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From Scroll to Sale: Modeling the Hidden Psychological Transitions between Passive Content Consumption and Active Purchase Intent

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Abstract
This paper develops a process model of the psychological transitions through which passive social-media content consumption may lead to purchase intention. Prior research distinguishes passive consumption from active participation and links social-media interactions with purchase intention through source- and content-related factors. Integrating these perspectives with evidence on browsing, engagement, and information processing in digital commerce, the model treats exposure, attention, evaluation, and engagement as analytically distinct stages rather than assuming a direct path from viewing to intention. It also identifies content characteristics and social cues as potential conditions shaping movement between stages, consistent with findings on user-generated brand content and peer communication. The framework offers a basis for examining how passive exposure becomes active consideration and, ultimately, stated purchase intention, while distinguishing intention from purchasing behavior.

Keywords: *Passive Content Consumption; Consumer Engagement; Psychological Transitions; Social Commerce; Purchase Intention; Digital Marketing.*

I. INTRODUCTION

Digital purchasing rarely begins with a transaction. It begins with exposure, followed by attention, browsing, interpretation, social response, and sometimes intention. Treating this process as a **sequence of psychological transitions** clarifies why visible engagement does not always produce commercial action and why apparently passive viewing can precede later search or purchase. Research on social media, digital advertising, and commerce has examined these states separately, but fewer studies connect them within one analytical model.

From Passive Exposure to Observable Engagement and Purchase Intent

Passive consumption includes viewing videos, reading comments, scanning posts, or observing other consumers without an overt response. YouTube research distinguishes viewing from active behaviours such as liking, commenting, uploading, and sharing, with different motives predicting each state [1]. **Engagement** therefore should not be reduced to a single count. It may involve attention, cognitive processing, affective involvement, interaction, or behavioural acts, while **purchase intention** represents a stated readiness that remains distinct from completed purchase.

The transition from exposure to intention is conditional rather than automatic. Visual salience can increase engagement and purchase intention in Instagram advertising [2], while information quality, credibility, and task fit can make electronic word-of-mouth useful enough to be adopted [3]. The central problem is to identify the psychological conditions under which attention becomes browsing, browsing becomes interaction, and interaction becomes trust or affect that supports intention. [4]

Research Questions, Scope, and Contribution of the Evidence Synthesis

This synthesis asks four questions. Which motives distinguish passive consumption from active participation? Which source, content, social, and platform mechanisms convert engagement into purchase intention? When do live commerce and influencer settings intensify affective or impulsive responses? Which methods can observe transitions rather than infer them from a single survey response?

The evidence spans YouTube, Facebook, Instagram, TikTok, mobile commerce, social commerce, e-commerce platforms, and live-streaming applications. It includes surveys, experiments, field data, interviews, big-data analysis, structural equation models, fuzzy-set analysis, machine learning, topic models, hidden Markov models, and point-process models. The contribution is a transition architecture that separates observable behaviours from latent states and identifies where causal interpretation remains weak.

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Operationalizing the Transition Chain: Consumption, Engagement, Intention, and Purchase Behavior
The proposed chain begins with **consumption**, defined as exposure, viewing, reading, or browsing. It then moves to **engagement**, measured through attention, liking, commenting, sharing, following, participation, or deeper cognitive and affective involvement. Studies of digital advertising distinguish several levels of consumer engagement and show that content categories have unequal associations with different engagement metrics [5].

Intention is a self-reported expectation or willingness to buy, whereas **purchase behaviour** requires an observed transaction, visit, expenditure, or repeat purchase. Actual purchase data from apparel customers showed that relationship quality and intention related differently to behaviour according to relationship strength [6]. The model therefore treats each transition as probabilistic, affected by prior experience, trust, involvement, platform design, and situational susceptibility rather than as a guaranteed funnel.[7]

II. LITERATURE REVIEW

Literature Review: Theoretical Foundations of Digital Consumption-to-Purchase Movement
The literature draws on complementary theories because digital consumption combines motivation, information processing, social influence, affect, and platform affordances. No single framework explains viewing, interaction, trust, and buying equally well. Uses and gratifications explains why users enter and remain in media environments, stimulus-organism-response connects platform stimuli to internal states and responses, and information-processing models specify how source and message characteristics become accepted information. Social learning, parasocial interaction, social presence, and psychological contract theories extend the account to relationships and perceived obligations.

Uses and Gratifications: Why Consumers Watch, Browse, Lurk, and Participate
Uses and gratifications treats media use as goal-directed, although users may not articulate every motive. In a survey of 1,143 registered YouTube users, relaxing entertainment most strongly predicted video viewing and liking or disliking, social interaction predicted commenting and uploading, and information giving predicted sharing [1]. Reading comments was most strongly associated with information seeking, showing that apparently passive actions can have an active informational purpose.

These findings separate media entry from participation. A viewer seeking relaxation may watch without interacting, whereas a user seeking social connection may comment or upload. Short-form advertising research similarly identifies entertainment, performance expectancy, tie strength, and sales approach as features associated with engagement behaviour, with product type changing some relationships [8]. Consumption should therefore be modelled as heterogeneous in purpose, not as an undifferentiated precursor to purchase.

Stimulus–Organism–Response and Flow in Impulse-Oriented Digital Commerce
The **stimulus-organism-response** framework distinguishes external conditions, internal states, and behavioural outcomes. In mobile commerce, portability, visual appeal, and interpersonal influence affect hedonic and utilitarian browsing, while hedonic browsing directly increases the urge to buy impulsively [9]. Facebook commerce research similarly links browsing and usage intensity to urge and impulse purchase, with the model explaining 33.0% of variance in urge to purchase and 61.7% in impulse purchase [10].

Flow adds absorption and continuity to this sequence. Research on virtual streamers reports that interactivity, entertainment, social presence, and telepresence influence flow, while streamer animacy, vividness, attractiveness, and intelligence influence trust; flow and trust then predict continued watching and purchase intention [11]. These findings suggest that purchase may follow sustained immersion rather than a single persuasive message.[12]

Information Adoption, Heuristic–Systematic Processing, and Elaboration
The **information adoption model** explains how information characteristics produce perceived usefulness, adoption, and behavioural intention. Evidence from eWOM indicates that information quality, credibility, and task fit contribute to usefulness, which predicts adoption and then purchase intention [3]. In social commerce, argument quality in consumer-generated content can increase trust in site members, while trust predicts purchase intention [13].

The **heuristic–systematic model** distinguishes rapid source-based judgments from more effortful evaluation of content. Fashion influencer research with 471 respondents found that engagement mediated the effects of source credibility and content characteristics on purchase intention, while product involvement moderated effects on engagement [14]. Review evidence also shows that low-involvement consumers respond more to review quantity, whereas high-involvement consumers rely on quantity mainly when review quality is high [15]. Processing depth therefore changes which signals matter.

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Social Learning, Parasocial Interaction, Social Presence, and Psychological Contracts

Social learning explains how consumers observe others, infer rewards, and reproduce behaviour. Mixed-method evidence indicates that observational and reinforcement learning can jointly contribute to online impulsive buying in social commerce [16]. Peer communication also affects purchase decisions directly through conformity and indirectly by increasing product involvement, although need for uniqueness moderates effects on product attitudes [17].

Parasocial interaction describes a perceived relationship with a media figure, while **social presence** concerns the felt presence of others or the seller. In live streaming, streamer, viewer, and product social presence increase affective intensity, and viewer or product presence reduces perceived risk; the urge to buy is driven more strongly by affective intensity than perceived risk [18]. Psychological contract research adds relational and transactional expectations: platform interactivity predicts relational contracts, while ratings and reviews predict transactional contracts, both of which mediate purchase intention [19], [20].

From Passive Consumption to Engagement: Attention, Browsing, and Interaction as Intermediate States

The first conversion point occurs before consumers state an intention to buy. A post must attract attention, support a reason to remain, and offer a response that feels worthwhile. The evidence distinguishes motivational consumption from behavioural engagement and shows that the same feature can support entertainment, information seeking, or social connection. These distinctions prevent the common error of interpreting every view, like, or click as equivalent evidence of commercial persuasion.

Motivational Differences Between Passive Content Consumption and Active Participation on YouTube

YouTube evidence offers a clear separation between passive and active states. Relaxing entertainment strongly predicts viewing and liking, whereas social interaction predicts commenting and uploading, and information giving predicts sharing [1]. Reading comments is associated with information seeking, indicating that a user who appears inactive may still be evaluating social information.[21]

The study also reports that greater YouTube experience negatively predicted liking, while anonymity affected sharing and uploading [1]. These findings imply that platform familiarity and identity conditions influence the likelihood that attention becomes visible action. A view may reflect entertainment, learning, or social monitoring, so its commercial meaning depends on the user's motive and subsequent behaviour.

