we propose the following actionable recommendations for mobile e-commerce platform operators and brand managers, organized by the specific ISMAS pathway they target.

5.3.1 Optimizing Visual Interest Stimulation (Targeting the Stimulus→Interest Path)

The significant direct effect of Interest on Sharing (H1) underscores the importance of the initial visual impression. Platform operators should:

Implement "Contextual Hotspot Overlays"

Embed clickable, semi-transparent nodes onto product images and videos. Tapping on specific features (e.g., fabric, color) should display specifications and related recommendations without navigating away, reducing friction between Interest and information engagement.

Deploy AR/3D Product Displays

For categories where visual inspection is critical (e.g., apparel, cosmetics), integrate augmented reality try-on features and 360-degree viewers. Our finding that Interest directly drives Sharing suggests that immersive visual experiences generate strong affective responses that motivate organic social sharing.

A/B Test Color and Layout Schemes

Systematically test color palettes and page layouts against target demographic profiles, using click-through rate and dwell time as proxy metrics for Interest generation (Labrecque & Milne, 2012).

5.3.2 Enhancing Search-to-Conversion Pathways (Targeting the Interest→Search→WOM Path)

The significant chain mediation through Search and WOM (H2) indicates that the critical challenge is transforming initial Interest into active information-seeking and social validation:

Adopt "Dual-Intent Tagging"

Systematically couple product semantic tags (e.g., "summer dress") with functional category tags (e.g., "breathable fabric") to ensure search results match both the aesthetic Interests and the functional information needs that drive search behavior.

Integrate Real-Time Peer Reviews into Search Results

Embed the top 3–5 most relevant peer reviews directly within search result cards. This operationalizes the Search→WOM transition, reducing the clicks required to access social proof.

Recalibrate Recommendation Algorithms

Increase the weight of the Search-to-Purchase conversion ratio over raw view counts. This ensures the platform surfaces products that not only attract visual Interest but also successfully convert Search into Action.

5.3.3 Activating the Post-Purchase Sharing Loop (Targeting the Action→Sharing Path)

The significant Action → Sharing pathway confirms that post-purchase experience is a critical driver of organic word-of-mouth:

Trigger Automated Content Generation

Upon transaction completion, prompt users with a one-tap tool to generate stylized, shareable digital assets (e.g., product photos with branded frames). This reduces the effort cost of Sharing and capitalizes on peak satisfaction.

Implement Tiered Sharing Incentives

Offer escalating rewards (points, coupons) based on the quality and reach of shared content, rather than a flat reward. This incentivizes high-quality word-of-mouth that serves as an effective secondary visual stimulus.

Close the Feedback Loop

Systematically feed user-generated content back into the platform's visual marketing pool (e.g., featuring customer photos on product pages). This operationalizes the cyclical ISMAS mechanism, in which Sharing re-enters the system as a new Stimulus.

5.3.4 Age-Adaptive Interface Design (Targeting the Age Moderation Finding)

Given that age significantly moderates the Search→WOM and WOM→Action transitions, platform design should be adapted accordingly:

For younger consumers (18–30)

Leverage their higher digital literacy by integrating social proof elements (peer reviews, influencer endorsements) directly into search and product pages. Their stronger Search→WOM→Action pathway suggests social validation cues are highly effective for this segment.

For older consumers (45+)

Provide additional institutional verification cues at the Search→WOM and WOM→Action transitions, such as official brand certifications, quality-guarantee badges, and accessible customer-service chatbots. These cues compensate for the weaker reliance on peer word-of-mouth identified in our moderation analysis.

5.4 Research Countermeasures

Based on the empirical findings, this study proposes the following strategic countermeasures to optimize the mobile e-commerce consumer journey.

