

The Impact of "Seeding" Content Features on Purchase Conversion of New Consumer Brands on Xiaohongshu

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Abstract

The practice of "content seeding" on social e-commerce platforms has been identified as one of the most crucial tactics in acquiring users for emerging consumer brands, but limited fine-grained empirical insights into the impact of specific content attributes on purchase conversion behaviors still exist. Following the theoretical perspective of the Elaboration Likelihood Model (ELM), this paper dissects the content features of seeding notes on Xiaohongshu into two dimensions, namely, informational features and emotional features, and then explores their impacts on purchase conversion behaviors, while examining the moderating role played by user interaction level and brand awareness as boundary conditions. Data were collected from 2,200 seeding posts released in 2024 and involving 15 emerging consumer brands in three categories of products. The measurements of content attributes were obtained based on the application of natural language processing and manual content coding methods, and statistical hypotheses were tested using hierarchical multiple regression models. The findings show that information attributes and emotion attributes have significantly positive impacts on purchase conversion metrics, among which information attributes have a higher impact. User interaction level positively moderates the conversion impact of informational features but is insignificant in moderating the conversion impact of emotional features. Compared with high-awareness brands, low-awareness brands display more sensitivity to information attributes and emotion attributes in terms of purchase conversion.

Keywords

Seeding content, content features, purchase conversion, new consumer brands, Xiaohongshu, elaboration likelihood model.

1. Introduction

In recent years, a cohort of emerging consumer brands has risen rapidly in the Chinese market thanks to social e-commerce platforms where they gain market share via content marketing methods relatively fast. Xiaohongshu (RedNote), being the leading "seeding" content community in China, has more than 300 million active users per month in 2024; the number of user-generated contents based on consumption experience on Xiaohongshu has reached a huge size [1]. The seeding notes, which are product experience recommendations generated by consumers and bloggers in graphics and video form, have become an important information channel connecting the brands and users [2]. In the seeding note ecosystem, the newly emerged consumer brands utilize seeding notes to find their target customers. Nevertheless, the "high exposure, low conversion" problem has long been a common issue in the practice of brand management. It has been discovered that the average click-through rates (CTR) of product links of seeding notes for most categories of products on Xiaohongshu are lower than 5%, while the payment conversion rate from click to final order falls further into the range of 1% to 3%. It means that despite a large number of seeding notes, which can lead to high engagement metrics,

only few of them are capable of stimulating purchases. It indicates the necessity of studying the factors affecting conversion performance of seeding notes.

Although abundant literature has already explored the impact of content marketing on consumer purchases through social media channels, several gaps need to be filled in this regard. First, concerning outcome variables, most current studies take consumers' declared purchase intentions as the outcome variables [3], but as has been revealed through many empirical studies, purchase intentions are not good predictors of actual consumer purchasing behavior [4], and hence cannot effectively serve as the basis for deriving actionable insights for brand conversion optimization. Related to this, another gap concerns the independent variable granularity problem-most current studies use content quality as an independent variable in a univariate manner, whereas seeding content can actually be composed of multidimensional features [5]. As per the Elaboration Likelihood Model (ELM) [6], information content and emotion content affect consumers' attitude and behavior through the central route and peripheral route, respectively, and hence a univariate measurement of the effect does not take this into consideration. Lastly, there has been little discussion about the contextual boundary conditions related to brand types-there is a clear distinction between new consumer brands and established brands in that the former has lower brand awareness than the latter, leaving consumers less trust and relying heavily on the persuasion of content [7].

Based on the above research deficiencies, this research aims to explore the link between content characteristics of seeding note on Xiaohongshu and the purchase conversion performance of new consumer brands. To be more specific, content features are categorized as two types – informational features and emotional features, and different impacts on purchase conversion performance indicators are compared and contrasted. This research also aims to explore the moderating impact of user interaction degree and the boundary condition of brand awareness. The contributions of this study are threefold. From the methodological perspective, measurable purchase conversion performance indicators rather than self-reported purchase intention are used, and hence the behaviorally validated DVs are utilized. From the theoretical perspective, the dual-pathway model proposed by ELM is introduced to the social e-commerce seeding research area, with solid evidence provided for the differing persuasion process of informational and emotional features. From the practical perspective, this study can provide systematic insights of how new consumer brands' content strategy should be different from that of established brands.