Hedonic and Utilitarian Browsing as the First Psychological Conversion Point

Browsing is more than a mechanical path to a product page. **Hedonic browsing** involves enjoyment and stimulation, whereas **utilitarian browsing** concerns instrumental information search. In mobile commerce, situational factors influence the two forms differently, and utilitarian browsing affects impulse buying indirectly through hedonic browsing [9].

Review consumption shows a similar sequence. Perceived hedonic and utilitarian value from online reviews increases browsing, browsing increases the urge to buy impulsively, and the urge predicts impulse buying behaviour [22]. Consumers high in impulsiveness attend more to hedonic review value, while consumers low in impulsiveness place greater emphasis on utilitarian value [22]. Browsing is therefore a measurable psychological bridge between exposure and response.

Content Format, Visual Engagement, and Short-Form Video Features That Activate Response

Content format changes the probability that exposure becomes attention or engagement. In an Instagram experiment, direct gaze and high product salience increased digital visual engagement, which in turn influenced purchase intention [2]. In digital content marketing, social-oriented text paired with concrete images produced more hedonic browsing and higher purchase intention than task-oriented text paired with abstract images for the tested conditions [23].

Big-data analysis of TikTok advertising identifies performance expectancy, entertainment, tie strength, and sales approach as significant correlates of consumer engagement behaviour [8]. Product type moderated these relationships, limiting any claim that one short-form formula generalizes across categories [8]. Content activates response when its informational, visual, social, and commercial cues fit the viewer's purpose.

Engagement Quality Versus Engagement Volume: Likes, Comments, Sharing, and Deep Consumer Engagement

Visible engagement metrics represent different levels of effort and meaning. Likes may require little cognitive investment, whereas comments, shares, uploads, and sustained interaction require stronger motivation. A field study matching Facebook engagement with store visits among 1,066 loyalty-program members found that stronger forms of engagement were more closely associated with purchase frequency than moderate or weak forms, although some engagement types showed no discernible association [24].

This distinction also appears in advertising research. Social media advertising features such as entertainment and promotional rewards can influence consumption intention through customer engagement, while social media dependency affects both consumption and sharing intention [25]. Engagement volume can therefore overstate commercial relevance when it counts low-effort reactions without measuring attention, interpretation, or relational investment.[26]

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Planned Evidence Displays: Engagement-Funnel Diagram and Cross-Study Effect-Path Table

The evidence supports a funnel that separates exposure, browsing, visible interaction, deeper engagement, and intention. It should be presented as a sequence of possible transitions, not as a deterministic progression.

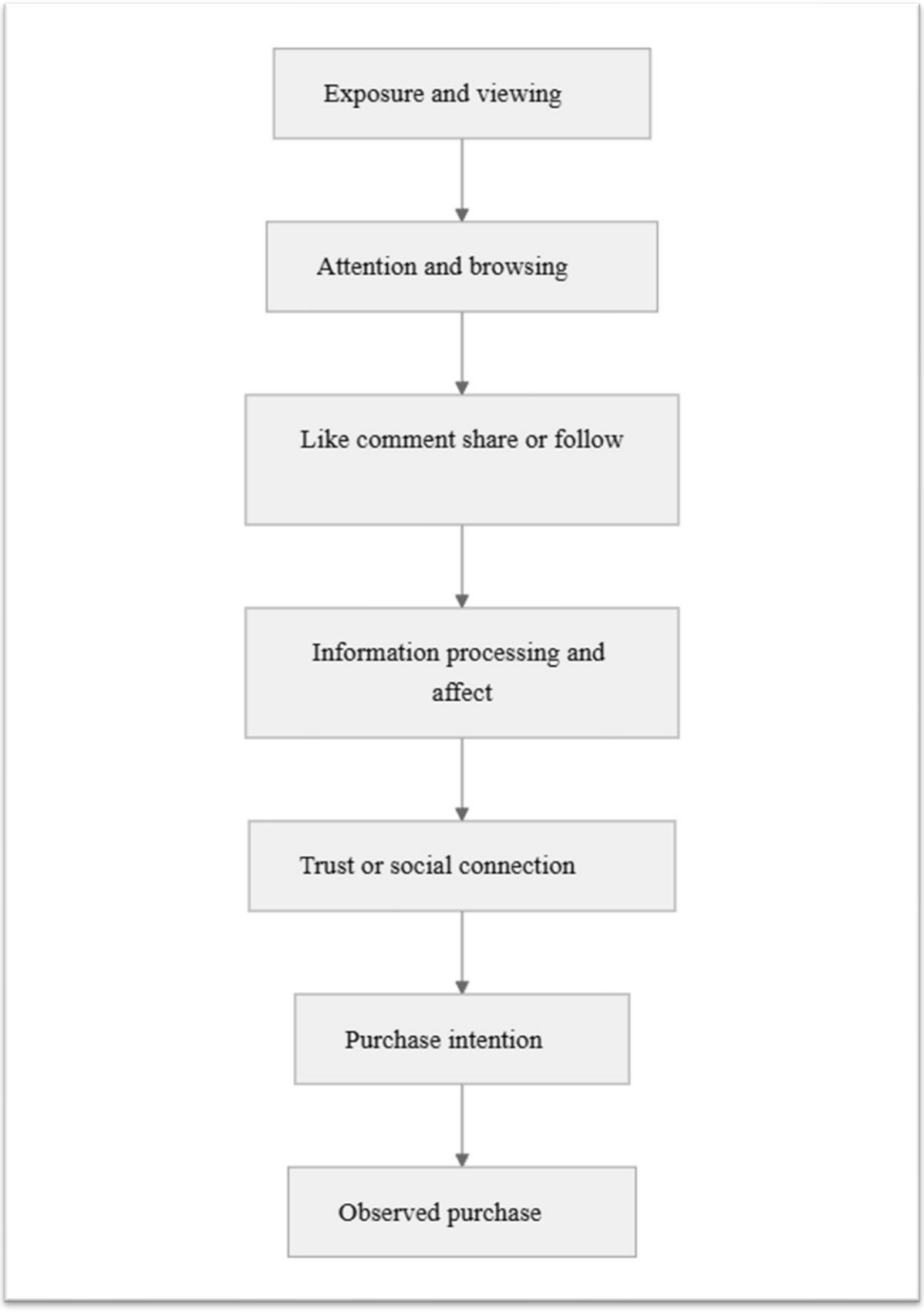


Diagram 1

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A cross-study table should align the endpoint and mechanism rather than combine unlike coefficients.

Evidence context	Intermediate state	Commercial endpoint
YouTube motives	Viewing, commenting, sharing	Participation and consumption [1]
Instagram imagery	Visual engagement	Purchase intention [2]
Mobile commerce	Hedonic browsing	Impulse-buying urge [9]
Facebook brand pages	Involvement and attitude	Future purchase intention [27]
Loyalty-program field data	Strong versus weak engagement	Purchase frequency [24]

Social and Informational Mechanisms That Convert Engagement into Purchase Intent

Engagement becomes commercially consequential when it changes how consumers evaluate information, sources, brands, or relationships. Social proof can reduce uncertainty, credible sources can increase acceptance, and high-quality content can make product information useful. These mechanisms do not operate uniformly: involvement, trust, demographic characteristics, social presence, and prior brand relations alter the transition from engagement to intention.

Peer Communication, User-Generated Content, and Electronic Word-of-Mouth as Social Proof

Peer communication supplies informational and normative signals. Among consumers discussing products on social media, tie strength and group identification increase peer communication outcomes, which affect purchase decisions directly through conformity and indirectly through product involvement [17]. User-generated brand posts can also produce higher purchase intention than disclosed advertisements or brand posts because they do not activate persuasion knowledge in the same way [28].

Electronic word-of-mouth is persuasive only when recipients regard it as credible and useful. On Xiaohongshu, information quality was associated with social psychological distance and trust, while trust predicted purchase intention [29]. The effect is therefore relational and informational at once. A high volume of peer content may attract attention, but adoption depends on whether consumers can apply it to their decision.[30]

Source Credibility, Influencer Expertise, Trustworthiness, Homophily, and Parasocial Connection

Source characteristics provide heuristic cues when consumers lack time or motivation for detailed evaluation. A meta-analysis of 176 effect sizes from 62 studies and 22,554 participants found moderate to high associations between influencer characteristics and engagement or purchase intention; entertainment had the strongest association with engagement, whereas credibility had the strongest association with purchase intention [31]. These results summarize heterogeneous studies and should not be treated as platform-invariant causal effects.