(1) Stimulating Visual Interest

Given the significant impact of Interest on subsequent behaviors, platforms should optimize visual strategies by: **1) Enhancing Content Design**: Utilizing high-definition imagery and creative videos, augmented by big data analytics on user preferences (e.g., color, style) for personalized displays. **2) Integrating Word-of-Mouth**: Embedding positive user feedback directly into visual content to create a simultaneous stimulus of Interest and social proof. **3) Leveraging Technology**: Implementing interactive technologies like AR try-ons and 3D displays to enhance immersion, supplemented by short videos or live broadcasts to strengthen scene substitution. **4) Refining Color Strategy**: Selecting color schemes based on color psychology to align with target customer preferences and improve visual conversion efficiency.

(2) Optimizing the Search Experience

As Search behavior significantly promotes downstream actions, platforms should: **1) Optimize Search Results**: Highlighting core information (e.g., price, rating) and embedding short reviews to improve decision-making efficiency. Personalized sorting and semantic Search should be integrated to enhance matching accuracy. **2) Refine Functional Design**: Providing instant customer service on search pages to reduce younger users' (19–25 years) reliance on external word-of-mouth, and establishing popular search recommendations to stimulate sharing willingness. **3) Iterate Technology**: Regularly updating search algorithms for timeliness and enhancing product presentation through AR/3D displays.

(3) Strengthening the Word-of-Mouth Effect

Since word-of-mouth significantly influences purchasing and sharing, platforms should: **1) Optimize the Evaluation System**: Implementing point-reward mechanisms to encourage user reviews while strictly auditing content to ensure authenticity and objectivity. **2) Refine Display Strategy**: Highlighting high-quality evaluations on product pages, providing screening functions, and collaborating with Key Opinion Leaders (KOLs) to enhance product trust. **3) Guide User Behavior**: For users aged 19–55 and those with a bachelor's degree (the identified negative regulation group), using targeted promotional pop-ups to stimulate conversion and providing convenient sharing functions to facilitate word-of-mouth communication.

(4) Promoting Purchase Action

Given that purchasing behavior significantly drives sharing, platforms should: **1) Optimize Interaction**: Simplifying the shopping process (e.g., one-click purchase/checkout), optimizing the mobile touch experience, supporting multiple payment methods, and enhancing order tracking and after-sales

services. **2) Leverage Data**: Providing personalized recommendations through user behavior analysis and collecting regular feedback to iterate interface design. 3) Implement Incentives: Offering points or coupon rewards for sharing behaviors and stimulating secondary dissemination through promotional activities.

(5) Driving Experience Sharing

As all preceding ISMAS stages influence Sharing, a holistic approach is required: Product pages should utilize high-definition, multi-angle imagery and branded visual design to stimulate Interest. Intelligent recommendation systems and hot-search modules should be implemented to optimize Search. A dedicated area for selected reviews and high-quality content should be used to manage Word-of-Mouth. Finally, the payment process should be simplified (e.g., one-click ordering, multiple payment methods), and 24-hour customer service should be provided to promote Action, thereby culminating in a higher propensity for Sharing.

5.5 Limitations and Future Directions

This study has five principal limitations that should be addressed in future research:

(1) Visual Marketing as Contextual Stimulus Rather Than Measured Variable.

The most consequential limitation is that visual marketing was operationalized as the ambient contextual environment within which ISMAS behaviors unfold, rather than as a directly measured independent variable with dedicated psychometric scales. The 34 measurement items capture consumer behavioral responses at each ISMAS stage but do not isolate the specific visual attributes—such as image resolution, color harmony, layout symmetry, typographic design, or visual richness—that drive these responses. Consequently, while our findings robustly demonstrate that the ISMAS sequential mechanism operates within visually rich mobile commerce contexts, they cannot specify which visual elements are most responsible for triggering each behavioral transition. This limitation has three implications for future research.