2. Theoretical Background and Hypotheses

2.1. Elaboration Likelihood Model and Its Applicability to Seeding Content

Elaboration Likelihood Model is considered one of the most well-founded theories in the field of persuasion studies. According to the theory, people process persuasive information using two ways. In the case of central processing, the subjects perform a thorough processing of messages used to influence them, and changes in their attitudes are determined by message strength. In peripheral processing, the subject has no desire or ability to deeply analyze the message and thus uses some other factors, such as attractiveness or credibility of the sender. The two routes are not mutually exclusive but may operate concurrently, with their relative dominance determined by the recipient's processing motivation and capacity.

The seeding note format used in seeding on Xiaohongshu is innately suited to ELM research. Whereas typical reviews of products on electronic commerce sites are mostly functional in nature, seeding notes incorporate elements of objective information about the products along with subjective lifestyles stories by the blogger, making seeding a good scenario to study ELM. Informational aspects such as product effectiveness, usage instructions, and cost-benefit considerations make up central route cues, which enable deep-level cognitive processing

among consumers regarding the value of the product. On the other hand, bloggers' stories, expressions of emotion, and lifestyle portrayal function as peripheral cues and can influence consumers to purchase the items based on identification and resonance. In light of these observations, this study distinguishes between informational and emotional features in seeding content and explores how they separately affect purchase conversion. In contrast to frameworks such as the S-O-R theory, which can describe the stimulation-to-response sequence generally, but not the cognitive processes involved in persuasion, ELM provides the distinction sought after here.

2.2. Hypothesis Development

The informational content features consist of factors associated with the objective characteristics of the product, including the level of explanation of the effectiveness of the product, the specific nature of the description of usage scenarios, and the amount of information presented about the prices. The existing studies have shown that high levels of information in the consumer-generated notes contribute to lowering the risks related to the consumers' perception of asymmetry of information and consequently make purchase easier [8]. Following the central processing route of ELM, adequate information provided on the product allows consumers to make informed assessments before purchasing the product by reducing their uncertainty [9]. Specifically, concrete usage scenario descriptions allow consumers to engage in mental simulation of product use, further strengthening purchase confidence.

H1. The richness of informational content features has a positive effect on purchase conversion indicators of new consumer brands.

Features of emotional content include elements concerning subjective experience of bloggers and their emotions, such as first-person experiences, positive affect vocabulary richness, and associations with lifestyle. Previous studies have found that emotional language used in UGC has been found to greatly improve positive attitudes and purchase intentions towards a product or service due to its capability to produce positive emotional responses [10]. By utilizing the peripheral route of persuasion, emotional content leads to the development of positive product attitudes through psychological processes like resonance and identification, not relying on cognitive processing. As far as the seeding context is concerned, sharing one's real-life experiences results in vicarious consumption experiences, which help consumers identify with the situation described by the blogger and reduce psychological distance to the product in question. Still, according to ELM, attitude changes generated via the peripheral route tend to be temporary and more easily influenced compared to those generated via the central route.

H2. The intensity of emotional content features has a positive effect on purchase conversion indicators of new consumer brands.

Level of user interaction includes visible signs like number of comments and how often bloggers reply to them. The results of one meta-analysis in social commerce have shown that user interaction and social support can make content much more persuasive and increase purchase conversion probability [11]. Comments from third-party users act as social proof, making informational argumentation even more credible and contributing to the central route to persuasion. However, since emotional persuasion is based on immediate reaction of the consumer during browsing, its enhancement due to user interaction is not so evident [12]. Nevertheless, similar emotions felt by others can maintain and boost the initial emotional resonance in a social way. So, although interaction will not have such a significant effect on emotional elements as on informational ones, there is still an assumption that interaction can positively moderate emotional features of notes as well.

H3a. User interaction level positively moderates the relationship between informational content features and purchase conversion.

H3b. User interaction level positively moderates the relationship between emotional content features and purchase conversion.