Primary studies reinforce the importance of fit and perceived similarity. C2C social media interactions influence source credibility and homophily, which predict behavioural engagement, while homophily partially mediates effects on purchase intention [32]. In livestream marketing, empathy and social avoidance increase perceived parasocial interaction, whereas loneliness decreases it; parasocial interaction predicts impulsive purchase [33]. The source converts engagement when viewers perceive competence, similarity, and relational connection.

Content Quality, Information Credibility, Task Fit, and Product Presentation

Content must answer a consumer's decision problem. Information quality, credibility, and task fit increase perceived usefulness and information adoption, which then predict purchase intention [3]. C2C research similarly identifies post quality as a partial mediator between social media interaction and purchase intention [32]. These findings support a content pathway distinct from emotional attraction.

Presentation determines how content is processed. An experiment with 202 participants found that social-oriented text with concrete imagery increased hedonic browsing and purchase intention under specified product, presentation, and gender conditions [23]. Live-commerce evidence likewise links service, information, and system quality to usefulness, ease of use, trust, perceived value, and purchase intention [34]. The relevant mechanism is not information volume alone, but fit between message form and consumer task.[35]

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Brand Familiarity, Brand Equity, Relationship Quality, and Customer Involvement

Engagement may strengthen the brand relationship without directly producing immediate intention. Brand familiarity and information quality increase involvement with brand social-media pages, involvement improves attitude toward the page, and attitude predicts future purchase intention; involvement itself did not directly predict intention in that study [27]. This pattern cautions against treating engagement as a sufficient endpoint.

Other evidence places relational constructs closer to purchase. Social media marketing affects brand equity, and brand equity predicts purchase intention in Ghana's fashion industry [36]. A multi-analytic study identifies consumer-based brand equity and consumer inspiration as partial mediators between social media marketing and purchase intention [37]. Relationship quality also predicts intention, while intention and relationship strength predict actual purchase behaviour [6].

Moderators of the Engagement-to-Intent Relationship: Involvement, Trust, Demographics, and Social Presence

Moderators determine whether the same engagement signal has the same meaning for different consumers. Product involvement changes the relationship between influencer source or content characteristics and engagement [14]. Review involvement changes whether consumers rely on quantity alone or on quality combined with quantity [15]. High involvement can therefore increase the value of diagnostic content while weakening the effect of superficial popularity cues.

Trust and social presence also condition conversion. Social presence moderates the relationship between trust in site members and purchase intention [13], while trust level, age, gender, and income alter some associations between fan-page actions and purchase intention [38]. Yet other evidence found no significant effects for age and gender on behavioural intention in casino social-media advertising [25]. Demographic moderation is thus context-dependent rather than a stable rule.[39]

Planned Evidence Displays: Source–Content Matrix, Mediation Diagram, and Meta-Analytic Statistics Summary

A source-content matrix should distinguish credibility, homophily, expertise, entertainment, information quality, task fit, and visual presentation. The mediation logic can be represented as follows.

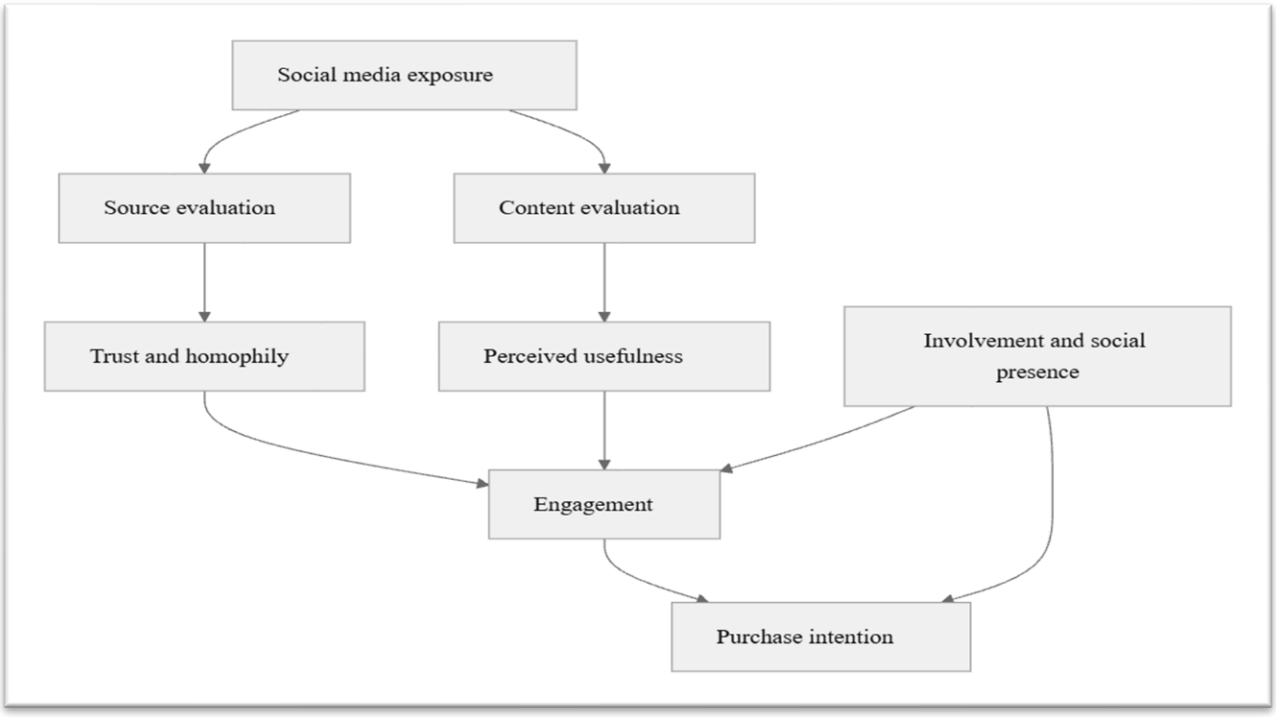


Diagram 2

The meta-analysis supplies a quantitative benchmark, with 176 effect sizes, 62 studies, and 22,554 participants, but it does not replace platform-specific evidence [31]. A planned statistics table should report sample, design, mediator, moderator, endpoint, and whether intention or behaviour was measured. This format prevents the common error of comparing an association with purchase intention to an association with actual purchase as if they were identical.

High-Intensity Conversion Contexts: Live Streaming, Influencer Commerce, and Impulse Buying

Live and influencer commerce compress exposure, evaluation, social interaction, and transaction into a shared environment. Synchronous exchange can reduce psychological distance, while sensory richness and scarcity-oriented presentation may intensify

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affect. The evidence also shows that high-intensity settings do not eliminate cognition: usefulness, information quality, trust, and perceived risk remain relevant, although affect may dominate under impulse conditions.[40]

Interactivity, Rich Sensory Stimuli, and Synchronous Consumer–Seller Exchange in Live Commerce

Live interaction includes personalization, responsiveness, entertainment, mutuality, and perceived control. These features increase perceived usefulness, reduce perceived risk and psychological distance, and promote social-commerce engagement [41]. Their effect is consistent with a stimulus-organism-response sequence in which interaction changes internal evaluation before producing engagement.

Live commerce also combines product demonstration with immediate communication. Service, information, and system quality affect usefulness, ease of use, trust, and perceived value, which then support purchase intention [34]. The commercial setting therefore contains both experiential and informational pathways. Interactivity attracts attention, but quality and trust determine whether attention remains commercially relevant.

Emotional Contagion, Social Presence, and Anchor Characteristics in Impulse Purchases

Impulse purchase in live streaming is strongly affective. Streamer, viewer, and product social presence increase affective intensity, while the urge to buy is driven by affective intensity rather than perceived risk in one study of 267 valid responses [18]. This does not show that cognition is absent; it indicates that affect better explains the immediate urge under that design.[42]

Anchor characteristics shape emotional contagion. In a study of 327 respondents, pleasure was the key influence on impulse buying, and attractiveness, similarity, professionalism, and interactivity supported pleasure; an artificial neural network ranked attractiveness highest among those characteristics [43]. Viewer engagement negatively moderated some effects of similarity and attractiveness, suggesting that crowded or highly active rooms may alter the anchor-consumer connection [43].

