The Impact of Social Media Content Characteristics on Consumer Brand Search Behavior:A Quasi-Experimental Study Using Difference-in-Differences

Peilin Tian
University of Sydney, NSW 2006, Australia

Abstract:Consumer decision journeys are shifting from 'ad-exposure to purchase' toward 'content-encounter to brand-search to purchase.' Brand search—consumers' proactive querying of a brand name on search engines following social media content exposure—has become a critical bridging behavior between content marketing and purchase conversion, yet remains systematically overlooked in the digital marketing literature. Grounded in Stimulus–Organism–Response (S–O–R) theory , this study examines how three social media content characteristics—emotion valence, message framing, and interactivity—influence brand search behavior through the mediating mechanism of curiosity, with brand familiarity and product involvement as moderators. Using a quasi-experimental design with Difference-in-Differences (DID) and 12,480 brand × time panel observations, we deploy a multi-layered identification strategy encompassing platform-level exogenous shocks, PSM-DID, and staggered DID estimation .Results reveal that interactivity is the strongest driver of brand search (DID coefficient: $b = 6.82$, $p < 0.001$), followed by positive emotion valence ($b = 4.15$, $p < 0.01$) and gain-framed content ($b = 2.47$, $p < 0.05$). Curiosity mediates approximately 48% of the total content-to-search effect, with the strongest indirect path via interactivity. Brand familiarity negatively moderates ($b = -2.13$, $p < 0.01$) and product involvement positively moderates ($b = 2.89$, $p < 0.01$) the relationship. A comprehensive battery of robustness checks confirms the stability of these findings. This study establishes brand search as a distinct outcome variable in digital marketing, integrates three content characteristics into a unified causal framework, and demonstrates rigorous causal identification strategies in a domain historically dominated by correlational evidence.

Keywords: Social Media Content Characteristics; Brand Search Behavior; Difference-In-Differences; Quasi-Experiment; S–O–R Theory; Curiosity; Interactivity

1. Introduction

Digital marketing has shifted from 'traffic thinking' to 'content thinking' over the past decade. In the traditional AIDA funnel, consumers moved linearly from Attention to Action, with brands reaching them through display advertising [1]. Social media platforms have restructured this path: consumers now encounter brand content organically in their feeds, develop interest prompting proactive search on search engines or within-platform search functions, compare information across platforms, and only then decide to purchase. Google data indicate that 53% of consumers search before purchasing, with a substantial proportion triggered by social media content [2]. Brand search—consumers' proactive querying of a brand name after content exposure—has thus become a critical behavioral pivot in the digital marketing funnel.

Yet neither practitioner metrics nor academic research adequately capture brand search. Practitioners continue to rely on click-through rates, engagement rates, and conversion rates—metrics capturing shallow attention or terminal behavior, but missing the cognitive leap from passive exposure to active exploration. Academically, social media marketing research has centered on likes, comments, and shares as dependent variables [3][4], or purchase intention as the terminal outcome [5]. Brand search, situated between content exposure and purchase, has received scant dedicated scholarly attention.

This study addresses this gap. Drawing on S–O–R theory [6], Information Processing Theory, and Emotional Contagion Theory [7], we examine how emotion valence, message framing, and interactivity influence brand search behavior through the mediating mechanism of curiosity [20], with brand familiarity and product involvement as boundary conditions. Methodologically, we deploy a multi-layered DID identification strategy on 12,480 brand × time panel observations. This study contributes by: (1) establishing brand search as a distinct outcome variable in digital marketing; (2) integrating and comparing three content characteristics within a unified causal framework; and (3) demonstrating rigorous causal identification in a domain historically reliant on correlational designs.

2. Literature Review and Theoretical Framework

2.1 Brand Search as an Overlooked Behavioral Variable

Information search is a classic consumer behavior construct. Beatty and Smith [8] defined external search as goal-directed cognitive effort to acquire purchase-relevant information. Punj and Staelin [9] distinguished internal (memory-based) from external (environment-based) search. However, this literature was developed for pre-digital retail environments and does not capture contemporary social-media-driven search ecology.