Brand awareness refers to consumer knowledge and recognition of the brand. Under the ELM framework, brand awareness acts as a moderator affecting the effectiveness of content features through processing motivation. In the case of high brand awareness, consumers have established brand schemas, and due to existing trust, processing motivation is lowered in relation to the note content, diminishing the role of content features marginally. On the other hand, in the case of new consumer brands with low brand awareness, consumers do not have a basis for their judgment, and thus depend solely on the note content to evaluate products, increasing the importance of content features.

H4a. Brand awareness negatively moderates the positive effect of informational features on purchase conversion.

H4b. Brand awareness negatively moderates the positive effect of emotional features on purchase conversion.

The conceptual model is illustrated in Fig. 1.

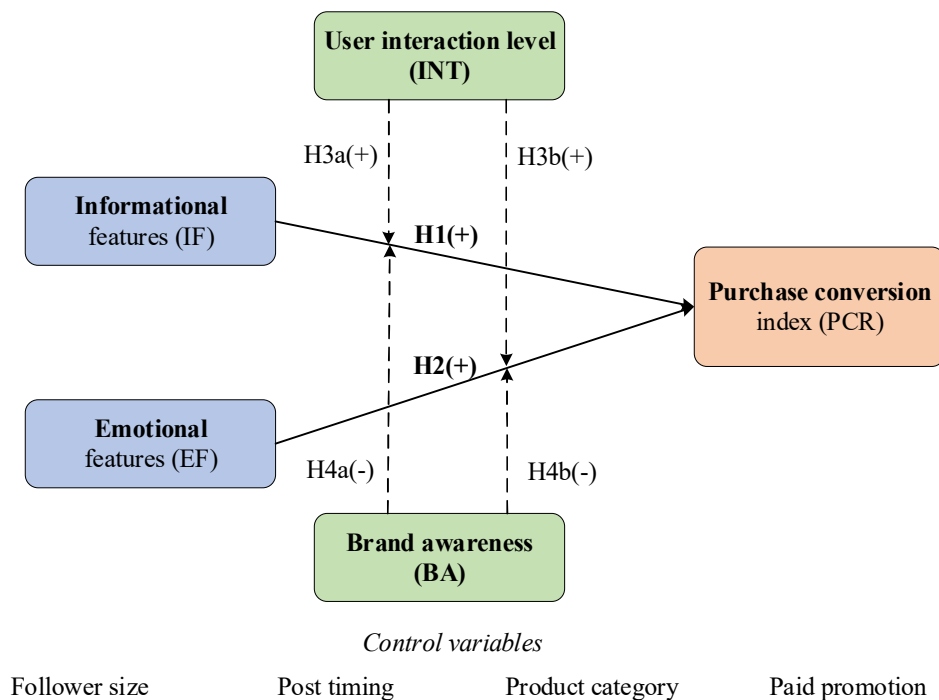


Fig. 1 Research Model

3. Research Methodology

3.1. Sample and Data Collection

The study adopted a strategy of purposive sampling of brands. "New consumer brands" were operationalized as satisfying three conditions simultaneously-formed in no more than eight years according to the time of business registration, selling their products mainly via online DTC channels, and having undergone institutional investment in at least one round of investment. In accordance with the white paper on China Consumer Brand Growth Power 2024 from CBNDData [13], brands were first selected according to the three criteria across three types of products-beauty & personal care, food & beverage, and home & living. In each category, the brands that had been selected were ranked according to the number of seeding notes on Xiaohongshu in decreasing order, and the top five brands for each type were chosen, totaling 15 brands. To achieve both a reasonable coverage of the three categories and enough number

of samples for each category to conduct further subsample analysis, three product categories were chosen. For reasons of commercial confidentiality, brand names are not revealed in the main text.