Virtual Streamers, Influencer Advertisements, and the Expansion of Parasocial Persuasion

Virtual streamers extend influencer commerce beyond human presentation. Among 577 virtual-streamer viewers, interactivity, entertainment, social presence, and telepresence influenced flow, while animacy, vividness, attractiveness, and intelligence enhanced trust; continued watching predicted purchase intention [11]. Gender differences appeared in the effect of intelligence on trust, with the reported effect present among female viewers but not male viewers [11].

Influencer advertising follows a related but more explicit persuasive route. In e-commerce livestream advertising, credibility, celebrity effect, entertainment, trust, and usefulness influenced attitudes toward advertisements, which predicted the urge to buy impulsively; the model explained 61.7% of variance in attitude and 19.4% in impulse-buying urge [44]. The figures refer to model variance, not conversion rates, and should not be interpreted as population-level purchase probabilities.

Online Shopping Experience, Mobile Commerce, and Situational Susceptibility to Impulse Buying

Mobile and online contexts make browsing available during ordinary activities, increasing the importance of situational susceptibility. Portability and visual appeal influence hedonic and utilitarian browsing, while hedonic browsing directly predicts the urge to buy impulsively [9]. Online reviews add both utilitarian and hedonic value, with browsing mediating the path to impulse buying [22].

Customer experience can extend this process beyond a single message. Among 1,489 customers of two Chinese e-commerce platforms, functional and psychological shopping-experience dimensions predicted online impulsive buying, attitudinal loyalty mediated the relationship, and self-control negatively moderated the path from loyalty to impulse buying [45]. These results suggest that situational stimulation interacts with durable attitudes and self-regulation rather than operating independently.[46]

Planned Evidence Displays: Live-Commerce Transition Diagram and Platform-Context Comparison Table

Live-commerce evidence can be organized as a transition from synchronous stimuli to social presence, flow or affect, trust, and intention or impulse.

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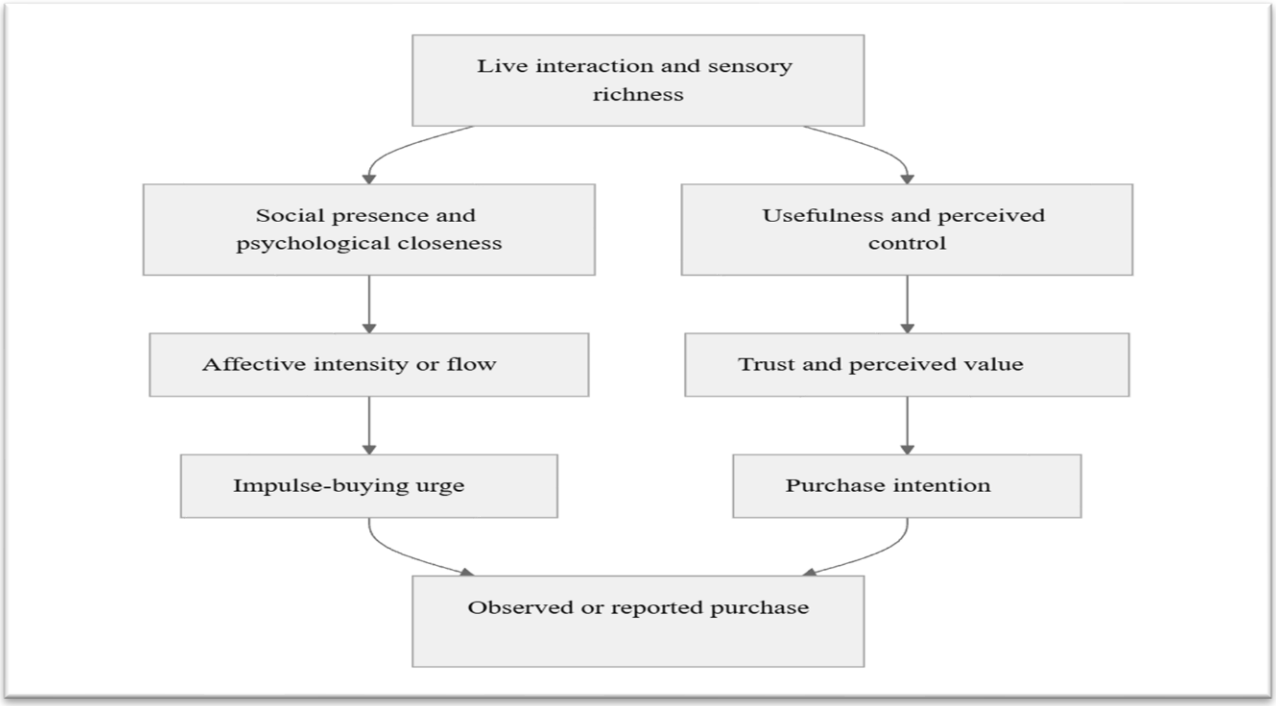


Diagram 3

Context	Primary internal state	Endpoint
Live social commerce	Usefulness, reduced risk, reduced distance	Engagement [41]
Live streaming commerce	Affective intensity	Impulse-buying urge [18]
Virtual streamer commerce	Flow and trust	Continued watching and purchase intention [11]
Mobile commerce	Hedonic browsing	Impulse-buying urge [9]
E-commerce platforms	Loyalty and self-control	Online impulsive buying [45]

Modeling the Hidden Transitions: From Attention and Interaction to Intention and Observable Purchase

A useful model must represent latent states that cannot be observed directly, including attention, trust, affect, flow, and perceived usefulness. It must also distinguish a user's current state from a cumulative history of exposures and interactions. The literature offers both psychological models and computational approaches, but these methods answer different questions and should not be treated as interchangeable.

A Sequential Scroll-to-Sale Model: Exposure → Browsing → Engagement → Trust and Affect → Purchase Intent

The proposed sequence begins with exposure, but the first transition is attention or browsing rather than purchase. Browsing can be hedonic or utilitarian, and it may be shaped by visual appeal, portability, interpersonal influence, or content presentation [9], [23]. Engagement then includes observable actions and deeper cognitive or affective states.

Trust, usefulness, social presence, and affect form the principal intermediate layer. Source credibility, homophily, and content quality mediate relationships between social media interaction, engagement, and purchase intention [32]. In live commerce, affective intensity can dominate perceived risk in predicting impulse-buying urge [18]. Purchase intention follows when these states combine with brand attitude, relationship quality, involvement, or perceived value.

Mediators and Moderators Identified Across the Corpus

Mediators include source credibility, homophily, content quality, perceived usefulness, information adoption, attitude toward advertising, brand equity, inspiration, customer relationship, loyalty, trust, flow, social presence, and affective intensity. Their placement differs by context. For example, customer engagement mediates effects of advertising entertainment and promotional

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rewards on consumption intention [25], whereas brand relationships fully mediate some social-media marketing effects in luxury fashion [47].

Moderators include product involvement, impulsiveness, self-control, social presence, relationship strength, need for uniqueness, income, marital status, internet use, gender, and product type. Some moderators are inconsistent across studies. Income did not moderate Facebook commerce effects, while marital status and internet hours did [10]. Relationship strength changed the association between intention and actual behaviour among apparel customers [6]. A model should therefore estimate conditional paths rather than assume universal coefficients.[48]

Dynamic Pathways, Repeated Advertising Touchpoints, and Conversion Timing

Repeated exposure can change states over time. A continuous-time hidden Markov model identified transitions among latent purchase-intention states and found that search advertising increased movement toward purchase, whereas repeated SMS advertising could produce fatigue and movement toward lower intention [49]. This approach captures movement that cross-sectional surveys cannot observe.

Point-process modelling provides a second dynamic perspective. Advertisement clicks can stimulate later clicks and purchases, and mutually exciting point processes outperform models that ignore those dependencies; display advertising showed a relatively low direct conversion effect but stimulated later visits through other formats [50]. Attribution based only on the final click can therefore undervalue earlier exposure. Conversion timing should be treated as a sequence of dependent events.

Comparing SEM, Mediation and Moderation, fsQCA, Machine Learning, Topic Models, and Point-Process Approaches

Structural equation modelling estimates relationships among latent constructs and is well suited to mediation hypotheses, but survey designs usually provide limited temporal evidence. **Mediation and moderation** clarify mechanisms and conditional effects, although their interpretation depends on measurement order and design. **Fuzzy-set qualitative comparative analysis** identifies combinations of conditions rather than average net effects; one social-network study used SEM and fsQCA to show that social influence and perceived risk could jointly form purchase-intention configurations [51].