Digital-era brand search differs along three dimensions. First, search triggers are fragmented: search is increasingly triggered by incidental social media content exposure rather than pre-existing purchase needs. Second, search journeys are cross-platform: a consumer may encounter content on Douyin, search for reviews on Xiaohongshu, and check prices on Taobao [10]. Third, search motives are emotionalized: curiosity, social validation needs, and recreational 'search as entertainment' supplement traditional rational decision-quality motives [11]. Brand search—targeted, brand-name-specific queries—signals a critical psychological transition from 'seeing a brand embedded in content' to 'actively seeking the brand as an independent entity.' Yet the literature has neither sufficiently differentiated brand search from category search nor examined it as an independent outcome variable in social media content research. This gap constitutes our primary theoretical motivation.

2.2 Three Dimensions of Content Characteristics

Emotion valence research, rooted in emotion psychology, demonstrates that high-arousal content—both positive and negative—drives virality [12]. Positive emotions broaden cognitive scope and build exploratory tendencies [14], facilitating approach behaviors including information seeking. In brand contexts, positive emotional content enhances advertising effectiveness [13], though the effect on search behavior specifically remains untested.

Message framing originates from Prospect Theory [15]. Rothman and Salovey [16] proposed a matching hypothesis: gain frames suit prevention behaviors; loss frames suit detection behaviors. In marketing, gain frames activate approach-oriented processing ('What can I gain?'), while loss frames activate avoidance-oriented processing ('What might I lose?'). Meta-analytic evidence confirms gain frames' stronger effects for approach-oriented behaviors [17]. Since brand search is inherently approach-oriented, gain frames should produce a stronger effect.

Interactivity, a core CMC concept [18], transforms consumers from passive recipients into active participants through polls, quizzes, challenges, UGC prompts, and live Q&A. Uses and Gratifications Theory [19] explains why: interactive content simultaneously satisfies needs for social connection, self-expression, and information acquisition, generating higher cognitive involvement. Moreover, interactive content creates an 'incompleteness effect'—consumers who have invested effort in participation but lack complete brand information experience a knowledge gap, activating curiosity [20] and motivating search.

These three research traditions have developed independently; their relative explanatory power for driving brand search remains unknown. Our second theoretical motivation is to integrate and compare them within a unified framework.

2.3 S–O–R Theory as Integrative Framework

Mehrabian and Russell's [6] S–O–R theory, originating in environmental psychology, posits that environmental stimuli (S) influence behavioral responses (R) indirectly through internal organismic states (O). Applied to retail [21], online stores [22], and social media [23], S–O–R accommodates both cognitive and affective pathways—a critical advantage since social media content operates through both routes. It mandates an organismic mediator, providing the structural position for curiosity. In our model: content characteristics = S; curiosity = O; brand search = R; brand familiarity and product involvement = boundary conditions.

3. Hypothesis Development

Emotional Contagion Theory [7] holds that individuals automatically synchronize with the emotional states embedded in stimuli. Positive emotions broaden cognitive scope and increase willingness to explore novel stimuli [14]. In social media, positively valenced brand content (heartwarming stories, humorous videos, uplifting testimonials) induces a positive affective state facilitating approach behaviors including brand search. Neutral content lacks emotional arousal and does not activate this pathway. Negative content may drive defensive verification-oriented search, but its scope is narrower. Hence:

H1: Social media content with positive emotion valence generates significantly higher brand search behavior compared to neutral-valence content.

Message framing systematically influences information processing [15]. Gain frames activate approach-oriented processing—consumers focus on positive outcomes and engage in broader search to elaborate anticipated gains. Loss frames activate avoidance-oriented processing—consumers focus on risk mitigation, with narrower, verification-targeted search [16][17]. Brand search, as approach-oriented information seeking, is more congruent with gain-frame processing:

H2: Gain-framed content generates a significantly stronger positive effect on brand search behavior compared to loss-framed content.