For the data collection stage, a Python-based web crawler was utilized to extract seeding notes uploaded on Xiaohongshu during January 2024 - December 2024, according to brands and core product keywords. The extracted note information included note text, number and type of images, likes, saves, number and text of comments, number of replies to comments, blogger following, inclusion of product link, as well as link clicks. To obtain the latter measure, the Brand Analytics functionality of the third-party data tracking tool Qiangua Data was used; this metric estimates link clicks based on API sampling and algorithmic interpolation of behavior on the platform. While such estimations may not be precise, previous research in the domain of social commerce has shown that the use of third-party estimated metrics as an approximation to platform-specific behavioral measures can be justified in the literature [2][11]. To minimize measurement error associated with estimated link clicks, z-score standardization of PCR was carried out in subsample analyses. Around 3,800 notes were collected initially. Cleaning of data entailed elimination of duplicate notes, exclusion of lottery/giveaway notes, removal of notes with fewer than 50 characters in the note text, elimination of notes with zero pageviews and abnormal comment text. After this processing, 2,200 valid notes were retained. With 13 predictors in the hierarchical regression analysis including main and interaction effects, a sample size of at least 100 observations per predictor variable is recommended in empirical practice; thus, the sample size used in this paper meets this requirement. This study was reviewed and classified as exempt by the authors' institutional review board, as it involved only publicly available data with no identifiable private information. The data for this study was collected only from publicly available materials on the Xiaohongshu platform, without any use of private user information. The details of the data collection process are summarized in Fig. 2.

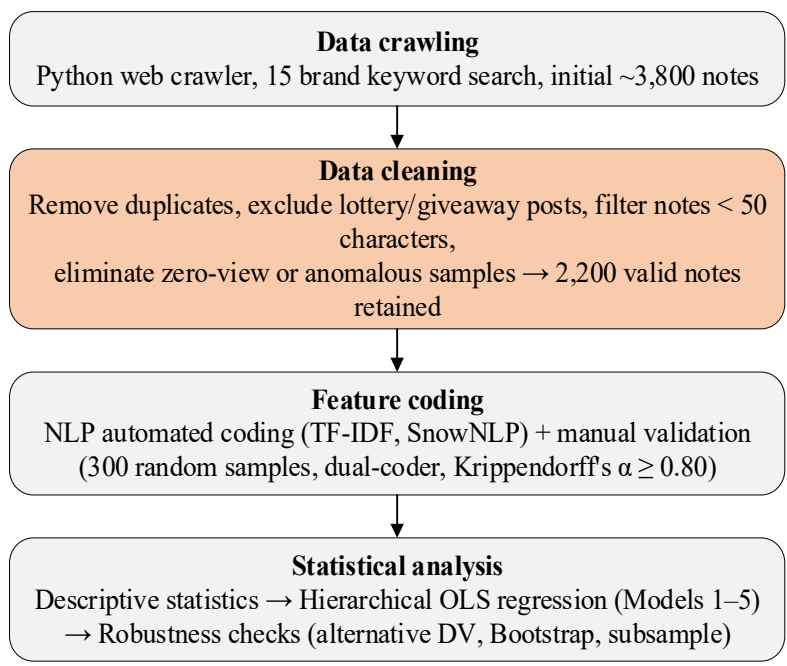


Fig. 2 Data Collection and Processing Flowchart

3.2. Variable Measurement

Variables, such as NLP-based and manually coded content attributes, behavioral metrics derived from platforms, and moderator attributes, have all been defined within Table 1, together with their sources and measures.