First, scholars should develop and validate a multidimensional visual marketing scale tailored to mobile e-commerce, incorporating dimensions such as image quality, color aesthetics, layout balance, dynamic visual elements (e.g., short-video autoplay, AR interactivity), and algorithmic visual personalization. Second, experimental designs that systematically manipulate specific visual elements (e.g., high vs. low image resolution; warm vs. cool color palettes; static vs. dynamic product displays) while measuring subsequent ISMAS stage transitions would provide the causal granularity that the present cross-sectional design cannot offer. Third, multi-method approaches that combine eye-tracking or clickstream data (to capture actual visual attention allocation) with self-reported ISMAS behavioral measures would more rigorously triangulate the stimulus–organism link than survey data alone. We note that this limitation does not invalidate the present findings; rather, it defines the boundary within which our conclusions hold and charts a clear agenda for subsequent investigation.

(2) Cross-Sectional Design and Causal Inference.

The cross-sectional survey design limits causal claims about the sequential ordering of ISMAS stages. While the chain mediation analysis (Process Model 6) tests the statistical plausibility of the proposed sequence, it cannot establish temporal precedence. Future research should employ longitudinal panel designs or experience-sampling methods to track individual consumers through the ISMAS sequence over time, or experimental designs that manipulate visual stimuli and observe subsequent behavioral stages.

(3) Non-Probability Sampling and Generalizability.

The use of convenience and snowball sampling limits the statistical generalizability of findings. The sample may over-represent younger, digitally literate, and socially connected individuals. Future research should employ stratified probability sampling across multiple regions, age cohorts, and product categories to enhance external validity. Cross-cultural replication in non-Chinese contexts is also recommended.

(4) Common Method Bias and Endogeneity.

Although Harman's single-factor test (< 40%) and wave analysis suggested that CMB is not a severe threat, the reliance on a single self-report questionnaire for all variables introduces potential common method variance. More critically, the sequential ISMAS design creates a potential endogeneity concern: each behavioral stage serves simultaneously as a dependent variable (predicted by the prior stage) and an independent variable (predicting the subsequent stage) within the same cross-sectional dataset. Future research should address this by (a) employing multi-source data collection (e.g., platform behavioral logs for Search and Action; peer-reported measures for WOM and Sharing); (b) using instrumental variable approaches or lagged panel designs; and (c) applying marker variable techniques (Lindell & Whitney, 2001) as additional CMB controls.

(5) Analytical Method.

This study employed the Hayes Process macro (regression-based path analysis) rather than full structural equation modeling (SEM). While Process Model 6 is appropriate for testing sequential mediation with observed variables, it does not account for measurement error in the latent constructs. Future research should replicate the findings using full SEM (e.g., AMOS, Mplus, or lavaan) with latent variable specifications to provide more rigorous estimates of path coefficients and model fit.

Declarations

Declaration of interest statement: Given their role as *[Scientific Reports]*, Long Sun, You-Yu Dai, Ning Zhang, and Xinyao Tang had no involvement in the peer review of this article and have no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to another journal editor.

Ethical approval from IRB: This study received ethical approval from the Institutional Review Board (IRB) of International Business School of Shandong Jiaotong University (approval #202706116) on October 14, 2023. This is an IRB-approved anonymized study; all participant information was de-identified, and participant consent was waived.