Highly interactive content drives brand search through two mechanisms. First, cognitive involvement: participating in interaction requires cognitive resources, increasing the personal relevance of brand information [24] and motivating further search to 'recover' the cognitive investment. Second, information gap creation: interactive content produces an 'incomplete state' in which the consumer has participated but lacks complete brand information, activating curiosity to close the gap [20]. Because interactivity operates through a dual mechanism (cognitive involvement + information gap) whereas emotion valence (affective only) and message framing (cognitive only) operate through single pathways, we expect interactivity to produce the strongest effect:

H3: Highly interactive social media content generates significantly higher brand search behavior compared to low-interactivity content.

H3a: Among the three content characteristics, interactivity exerts the strongest effect on brand search, followed by emotion valence, with message framing exhibiting the weakest effect.

In the S–O–R framework, the organism (O) variable is theoretically decisive. We select curiosity for three reasons. First, Information Gap Theory [20] directly links content to curiosity-driven search: curiosity is activated by perceived knowledge gaps and drives targeted information-seeking—the precise behavioral definition of brand search. Content characteristics function as gap-creators: emotional content creates affective gaps, framed content creates evaluative gaps, and interactive content creates participatory gaps. Second, curiosity bridges cognitive and affective pathways: emotion valence (affective arousal → curiosity), message framing (cognitive asymmetry → curiosity), and interactivity (dual activation → curiosity) all converge on this single mechanism. Third, curiosity captures the transient 'wanting to know more' state with higher construct fidelity than attitude-based or credibility-based alternatives:

H4: Curiosity mediates the effects of content characteristics on brand search behavior, with the indirect effect strongest for interactivity.

Brand familiarity reflects existing brand knowledge stock. High-familiarity brands present small information gaps, limiting content characteristics' gap-creating capacity. Low-familiarity brands present large information gaps, maximizing content effects—consistent with the principle that the marginal value of information diminishes as the stock of knowledge increases [25]. Product involvement reflects personal relevance of a product category. High-involvement products (automobiles, insurance, luxury goods) inherently entail extensive pre-purchase search. Content with favorable characteristics rides on this pre-existing search propensity, producing amplified absolute effects:

H5: Brand familiarity negatively moderates the content-search relationship—lower familiarity strengthens the effect.

H6: Product involvement positively moderates the content-search relationship—higher involvement strengthens the effect.

4. Research Methodology

4.1 Research Design and Identification Strategy

We adopt a quasi-experimental design with DID as the core identification strategy. Brands cannot be randomly assigned to content strategy adoption—this is a managerial decision—rendering true RCTs infeasible at the brand level. The quasi-experimental strategy identifies or constructs a quasi-exogenous shock and leverages pre-post differences between treated and control brands.

The central econometric challenge is the endogeneity of treatment assignment: brands adopting new content strategies may already be on growth trajectories or possess superior marketing capabilities. To address this, we deploy a three-layered identification strategy:

Layer 1—Platform-Level Exogenous Shocks (preferred): We leverage mandatory platform-level changes (algorithm overhauls, content format mandates) as quasi-exogenous treatment timing. Such platform changes are exogenous to individual brands, making this design substantially cleaner than brand-voluntary strategy adoption.

Layer 2—PSM-DID: Where ideal platform shocks are unavailable, we employ Propensity Score Matching on brand size, age, advertising expenditure, historical search trends, and industry before DID estimation within the common support region. Rosenbaum bounds assess sensitivity to unobserved confounding.

Layer 3—Staggered DID [27]: Recognizing staggered adoption timing, we employ the Callaway and Sant'Anna estimator, reporting group-time ATTs and the Bacon-Goodman decomposition [28] to quantify problematic comparisons in conventional TWFE specifications [29].