Machine learning emphasizes prediction. A study comparing eight algorithms found gradient boosting achieved 0.91 accuracy and a 0.91 macro F1 score when attitude, social norm, and perceived behavioural control were included, with LIME used for explanation [52]. Topic models infer latent needs from search phrases, and a model using textual information improved prediction of website visits and purchase decisions across more than 8,000 search phrases [53]. Point processes and hidden Markov models add time, which is essential for transition research.

Planned Evidence Displays: Integrated Conceptual Diagram, Path-Coefficient Table, and Conversion-Sequence Graph

The integrated model should distinguish psychological states from observed indicators and should permit feedback from purchase or continued use to later exposure.

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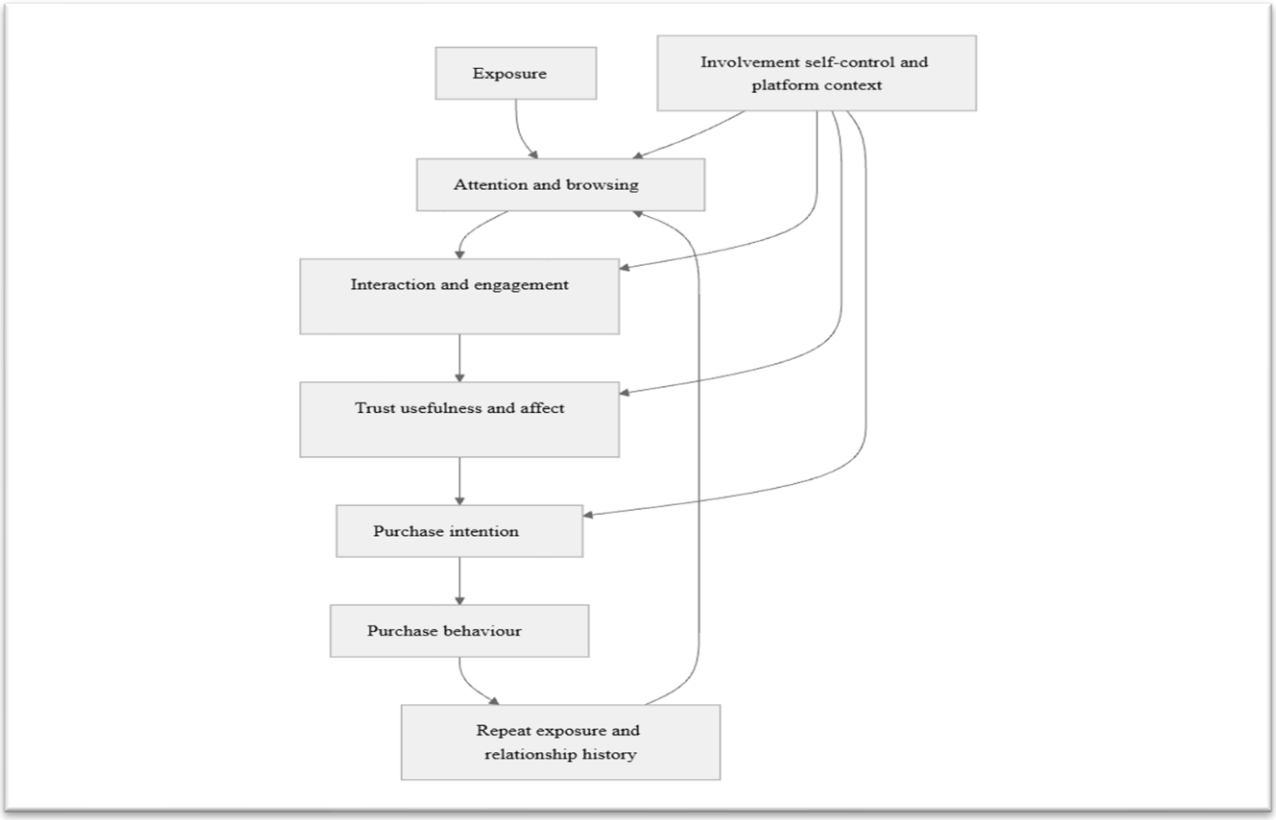


Diagram 4

A path-coefficient table should record whether each estimate comes from SEM, experiment, field data, or predictive modelling. It should also record whether the endpoint is intention, impulse urge, purchase frequency, or actual purchase. A conversion-sequence graph can then combine event timestamps with survey measures, avoiding the assumption that a single coefficient represents the whole scroll-to-sale process.

Measurement and Methodological Evidence: What the Existing Studies Can and Cannot Establish

The corpus contains substantial methodological variety, but evidence strength varies by endpoint and design. Surveys efficiently measure latent evaluations, yet they often measure exposure, mediator, and intention at one time. Field data and experiments improve behavioural interpretation, while computational models capture scale and sequence. Cross-platform comparisons remain difficult because the same label, such as engagement or purchase intention, can represent different behaviours.[54]

Survey-Based Structural Equation Models and Mediation Tests Across Social Commerce Settings

Survey-based SEM dominates the evidence. Samples include 288 social-commerce respondents, 430 consumers on a Chinese social-commerce site, 471 fashion-influencer respondents, 500 fashion customers in Ghana, and 1,489 customers of two Chinese e-commerce platforms [13], [14], [19], [36], [45]. These studies estimate complex relationships among trust, quality, involvement, loyalty, engagement, and intention.

The strength of SEM lies in testing theoretically specified indirect paths. Its limitation is that cross-sectional mediation does not establish temporal mediation. A respondent may report engagement because they already intend to buy, rather than develop intention because of engagement. The evidence is therefore strongest for covariation and model compatibility, not for definitive moment-to-moment causation.

Big Data, Predictive Modeling, Topic Modeling, and Multi-Analytic Designs

Big-data studies observe naturally occurring content and behaviour. TikTok analysis identifies short-form video features associated with engagement [8], while search-phrase modelling links latent topics to website visits and purchase decisions using more than 8,000 phrases [53]. These approaches improve ecological validity and scale, but platform algorithms and selection processes can confound associations.[55]

Multi-analytic designs combine explanation with prediction. PLS-SEM and artificial neural networks jointly assessed social-media marketing, brand equity, inspiration, and purchase intention [37]. The neural-network analysis ranked predictors, while SEM tested theoretical paths. Artificial neural networks also ranked anchor characteristics in livestream impulse buying [43].

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Predictive importance does not by itself establish a psychological mechanism, so computational outputs require theoretically interpretable measurement.

Experimental, Behavioral, and Actual-Purchase Evidence Versus Self-Reported Intentions

Experiments improve causal inference for specific stimuli. Instagram imagery was manipulated to test gaze and product salience [2], while digital product presentation used a factorial design with 202 participants [23]. User-generated posts were experimentally compared with disclosed advertisements and brand posts, including manipulation of attention [28]. These designs identify immediate responses but often use one product category or short exposure.

Behavioural evidence addresses the intention-behaviour gap. Facebook engagement was matched to store visits among loyalty-program members [24], and apparel research combined survey responses with total expenditure, visits, and product types purchased [6]. Intentions can change over time and contain systematic bias, so models linking intentions to actual purchase improve individual-level prediction [56]. Satisfaction research likewise found different moderators for objective repurchase and self-reported intention [57].

Cross-Platform and Contextual Comparability: YouTube, Facebook, Instagram, Short-Form Video, and Live Commerce

Platforms differ in affordances, user motives, and commercial proximity. YouTube separates viewing, reading comments, liking, commenting, sharing, and uploading [1]. Instagram emphasizes visual attention and product salience [2], while Facebook supports fan-page following, peer communication, and commerce groups [38], [58]. TikTok foregrounds short-form video features and algorithmic distribution [8].

Live commerce adds synchronous interaction, sensory demonstration, and immediate social presence. Its impulse-buying endpoint should not be combined without qualification with planned purchase intention in static social-media studies. Cross-platform research should harmonize constructs through behavioural definitions, record platform context, and preserve distinctions between intention, urge, engagement, and purchase.[59]

Planned Evidence Displays: Methods Taxonomy, Sample-and-Measure Table, and Evidence-Strength Heat Map

A methods taxonomy should map design to inference rather than rank methods generically. The following table illustrates the required alignment.