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Figures

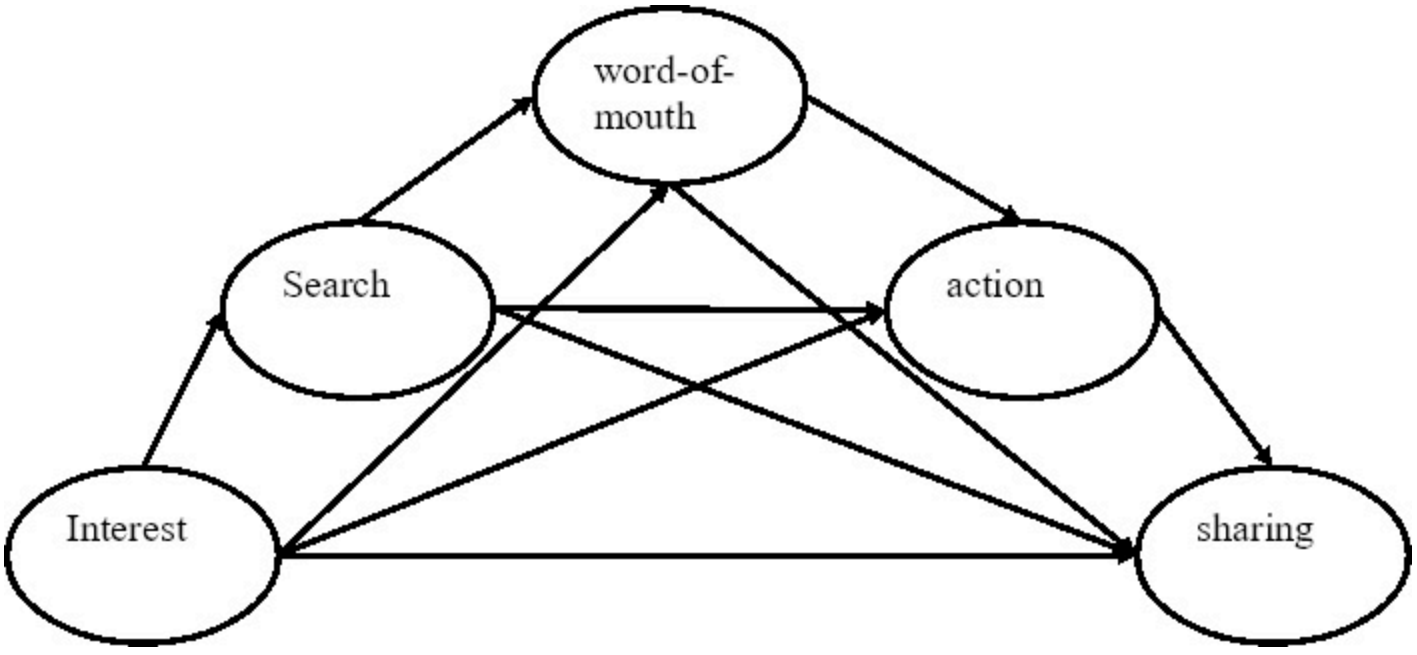


Figure 1

Research model