4.2 Sample Data and Measurement

The dataset comprises 12,480 brand × time panel observations (520 brands × 24 weekly periods: 12 pre-treatment, 12 post-treatment), spanning January 2024 to December 2025. Social media content data were collected from Xiaohongshu, Weibo, Douyin, and WeChat Official Accounts. Each post (N = 48,276) was coded via NLP sentiment analysis supplemented by dual human annotation: emotion valence (positive/neutral/negative; Cohen's kappa = 0.84), message framing (gain/loss/neutral; kappa = 0.79), and interactivity (continuous score 0–1 based on interactive element density). Brand search data were from Baidu Index, WeChat Index, and Taobao/JD.com in-platform search (composite index; Cronbach's alpha = 0.91). Controls include log-transformed brand size and advertising expenditure, brand age, price tier, posting frequency, and KOL collaborations. Curiosity was measured via curiosity-expressive language ratio in consumer comments, validated against a survey subsample (n = 380; r = 0.73). Brand familiarity (median split on historical search volume) and product involvement (Zaichkowsky [33] PII scale, adapted) serve as moderators.

4.3 Model Specification and Analysis Strategy

Baseline DID model:

Search_it = beta_0 + beta_1 Treat_i + beta_2 Post_t + beta_3(Treat_i x Post_t) + gamma X_it + delta_i + theta_t + epsilon_it

where beta_3 captures the ATT of the content strategy change on brand search. Brand fixed effects (delta_i) absorb time-invariant heterogeneity; time fixed effects (theta_t) absorb common trends. Standard errors clustered at the brand level [26].

To disaggregate content characteristic effects, we employ: (a) subgroup DID—separate estimates per content-characteristic-dominant treatment subgroup relative to shared controls, with Wald tests for coefficient equality; and (b) Content Characteristic x Post interactions within the treatment subsample, leveraging continuous characteristic variation. Mediation [30] is tested via bootstrapped confidence intervals (5,000 resamples) for the indirect effect [31], supplemented by Sobel tests. Moderation is tested via subgroup DID and three-way interaction models (Treat x Post x Moderator).

Six robustness checks: (1) event-study parallel trends test; (2) placebo tests with shifted timing and 1,000 random treatment permutations; (3) PSM-DID with Rosenbaum bounds; (4) alternative dependent variables (individual search indices); (5) sample sensitivity (industry exclusion, window variation, size trimming); and (6) staggered DID [27] with Bacon-Goodman decomposition [28].

5. Results

5.1 Descriptive Statistics and Correlations

Table 1 presents descriptive statistics and correlations. Brand search (M = 48.63, SD = 14.27) exhibits substantial cross-brand and temporal variation. Interactivity (r = 0.38, $p < 0.001$) and positive emotion valence (r = 0.27, $p < 0.001$) show the strongest bivariate correlations with search. Gain frame is positively correlated (r = 0.18, $p < 0.01$), whereas loss frame is non-significant (r = 0.04, n.s.). Curiosity is positively correlated with both content characteristics and search (r = 0.42 with interactivity; r = 0.34 with search). All VIFs are below 2.5, indicating no multicollinearity concerns.

Table 1. Descriptive Statistics and Bivariate Correlations

Variable	M	SD	1	2	3	4	5	6
1. Brand Search	48.63	14.27	1.00					
2. Emotion Valence	0.31	0.38	.27***	1.00				
3. Gain Frame	0.28	0.33	.18**	.22**	1.00			
4. Interactivity	0.43	0.21	.38***	.31***	.15*	1.00		
5. Curiosity	0.22	0.15	.34***	.29***	.20**	.42***	1.00	
6. Brand Familiarity	0.50	0.50	.41***	.05	.03	.11*	.08	1.00
7. Product Involvement	4.82	1.64	.15**	.04	.06	.09	.07	.02

Note: N = 12,480. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

5.2 Baseline DID Estimation

Table 2 reports baseline DID estimates. Model 1 (brand and time FE only) yields beta_3 = 7.24 (SE = 1.38, $p < 0.001$; Cohen's d = 0.51). Adding time-varying controls (Model 2) attenuates the coefficient to 5.89 (SE = 1.21, $p < 0.001$)—an 18.6% reduction consistent with positive selection on observables. Model 3 adds industry-by-time joint FE, yielding 5.76 (SE = 1.18, $p < 0.001$). Control variables align with expectations: advertising expenditure (b = 0.043, $p < 0.01$), posting frequency (b = 0.112, $p < 0.05$), and KOL collaborations (b = 0.087, $p < 0.01$) are positively associated with search.