Table 1. Variable Operationalization

Variable	Symbol	Measurement	Source
Informational Features	IF	(a) TF-IDF weighted density scores for efficacy, ingredient, and usage scenario terms; (b) manual coding of usage scenario specificity on a 1–5 scale, with 300 randomly sampled notes coded independently by two coders (<i>Krippendorff's</i> $\alpha = 0.84$); after achieving acceptable reliability, discrepancies were resolved through discussion, and one trained coder completed the remaining notes; (c) both sub-indicators z-score standardized and arithmetically averaged into a composite IF score	Note text
Emotional Features	EF	(a) SnowNLP sentiment score on a 0–1 continuous scale; (b) first-person pronoun ratio; (c) manual coding of experiential narrative intensity on a 1–5 scale, following the same dual-coder procedure (<i>Krippendorff's</i> $\alpha = 0.82$); (d) all three sub-indicators z-score standardized and arithmetically averaged into a composite EF score	Note text
User Interaction Level	INT	$\ln(\text{comments} + 1) \times \text{reply rate}$, where $\text{reply rate} = \text{blogger replies} \div \text{comments}$; when the comment count equals zero, INT is directly assigned a value of 0	Platform data
Brand Awareness	BA	$\ln(\text{mean Baidu Search Index})$, computed as the natural logarithm of the 12-month average of the Baidu Search Index for the brand name	Baidu Index
Purchase Conversion Index	PCR	For notes with embedded product links, $\text{PCR} = \text{link clicks} \div \text{page views}$; for notes without links, $\text{PCR} = \text{purchase intent comments} \div \text{total comments}$, where purchase intent comments contain keywords such as "already ordered," "need the link," or "just bought"	Third-party monitoring + comment text
Controls	—	Blogger follower size $\ln(\text{followers} + 1)$; posting period (weekday = 0, weekend = 1); category dummy variables (2 dummies); paid promotion (no = 0, yes = 1)	Platform data + manual annotation

A word about the dependent variable should be added at this point. Actual transaction data from Xiaohongshu's internal systems were unavailable, and thus link click-through rate along with comment section intent expressions can only act as proxies for measuring conversion activity. The link click throughs indicate one crucial step when consumers proceed towards making a purchase decision following exposure to certain content, whereas intent expressions represent public declarations of the consumers' conversion activity or intent. Neither can be seen as final orders placed, but they give an adequate representation nonetheless.

Out of the total 2,200 valid notes, 908 (41.3%) included product links and their PCR was calculated by measuring the click-through rate, while 1,292 (58.7%) had no links in the note and PCR was measured by calculating the purchase intention in the comments section. Since both measures have different scales, they were standardized with z-scores before being pooled together to form PCR scores. To ensure robustness of the results, another regression analysis was carried out for only 908 observations including product links and again all hypotheses were validated.

3.3. Analytical Approach

This study used Hierarchical OLS Regression, which included stepwise inclusion of independent variables across five models, thus enabling the identification of contributions made by each of the sets of predictors. Model 1 included the control variables only. In Model 2, informational features (IF) and emotional features (EF) were included to test H1 and H2. In model 3, in addition to the control variables, the level of user interaction (INT), and brand awareness (BA)

were entered as main effects, thereby establishing the base for main effects analysis prior to performing interaction effects analyses. In Model 4, interaction terms between user interaction level and the two content feature variables (IF $\times$ INT and EF $\times$ INT) were introduced to test H3a and H3b. Model 5 introduced interaction terms between brand awareness and the two content feature variables (IF $\times$ BA and EF $\times$ BA) to test H4a and H4b.

All continuous predictor variables were mean-centered before including interactions terms to alleviate the problems of multicollinearity posed by the interactions. In cases of statistically significant moderation, the simple slopes were analyzed ± 1 standard deviation of the moderator to understand the direction and extent of moderation. Since the notes are nested within brands, all regressions were computed using brand-clustered robust standard errors due to correlated errors across notes in the same brand. The small number of clusters at the brand level ($N = 15$) being below the threshold generally suggested for the asymptotic validity of cluster-robust methods, the bias-corrected bootstrap CIs provided as robustness tests (Table 4) provide complementary testing of our hypotheses.

4. Results

4.1. Descriptive Statistics and Correlation Analysis

Table 2 shows the descriptive statistics and correlation table for all variables. Before conducting the primary analysis, the inter-coder reliability of the manual coding was evaluated by using 300 manually coded observations. The Krippendorff's α value obtained for the use scenarios indicator was 0.84 while the value obtained for the experiential narratives indicator was 0.82, which is above the 0.80 reliability threshold.