Method	Typical strength	Main limitation	Example
Cross-sectional SEM	Tests latent paths and mediation	Weak temporal identification	Social-commerce trust and intention [13]
Experiment	Identifies effects of manipulated content	Narrow stimulus and short exposure	Instagram visual features [2]
Field behavioural data	Measures real visits or purchases	Confounding and attribution	Facebook engagement and store visits [24]
Big-data text analysis	Scale and naturalistic content	Algorithmic selection	TikTok advertising features [8]
Hidden-state or point-process model	Represents timing and transitions	Requires detailed event data	Advertising clicks and conversion [50]

An evidence-strength heat map should separately score construct measurement, temporal ordering, behavioural endpoint, causal identification, and external validity. This prevents large samples from being mistaken for strong evidence when the design measures only self-reported intention.

Active Debates and Boundary Conditions in the Scroll-to-Sale Literature

The literature contains several unresolved tensions. Engagement may signal attention without persuasion, intention may fail to become purchase, and emotional stimulation may conflict with deliberate evaluation. These tensions challenge a simple funnel and require models that preserve alternative pathways, reversals, and feedback.

Engagement Is Not Conversion: Why Visible Interaction May Fail to Predict Purchase

Visible interaction is heterogeneous. Some Facebook engagement types were associated with store visits, while others had no discernible effect [24]. On brand pages, involvement predicted attitude toward the page, but not purchase intention directly [27]. These findings indicate that interaction can terminate in social expression, information seeking, or entertainment rather than shopping.[60]

Engagement may also arise from criticism or disagreement. YouTube research found different motives for liking, disliking, commenting, and sharing [1]. A count of reactions therefore obscures valence, purpose, and effort. Conversion models should distinguish passive reach, low-effort response, high-effort contribution, and commercially directed behaviour.@

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Purchase Intention Versus Actual Purchase Behavior: Temporal Instability, Bias, and Attribution Error

Intention is a proximal psychological measure, not a transaction. Intentions change over time and can produce biased forecasts when discrepancies with actual purchase are ignored [56]. Actual purchase is affected by price, availability, convenience, competing offers, self-control, and relationship strength, even when intention is high.

Evidence from apparel customers shows that intention and relationship strength predict behaviour, but the strength of the intention-behaviour association varies with relationship strength [6]. Satisfaction research similarly reports different moderating effects for objective repurchase and repurchase intention [57]. Attribution models must therefore specify whether the outcome is stated intention, urge, click, store visit, expenditure, or completed purchase.

Hedonic Stimulation and Impulse Buying Versus Systematic Information Processing and Deliberation

Hedonic browsing can directly increase impulse-buying urge, while utilitarian browsing may operate through hedonic browsing [9]. Live-streaming evidence also gives affective intensity greater explanatory weight than perceived risk for impulse-buying urge [18]. These findings support rapid affective conversion in high-stimulation environments.

Systematic processing remains relevant for high-involvement decisions. Review quality matters especially when involvement is high, and information quality, credibility, and task fit support adoption [3], [15]. The competing processes may coexist: consumers can enjoy content, assess information, and defer purchase until trust or task fit is sufficient.

Linear Funnel Assumptions Versus Dynamic, Nonlinear, and Configurational Purchase Paths

A linear funnel implies that exposure precedes browsing, engagement, intention, and purchase in a stable order. Hidden Markov evidence shows that consumers can move between higher and lower purchase-intention states, with advertising sometimes producing fatigue [49]. Point-process evidence shows that one advertisement can stimulate later clicks through another format rather than convert directly [50].

Configurational methods reach a related conclusion. fsQCA identifies combinations of social influence, perceived risk, credibility, and other conditions associated with purchase intention, rather than one universal path [51]. The appropriate model is therefore a state-transition system with feedback, competing routes, and possible reversal.

Planned Evidence Displays: Contradictory-Findings Table and Competing-Mechanisms Diagram

Tension	Evidence supporting one side	Boundary or counterpoint
Engagement predicts purchase	Stronger engagement associated with purchase frequency [24]	Some engagement types show no association [24]
Affect drives impulse	Affective intensity predicts impulse-buying urge [18]	Quality and trust predict planned intention [34]
Social proof persuades	Peer communication affects decisions [17]	Need for uniqueness moderates product attitudes [17]
Intention predicts behaviour	Intention and relationship strength predict purchase behaviour [6]	Intentions contain systematic bias [56]

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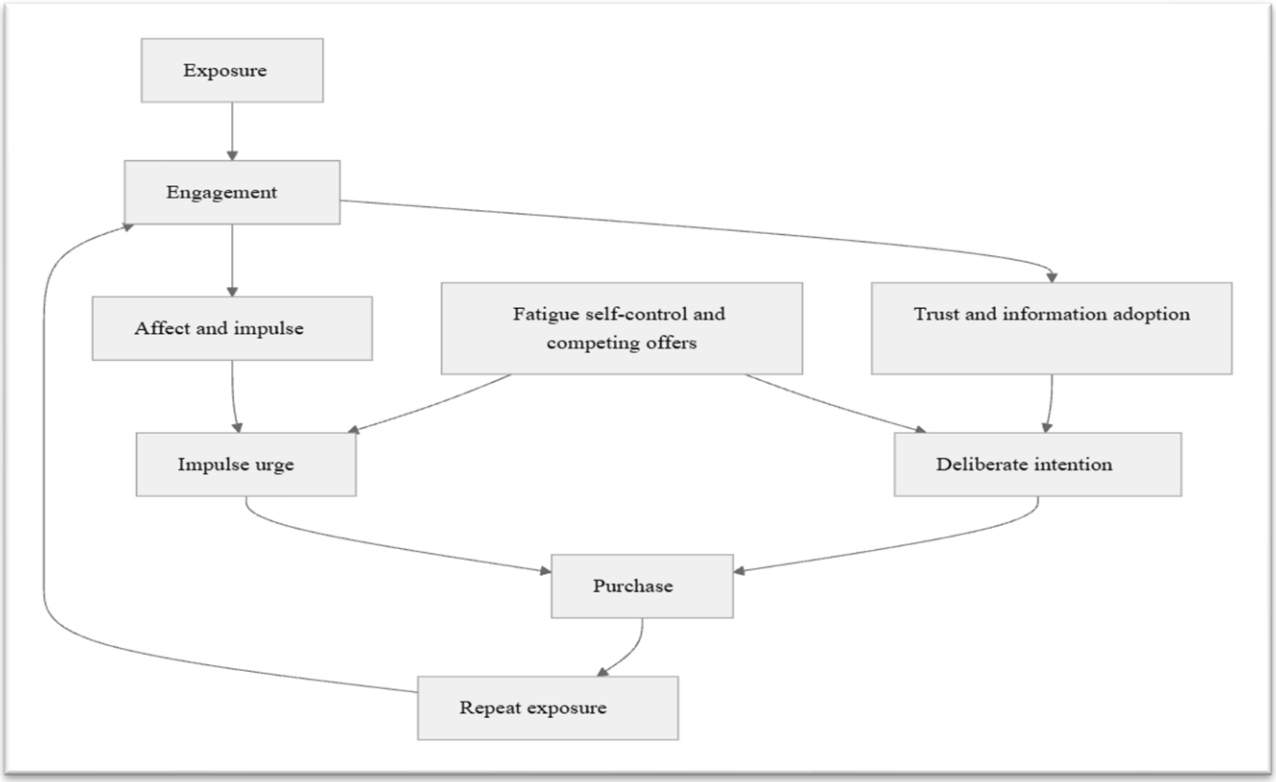


Diagram 5

Research Gaps: Toward an Integrated and Testable Model of Psychological Transition

The corpus establishes many associations among digital stimuli, internal evaluations, engagement, intention, and purchase. It provides less direct evidence about how these states change within individuals over time. The next research agenda should therefore combine psychological measurement with behavioural traces and temporal models.

The Missing Middle: Limited Direct Measurement of Moment-to-Moment Psychological State Changes

Most studies infer attention, trust, affect, or flow from retrospective survey responses. SEM can estimate indirect paths, but it rarely observes when a viewer shifts from browsing to evaluation or from interest to hesitation. Live-commerce studies identify affective intensity, usefulness, and social presence, yet usually measure them after exposure rather than continuously [18], [41]. Momentary designs could combine timestamps, click sequences, viewing duration, comment reading, and repeated state reports. Hidden Markov models already demonstrate the value of representing latent intention states [49]. Future work should connect such states to validated measures of trust, affect, involvement, and perceived usefulness.

Underdeveloped Links Between Passive Viewing, Active Engagement, and Repeated Purchase Behavior

YouTube research distinguishes passive viewing from active participation, but the evidence does not establish whether viewing later produces engagement or purchase [1]. Field data connect engagement to store visits, yet do not fully identify the psychological transition connecting them [24]. Repeated purchase behaviour remains especially underexamined relative to one-time intention.