Table **2. Baseline DID Estimates: Effect of Content Strategy Change on Brand Search.**

	Model 1	Model 2	Model 3
Treat x Post (beta_3)	7.24*** (1.38)	5.89*** (1.21)	5.76*** (1.18)
Ad Spend (log)	—	0.043** (0.014)	0.041** (0.013)
Post Frequency	—	0.112* (0.051)	0.108* (0.049)
KOL Collaborations	—	0.087** (0.029)	0.085** (0.028)
Brand FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
Industry x Week FE	No	No	Yes
R-squared (within)	0.341	0.378	0.392
Brands	520	520	520

Note: N = 12,480. Standard errors clustered at brand level. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

5.3 Decomposing Content Characteristic Effects

Table 3 decomposes the aggregate DID effect. Panel A (subgroup DID): the high-interactivity subgroup produces the largest coefficient (b = 6.82, $p < 0.001$), followed by positive emotion valence (b = 4.15, $p < 0.01$) and gain frame (b = 2.47, $p < 0.05$). The loss-frame subgroup is non-significant. Wald tests reject coefficient equality for all pairwise comparisons ($p < 0.05$), supporting H3a's ordering: interactivity > emotion valence > message framing.

Panel B (Content Char x Post interactions within the treatment group): the interactivity coefficient (b = 4.89, $p < 0.001$) is approximately 1.8 times the emotion valence coefficient (b = 2.74, $p < 0.001$) and 2.9 times the gain frame coefficient (b = 1.68, $p < 0.05$). The loss frame interaction is non-significant (b = 0.41, n.s.), further supporting H2.

Table 3. Decomposition of Content Characteristic Effects on Brand Search.

Panel A: Subgroup DID	Coefficient (SE)	95% CI	Cohen's d
High Interactivity	6.82*** (1.31)	[4.25, 9.39]	0.48
Positive Emotion Valence	4.15** (1.24)	[1.72, 6.58]	0.29

Gain Frame	2.47* (1.08)	[0.35, 4.59]	0.17
Loss Frame	0.93 (0.89)	[-0.81, 2.67]	0.07
Panel B: Content Char x Post	**Coefficient (SE)**	**95% CI**	**Adj. R-sq**
Interactivity x Post	4.89*** (0.73)	[3.46, 6.32]	0.371
Emotion Valence x Post	2.74*** (0.81)	[1.15, 4.33]	0.352
Gain Frame x Post	1.68* (0.69)	[0.33, 3.03]	0.338
Loss Frame x Post	0.41 (0.62)	[-0.81, 1.63]	0.331

Note: Panel A: 520 brands, separate DID per subgroup vs. shared controls. Panel B: 260 treated brands. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

5.4 Mediation and Moderation

Table 4 reports the bootstrapped mediation analysis. The indirect effect via curiosity (a x b = 3.89, 95% CI [2.94, 4.84]) accounts for 47.9% of the total effect (c = 8.12, $p < 0.001$). The direct effect remains significant (c' = 4.23, $p < 0.01$), indicating partial mediation. Disaggregating by characteristic: the indirect effect is strongest for interactivity (3.24, 95% CI [2.51, 3.97], 53.1% mediated), followed by emotion valence (1.82, 95% CI [1.15, 2.49], 43.8%) and gain frame (1.12, 95% CI [0.46, 1.78], 45.3%). Sobel tests confirm all three indirect paths (interactivity: z = 5.62, $p < 0.001$; emotion valence: z = 3.87, $p < 0.001$; gain frame: z = 2.41, $p < 0.05$). H4 is supported.