Table 2. Descriptive Statistics and Pearson Correlation Matrix ($N = 2,200$)

Variable	M	SD	1	2	3	4	5	VIF
1. IF	0.00	0.72	1					1.52
2. EF	0.00	0.61	0.38**	1				1.61
3. INT	0.85	0.63	0.25**	0.21**	1			1.34
4. BA	7.24	0.91	0.08	0.05	0.12**	1		1.11
5. PCR	0.034	0.026	0.34**	0.26**	0.19**	-0.06	1	—

Note: ** $p < 0.01$. IF is the composite score averaging two z-score standardized sub-indicators; EF is the composite score averaging three z-score standardized sub-indicators. The difference in the number of sub-indicators accounts for the SD difference between the two composites. PCR descriptive statistics are reported on the raw (pre-standardization) scale. For the 908 linked notes, raw PCR (link CTR) had $M = 0.038$, $SD = 0.029$; for the 1,292 non-linked notes, raw PCR (comment intent ratio) had $M = 0.031$, $SD = 0.023$. The z-score standardized PCR was used as the dependent variable in all regression analyses.

All VIF scores fell below 2.0, far below the usual cutoff value for multicollinearity of 10, suggesting that multicollinearity did not exist. The correlation between IF and EF was found to be 0.38, which indicates that even though the two factors are correlated, they still have adequate discriminant validity and thus can be used separately within the regression model. The correlation of brand awareness with both of the content feature factors is low, at $r = 0.08$ and $r = 0.05$, respectively, and thus, brand awareness can be considered independent of content features and suitable as a moderator factor. Mean centering controlled multicollinearity due to interaction terms since all VIF scores fell below 3.0.

4.2. Hierarchical Regression Analysis

Five hierarchical models were estimated to progressively isolate control, main, and interaction effects; the full results with standardized coefficients appear in Table 3.

Table 3. Hierarchical Regression Results (DV = PCR)

Variable	M1 (β)	M2 (β)	M3 (β)	M4 (β)	M5 (β)
Follower size (ln)	0.12**	0.09*	0.08*	0.08*	0.07*
Weekend posting	0.03	0.02	0.02	0.02	0.02
Category dummy 1	0.05	0.04	0.03	0.03	0.03
Category dummy 2	-0.02	-0.01	-0.01	-0.01	-0.01
Paid promotion	0.09*	0.07*	0.06	0.06	0.06
IF		0.24***	0.23***	0.24***	0.23***
EF		0.17**	0.16**	0.16**	0.15**
INT			0.08*	0.07*	0.07*
BA			-0.05	-0.05	-0.04
IF $\times$ INT				0.10*	0.10*
EF $\times$ INT				0.04 n.s.	0.04 n.s.
IF $\times$ BA					-0.13**
EF $\times$ BA					-0.10*
R ²	0.09	0.19	0.20	0.22	0.24
Δ R ²	—	0.10***	0.01*	0.02*	0.02*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; n.s. = not significant. All models estimated with brand-level cluster-robust standard errors (15 clusters). All continuous predictors were mean-centered prior to interaction term construction. After the entry of interaction terms in Models 4 and 5, the maximum VIF was 2.41, remaining below the conventional threshold of 10. $N = 2,200$ for all models.

In Model 1 (controls only), follower size among bloggers ($\beta = 0.12$, $p < 0.01$) and paid promotions ($\beta = 0.09$, $p < 0.05$) were found to be positively related to PCR, while posting period ($\beta = 0.03$, n.s.) and the two category dummies did not reach significance. R^2 of the controls-only regression model stood at 0.09. For Model 2, it is evident that both the informational content feature ($\beta = 0.24$, $p < 0.001$) and the emotional content feature ($\beta = 0.17$, $p < 0.01$) have significant positive impacts on purchase conversion index, supporting H1 and H2. Though there exists moderate collinearity between the constructs IF and EF ($r = 0.38$), both the constructs remain statistically significant even in combination. IF has a higher standardized coefficient as compared to EF, implying that the central route persuasion via product information had a relatively greater impact on purchase conversion than the peripheral route persuasion via emotional arousal. Content features in total accounted for a substantial $\Delta R^2 = 0.10$ ($p < 0.001$). It should be noted that paid promotion fell from being significant ($\beta = 0.09$, $p < 0.05$) to being non-significant ($\beta = 0.06$) in the third model due to the sequential introduction of content and moderator variables, indicating that the advantage of promoted notes' initial conversion rate was mainly due to their content features. In Model 3, the main effects of user interaction level (INT) and brand awareness (BA) were controlled. It was found that the effect of INT on PCR was moderate and significant ($\beta = 0.08$, $p < 0.05$), whereas the effect of BA on PCR was non-significant ($\beta = -0.05$, $p > 0.10$), consistent with its negligible bivariate correlation with PCR ($r = -0.06$). With the addition of moderator main effects, ΔR^2 was equal to 0.01 ($p < 0.05$), which