Longitudinal platform records could test whether early viewing predicts later commenting, searching, visiting, and purchasing. Relationship strength and prior purchase should be included because they alter the intention-behaviour link [6]. Such designs would distinguish acquisition, conversion, and retention pathways.

Insufficient Integration of Cognitive, Affective, Social, and Platform-Level Mechanisms

Current studies often isolate one explanatory family. Information adoption emphasizes quality and usefulness, social presence emphasizes relational experience, and SOR models connect stimuli to internal states. Live commerce demonstrates that these mechanisms can operate simultaneously, with interactivity affecting usefulness, risk, distance, affect, trust, or flow [11], [41].

An integrated model should allow multiple mediators and competing routes. It should also include platform affordances, product type, involvement, self-control, and source characteristics. The objective is not to maximize constructs, but to test which mechanism explains each transition under specified conditions.

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Need for Longitudinal, Cross-Platform, Behavioral, and Causal Evidence

Cross-sectional samples dominate the corpus, while experiments usually isolate one content feature and behavioural studies often concern one brand or platform. Actual purchase evidence is stronger but less common [6], [24]. Cross-platform comparisons must preserve differences among YouTube viewing, Instagram visual engagement, TikTok short-form interaction, and livestream commerce.

Longitudinal field experiments, platform logs, purchase records, and repeated surveys would improve temporal and causal inference. Point-process models can estimate how exposures stimulate later events [50], while machine learning can calibrate individual prediction when paired with out-of-sample validation [52]. The resulting evidence would connect psychological interpretation to observable commercial outcomes.

Proposed Research Agenda: Multimodal Data, Transition Modeling, and Calibrated Conversion Prediction

Future studies should collect synchronized content features, viewing and interaction events, self-reported states, search behaviour, and purchase records. A multimodal design could test whether visual salience predicts attention, whether attention predicts browsing, and whether trust or affect predicts intention conditionally on involvement. Hidden-state and point-process models could represent transitions and timing, while experiments could identify causal effects of selected content features.

Prediction should be calibrated against actual purchase, not intention alone. Models should report discrimination, calibration, subgroup performance, and attribution uncertainty. The goal is a testable account of when scrolling becomes shopping, with explicit boundaries around platform, product, relationship, and consumer state.

Explaining When Scrolling Becomes Shopping

The evidence supports a transition architecture rather than a single conversion mechanism. Exposure can become browsing when content fits hedonic or utilitarian motives; browsing can become engagement when visual, social, or informational cues invite response; engagement can become intention when trust, usefulness, affect, relationship, or perceived value develops. Actual purchase remains conditional on timing, self-control, relationship strength, availability, and competing stimuli.

The Evidence-Based Transition Architecture from Content Exposure to Purchase Intent

The most defensible model is:

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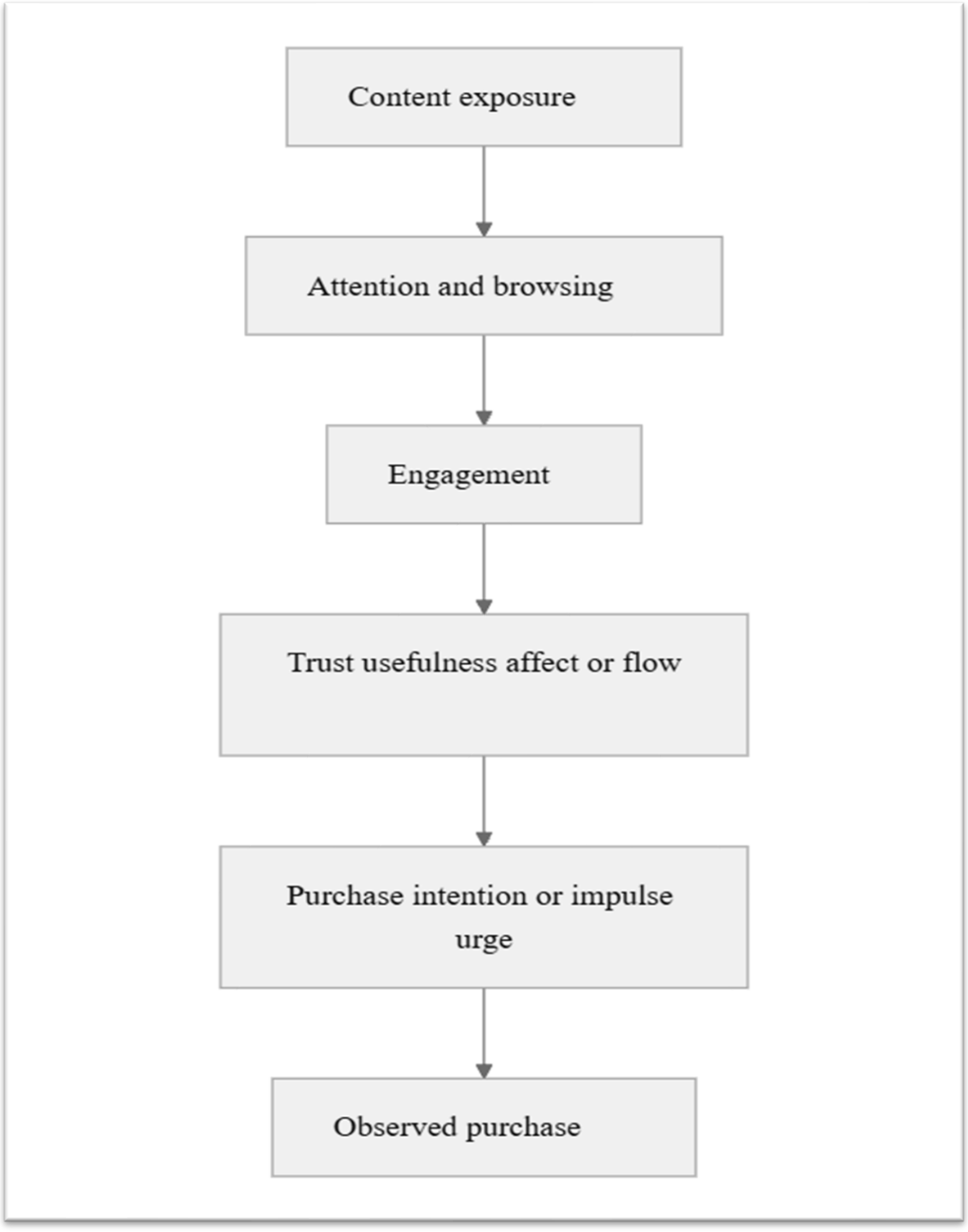


Diagram 6

Each arrow represents a transition requiring measurement. The same engagement metric can have different meanings across platforms, products, and consumer states.

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Theoretical and Managerial Implications for Content, Influencer, and Social-Commerce Design
The findings support content matched to consumer purpose, credible sources, appropriate visual presentation, responsive interaction, and transparent information. Managers should distinguish reach from deep engagement and intention from purchase. Influencer selection should consider credibility, expertise, similarity, product fit, and entertainment rather than follower volume alone [31].

Final Limitations, Reporting Standards, and Priorities for Future Validation
The evidence remains limited by cross-sectional surveys, self-reported intention, platform-specific samples, and inconsistent engagement measures. Reporting should identify the endpoint, design, temporal order, sample, platform, mediator, moderator, and behavioural validation. Future validation requires longitudinal and experimental evidence linked to actual purchase, with dynamic models that preserve both affective and deliberative pathways.Active Debates and Boundary Conditions in the Scroll-to-Sale Literature

Engagement Is Not Conversion: Why Visible Interaction May Fail to Predict Purchase
Engagement is heterogeneous: liking, commenting, sharing, viewing, and following reflect different motivations and cognitive investments. YouTube participation is associated with relaxation, social interaction, or information giving, whereas viewing is primarily linked to relaxing entertainment [1]. Archived Facebook data likewise show that some engagement forms correlate with store visits while others have no discernible association with purchase frequency [24]. Thus, visible activity should not be treated as a uniform proxy for commercial readiness.

Purchase Intention Versus Actual Purchase Behavior: Temporal Instability, Bias, and Attribution Error
Purchase intention is a proximal psychological outcome, not an observed transaction. Intentions change over time and contain systematic biases, so models based on intention alone can misestimate individual purchase probability [56]. Actual behavior also depends on relationship strength, convenience, competition, income, and involvement, producing different intention and behavior coefficients [57]. Attribution is further complicated when earlier advertising clicks stimulate later visits rather than immediate conversion [50].