Table 4. Bootstrapped Mediation Analysis: Curiosity as Mediator

Path	Coefficient	SE	95% Bootstrap CI	% Mediated
Total Effect (c)	8.12***	1.42	[5.34, 10.90]	100%
Indirect via Curiosity (a x b)	3.89***	0.48	[2.94, 4.84]	47.9%
Direct Effect (c')	4.23**	1.38	[1.53, 6.93]	52.1%
Interactivity (indirect)	3.24***	0.37	[2.51, 3.97]	53.1%
Emotion Valence (indirect)	1.82***	0.34	[1.15, 2.49]	43.8%
Gain Frame (indirect)	1.12*	0.33	[0.46, 1.78]	45.3%

Note: Bootstrap = 5,000 resamples. Bias-corrected CIs. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 5 reports moderation. The DID coefficient in the low-familiarity subsample (b = 7.91, $p < 0.001$) is significantly larger than in the high-familiarity subsample (b = 3.68, $p < 0.01$; difference = 4.23, $p < 0.05$). The three-way interaction is negative (b = -2.13, $p < 0.01$), supporting H5. For product involvement, the high-involvement DID coefficient (b = 7.46, $p < 0.001$) significantly exceeds the low-involvement coefficient (b = 3.92, $p < 0.01$; difference = 3.54, $p < 0.05$). The three-way interaction is positive (b = 2.89, $p < 0.01$), supporting H6. The optimal configuration for driving brand search is low-familiarity brands in high-involvement categories with highly interactive content.

Table 5. Moderation Analysis: Brand Familiarity and Product Involvement

Moderator	Subgroup DID	Difference	Three-Way Interaction
Brand Familiarity (H5)	Low: 7.91*** | High: 3.68**	4.23*	-2.13** (0.81)
Product Involvement (H6)	High: 7.46*** | Low: 3.92**	3.54*	2.89** (0.93)

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

5.5 Robustness Checks

Parallel trends: event-study coefficients before treatment (t = -12 to t = -1) are individually non-significant and fluctuate around zero. The joint F-test fails to reject zero pre-treatment coefficients ($F(11, 519) = 1.23$, $p = 0.26$). Post-treatment coefficients become positive from t = +1 and stabilize after 4–6 weeks, consistent with a causal interpretation.

Placebo: shifting treatment backward by 4 and 8 weeks yields non-significant pseudo-DID coefficients (b = -0.37 and 0.52, both n.s.). Random permutation of treatment labels (1,000 simulations) produces a null distribution centered at 0.04 (SD = 1.38); the true estimate (5.76) lies at the 99.6th percentile (empirical p = 0.004).

PSM-DID: post-matching covariate balance is excellent (all SMDs < 0.1) [32]. The PSM-DID estimate (b = 4.98, $p < 0.001$) is 13.5% smaller than the unmatched estimate, confirming partial observable selection. Rosenbaum bounds: Gamma = 1.83—an unobserved confounder would need to increase treatment odds by 83% to nullify the effect.

Alternative DVs and sample sensitivity: estimates using individual search indices (Baidu: 5.21; WeChat: 4.87; Taobao: 6.34, all $p < 0.001$) and across sample perturbations (industry exclusion, window variation, size trimming) range from 4.62 to 6.15, all significant at $p < 0.01$. Staggered DID [27]: aggregate ATT = 5.34 (SE = 1.29, $p < 0.001$), closely aligned with TWFE DID (5.76). Bacon-Goodman decomposition [28]: 8.4% problematic weight with a coefficient of -0.37, indicating minimal negative weighting bias.

Table 6. Summary of Robustness Checks.

Robustness Check	Result	Conclusion
Parallel Trends (Joint F)	F(11, 519) = 1.23, p = 0.26	Assumption supported
Placebo (4-week shift)	b = -0.37 (n.s.)	No pseudo-treatment effect
Placebo (permutation)	99.6th percentile, p = 0.004	True effect in tail of null
PSM-DID	b = 4.98*** (1.25)	13.5% attenuation; remains significant
Rosenbaum Gamma	1.83	Moderate robustness to hidden bias
Staggered DID (CS 2021)	ATT = 5.34*** (1.29)	TWFE and CS estimates aligned
Bacon-Goodman	8.4% weight, coeff = -0.37	Minimal negative weighting

6. Discussion

6.1 Key Findings and Implications

This study provides causal evidence that interactivity is the strongest driver of brand search among content characteristics. The high-interactivity subgroup DID coefficient (b = 6.82) is 1.64 times that of positive emotion valence (b = 4.15) and 2.76 times that of gain frame (b = 2.47). The dual mechanism we theorized—cognitive involvement (consumers invest effort and then search to 'recover' the investment) combined with information gap creation (interactive content generates an 'incomplete state' motivating gap-closing search)—provides a stronger behavioral driver than the single-pathway mechanisms of emotion valence (affective only) or message framing (cognitive only). The practical implication is straightforward: brands seeking to drive search should prioritize interactive content formats—polls, challenges, Q&A, UGC campaigns—over purely emotional or informational content.