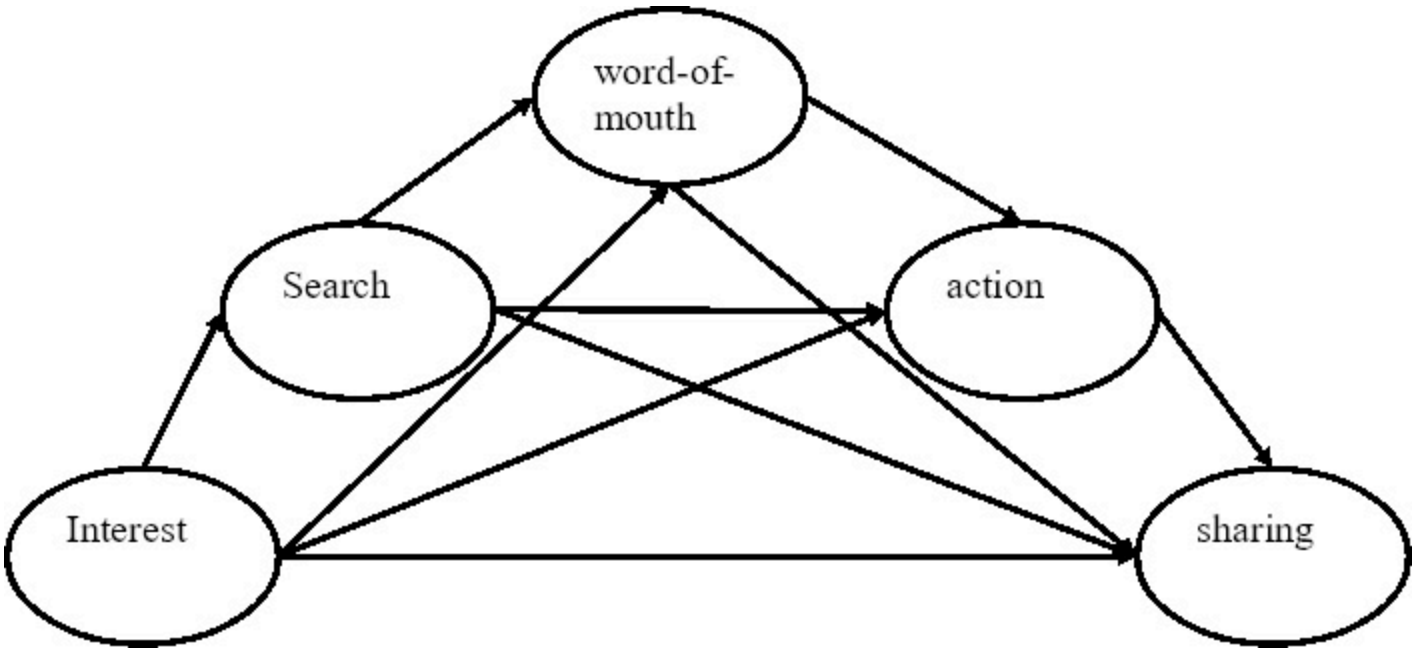


Figure 1

Research model

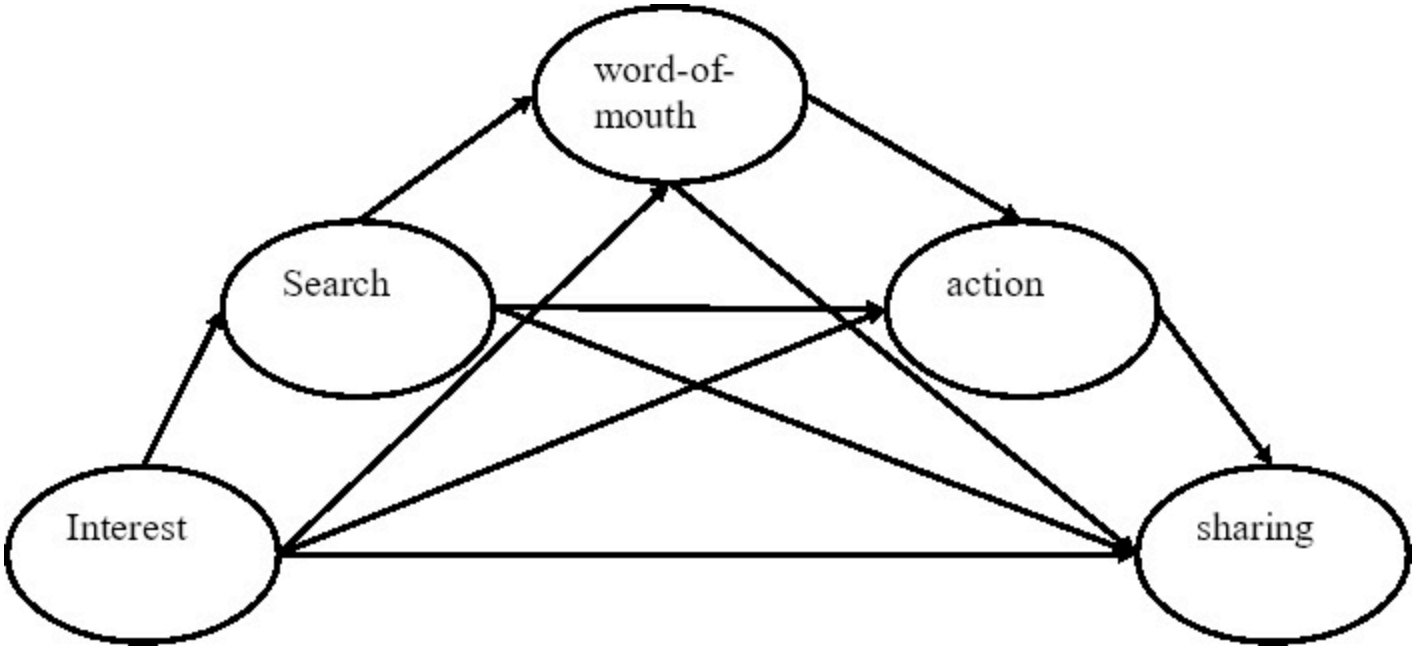


Figure 1