Hedonic Stimulation and Impulse Buying Versus Systematic Information Processing and Deliberation
The literature supports two partially distinct routes. Hedonic browsing increases the urge to buy impulsively, while utilitarian browsing may operate indirectly through hedonic browsing [9]; in live commerce, affective intensity predicts impulse urges more directly than perceived risk [18]. Conversely, review quality, credibility, task fit, and information adoption support deliberative purchase intention [3]. Product involvement determines whether consumers respond mainly to review quantity or to quality as well [15].

Linear Funnel Assumptions Versus Dynamic, Nonlinear, and Configurational Purchase Paths
A sequential funnel remains useful as a measurement heuristic, but it does not establish that every consumer passes through identical stages. A continuous-time hidden Markov model represents movement between latent intention states, while point-process models capture mutually stimulating advertising clicks and delayed conversion [49], [50]. Configurational analysis also indicates that combinations of social influence and perceived risk can predict intention even when individual direct effects are weak [51].

Planned Evidence Displays: Contradictory-Findings Table and Competing-Mechanisms Diagram

A synthesis table should distinguish endpoint, design, and mechanism rather than aggregate all “engagement” findings.

Evidence	Endpoint	Mechanism
Facebook field data	Store-visit frequency	Stronger engagement forms align more closely with purchase frequency [24]
YouTube survey	Participation and viewing	Motives differ across active and passive use [1]
Live-commerce survey	Impulse urge	Affect exceeds perceived risk as a predictor [18]
Social-commerce SEM	Purchase intention	Trust, argument quality, and social presence condition effects [13]

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The competing mechanisms can be represented as follows:

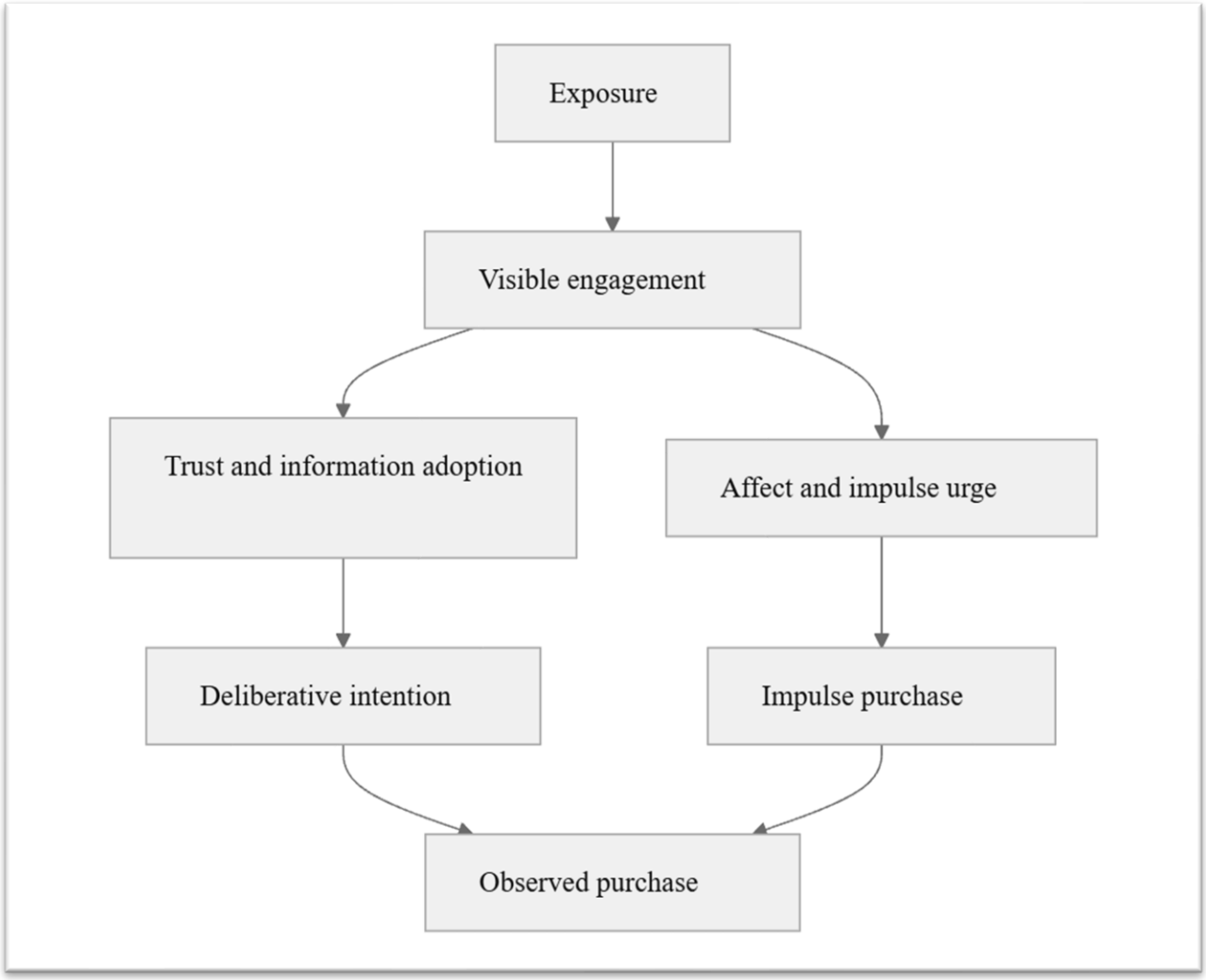


Diagram 7Research Gaps: Toward an Integrated and Testable Model of Psychological Transition

The Missing Middle: Limited Direct Measurement of Moment-to-Moment Psychological State Changes
Most evidence estimates associations among constructs through cross-sectional surveys and SEM. Such designs rarely observe the transition from attention to browsing, trust, affect, intention, and purchase within the same episode. Hidden-state modeling offers a stronger representation of changing psychological states, but the cited transition study concerns advertising channels rather than multimodal content and self-reported states [49].

Underdeveloped Links Between Passive Viewing, Active Engagement, and Repeated Purchase Behavior
YouTube research separates passive consumption from active participation [1], while field evidence connects selected engagement types to store visits [24]. Few studies connect these stages longitudinally to repeated purchases, leaving unclear whether viewing accumulates commercial value or merely reflects entertainment use.

Insufficient Integration of Cognitive, Affective, Social, and Platform-Level Mechanisms
Existing studies usually emphasize one mechanism: information adoption, social presence, parasocial interaction, trust, affect, or platform interactivity. Their joint operation remains underspecified, despite evidence that source, content, and platform characteristics can simultaneously shape engagement and intention [32], [41].

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Need for Longitudinal, Cross-Platform, Behavioral, and Causal Evidence

The evidence base is concentrated in convenience samples, platform-specific settings, and self-reported outcomes. Cross-platform comparison is also difficult because a comment, live-room interaction, video view, and store visit have different meanings. Actual purchase records and repeated observations are therefore needed to test temporal order and attribution.

Proposed Research Agenda: Multimodal Data, Transition Modeling, and Calibrated Conversion Prediction

Future studies should synchronize content features, exposure, viewing duration, interaction events, self-reported states, searches, and transactions. Hidden-state, point-process, and machine-learning models can estimate transitions, timing, heterogeneity, and calibrated purchase probability, extending predictive work that achieved 0.91 accuracy and a 0.91 macro F1 score in one TPB-based model [52].

Synthesis and Conclusion:

The Evidence-Based Transition Architecture from Content Exposure to Purchase Intent

Scrolling becomes shopping when exposure generates attention, attention supports browsing, and browsing activates engagement that develops into trust, usefulness, affect, or flow. Purchase remains conditional on relationship strength, self-control, product involvement, platform conditions, and timing.

Theoretical and Managerial Implications for Content, Influencer, and Social-Commerce Design

The evidence supports matching content format to consumer purpose, strengthening credible information, and distinguishing deep engagement from low-cost activity. Influencer selection should consider credibility, expertise, similarity, entertainment, informativeness, and product congruence, with credibility most strongly associated with purchase intention in a meta-analysis of 176 effect sizes from 62 studies.

Final Limitations, Reporting Standards, and Priorities for Future Validation

Future reports should identify platform, endpoint, temporal design, mediator, moderator, sample, and behavioural validation. The central test is whether measured psychological transitions predict observed purchase better than engagement counts or intention alone.

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