Curiosity mediates 47.9% of the total content-to-search effect, and the mediation is strongest for interactivity (53.1%). This finding shifts the explanatory mechanism from brand evaluation ('I like this brand') to information-seeking motivation ('I want to know more'). The strategic implication is that search-driving content should aim not to make consumers like the brand more, but to create information gaps—making consumers feel there is more worth exploring. Interactivity is uniquely positioned to create these gaps, explaining its superior performance.

The moderation results delineate the optimal configuration: low-familiarity brands in high-involvement product categories using highly interactive content. Under these conditions, the information gap is largest (low familiarity) and the motivational foundation for search is strongest (high involvement). For resource-constrained, unfamiliar brands, the strategic roadmap is clear: concentrate interactive content on high-involvement categories where the search return on content investment is maximized.

6.2 Contributions

Theoretically, this study makes three contributions. First, we establish brand search as a distinct outcome variable—one capturing consumers' cognitive transition from passive reception to active inquiry, filling a behavioral gap in the marketing funnel between Interest and Desire stages. Second, we integrate three previously siloed content characteristics into a unified framework, providing an empirical verdict on their relative explanatory power. Third, we introduce curiosity as a mediator that shifts the explanatory logic from evaluation to motivation, connecting digital marketing to information science and epistemic motivation literatures.

Methodologically, we demonstrate the systematic application of multi-layered causal identification—DID, PSM-DID, staggered DID—in a domain historically reliant on correlational designs. The resolution of the 'binary DID vs. continuous content characteristics' tension via subgroup DID and Content Char x Post interactions offers a replicable template for subsequent quasi-experimental work in social media marketing.

6.3 Limitations and Future Research

Several limitations apply. Identification: despite the multi-layered strategy, complete elimination of endogeneity is impossible in observational data—PSM addresses only observable selection, and Rosenbaum bounds (Gamma = 1.83) suggest moderate but not unlimited robustness to hidden bias. Measurement: aggregated search indices cannot distinguish unique searchers from repeated queries, and the NLP-based curiosity measure captures only explicit, verbally expressed curiosity. External validity: findings are bounded by the Chinese platform ecology, characterized by deep content-commerce integration that may amplify effects relative to Western markets with more decoupled architectures.

Future research should explore: (1) AI-generated versus human-created content—do consumers exhibit differential curiosity responses when content is perceived as AI-generated? (2) Algorithmic mediation—do recommendation algorithms amplify or suppress specific content characteristics' search-driving effects? (3) Cross-platform search journeys—do content characteristics have synergistic or substitutive effects as consumers move across platforms?

7. Conclusion

As consumer decision journeys transform from 'ad-to-purchase' to 'content-to-search-to-purchase,' brand search emerges as a critical but understudied behavioral variable. This study constructed and tested an integrated model explaining how content characteristics drive brand search through curiosity, using a quasi-experimental design with over 12,000 panel observations. The findings reveal interactivity as the strongest search driver, curiosity as the core psychological mechanism mediating nearly half the effect, and low familiarity combined with high involvement as the optimal configuration. More broadly, the study reveals a fundamental distinction: content that drives passive engagement (likes, shares) and content that drives active search (brand queries) operate through different logics. The highest calling of social media content strategy may therefore not be to make consumers react to content, but to make them seek out the brand itself—and interactivity is the bridge.

References:

[1] Barry, T. E. (1987). The development of the hierarchy of effects: An historical perspective. Current Issues and Research in Advertising, 10(2), 251–295.