Research model

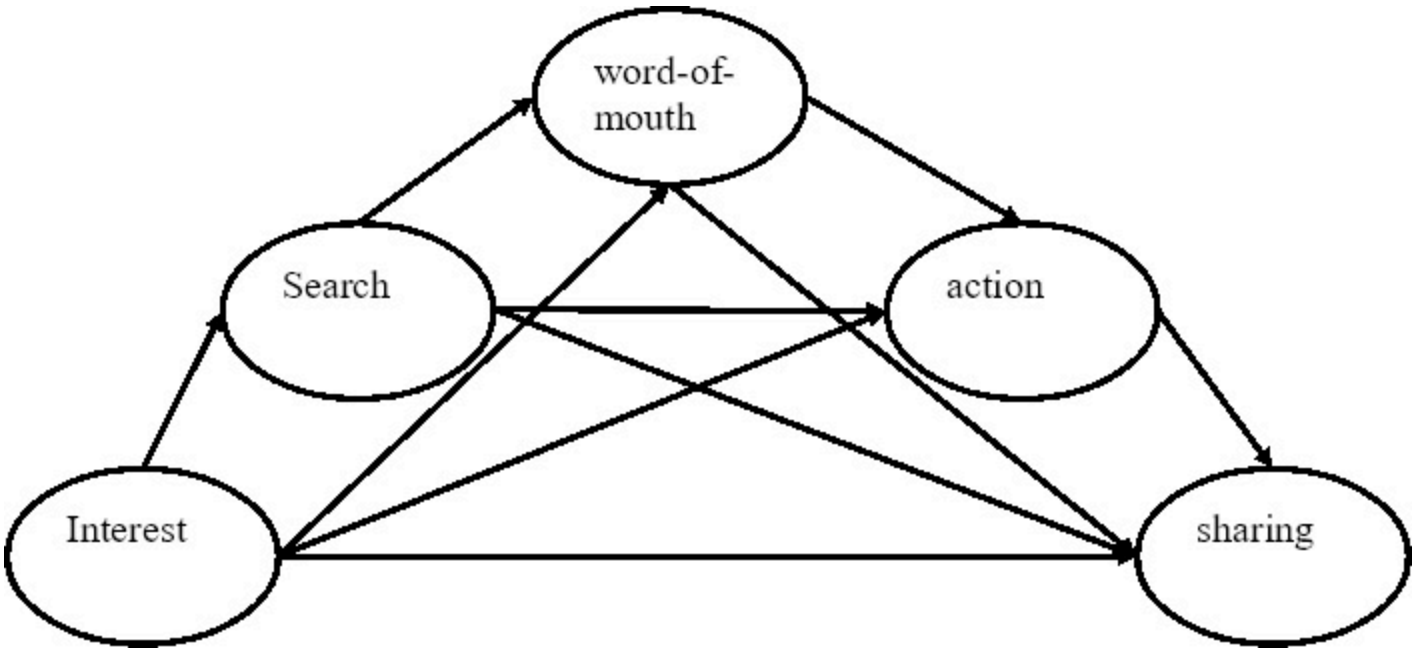


Figure 1

Research model

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