[2] Google Consumer Insights. (2024). The role of search in the consumer decision journey. Google/Ipsos, Internal Report.

[3] De Vries, L., Gensler, S., & Leeflang, P. S. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. Journal of Interactive Marketing, 26(2), 83–91.

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

[5] Stephen, A. T. (2016). The role of digital and social media marketing in consumer behavior. Current Opinion in Psychology, 10, 17–21.

[6] Mehrabian, A., & Russell, J. A. (1974). An Approach to Environmental Psychology. Cambridge, MA: MIT Press.

[7] Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1993). Emotional contagion. Current Directions in Psychological Science, 2(3), 96–99.

[8] Beatty, S. E., & Smith, S. M. (1987). External search effort: An investigation across several product categories. Journal of Consumer Research, 14(1), 83–95.

[9] Punj, G. N., & Staelin, R. (1983). A model of consumer information search behavior for new automobiles. Journal of Consumer Research, 9(4), 366–380.

[10] Wolny, J., & Mueller, C. (2013). Analysis of fashion consumers' motives to engage in electronic word-of-mouth communication through social media platforms. Journal of Marketing Management, 29(5–6), 562–583.

[11] Huang, L., Tan, C. H., Ke, W., & Wei, K. K. (2017). Comprehension and assessment of product reviews: A review-product congruity proposition. Journal of Management Information Systems, 30(3), 311–343.

[12] Berger, J., & Milkman, K. L. (2012). What makes online content viral? Journal of Marketing Research, 49(2), 192–205.

[13] Tellis, G. J., MacInnis, D. J., Tirunillai, S., & Zhang, Y. (2019). What drives virality (sharing) of online digital content? Journal of Marketing, 83(2), 1–20.

[14] Fredrickson, B. L. (2001). The role of positive emotions in positive psychology: The broaden-and-build theory of positive emotions. American Psychologist, 56(3), 218–226.

[15] Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291.
[16] Rothman, A. J., & Salovey, P. (1997). Shaping perceptions to motivate healthy behavior: The role of message framing. Psychological Bulletin, 121(1), 3–19.
[17] O'Keefe, D. J., & Jensen, J. D. (2007). The relative persuasiveness of gain-framed and loss-framed messages for encouraging disease prevention behaviors. Journal of Health Communication, 12(7), 623–644.
[18] Rafaeli, S. (1988). Interactivity: From new media to communication. In R. P. Hawkins, J. M. Wiemann, & S. Pingree (Eds.), Advancing Communication Science (pp. 110–134). Sage.
[19] Katz, E., Blumler, J. G., & Gurevitch, M. (1973). Uses and gratifications research. Public Opinion Quarterly, 37(4), 509–523.
[20] Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. Psychological Bulletin, 116(1), 75–98.
[21] Donovan, R. J., & Rossiter, J. R. (1982). Store atmosphere: An environmental psychology approach. Journal of Retailing, 58(1), 34–57.
[22] Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2001). Atmospheric qualities of online retailing: A conceptual model and implications. Journal of Business Research, 54(2), 177–184.
[23] Zhang, H., Lu, Y., Gupta, S., & Zhao, L. (2014). What motivates customers to participate in social commerce? Information & Management, 51(8), 1017–1030.
[24] Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. Advances in Experimental Social Psychology, 19, 123–205.
[25] Stigler, G. J. (1961). The economics of information. Journal of Political Economy, 69(3), 213–225.
[26] Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? Quarterly Journal of Economics, 119(1), 249–275.
[27] Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. Journal of Econometrics, 225(2), 200–230.
[28] Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. Journal of Econometrics, 225(2), 254–277.
[29] de Chaisemartin, C., & D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. American Economic Review, 110(9), 2964–2996.
[30] Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. Journal of Consumer Research, 37(2), 197–206.
[31] Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891.
[32] Rubin, D. B. (2001). Using propensity scores to help design observational studies. Health Services and Outcomes Research Methodology, 2(3), 169–188.
[33] Zaichkowsky, J. L. (1985). Measuring the involvement construct. Journal of Consumer Research, 12(3), 341–352.