set up the necessary baseline for further moderation tests. The final model (Model 5) R^2 of 0.24 falls within the 0.15–0.30 range typically reported in social media content marketing studies on the impact of content on social media users [14][15]. Considering the fact that there are many variables influencing purchase conversion behavior apart from content, such as personal consumer peculiarities and actions of competitors, the achieved $R^2 = 0.24$ seems to be substantial.

The results for moderation effects showed that there was a positive relationship between the interaction of the features of information and the level of user interaction in model 4 ($\beta = 0.10$, $p < 0.05$), hence H3a is accepted. In simple slope analysis (Fig. 3), it was seen that when the condition was high (+1SD), then the value of the slope of the relationship between IF and PCR was $\beta = 0.34$ ($p < 0.001$) while at low interaction (-1SD), it became $\beta = 0.14$ ($p < 0.05$).

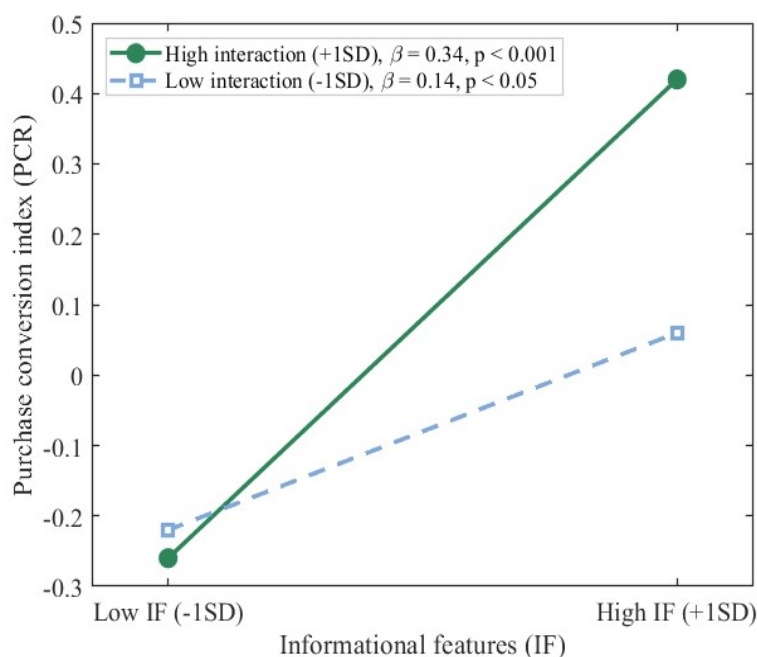


Fig. 3 Moderating Effect of User Interaction Level on the IF→PCR Relationship

The coefficient for the interaction between emotional characteristics and user interaction levels was non-significant ($\beta = 0.04$, $p > 0.10$), thus rejecting H3b. The results of this hypothesis test were expected to be asymmetrical due to theory suggesting that commenting and verification will mainly impact the credibility of central route messages by validating information and less on emotional appeal.

Regarding the boundary condition aspect, the coefficient for the interaction term between IF and BA in Model 5 was significantly negative ($\beta = -0.13$, $p < 0.01$), hence providing evidence in support of hypothesis H4a. In addition, the interaction term of EF × BA was also significant, negative ($\beta = -0.10$, $p < 0.05$), hence validating H4b. Upon dividing the sample into two groups based on high/low awareness (BA at median, Fig. 4), it is evident that the regression coefficients of IF → PCR ($\beta = 0.30$) and EF → PCR ($\beta = 0.22$) in the low awareness group were both higher compared to those in the high awareness group ($\beta = 0.13$, $\beta = 0.08$ respectively), such differences being significant (IF: $F = 6.54$, $p < 0.01$; EF: $F = 4.15$, $p < 0.05$).

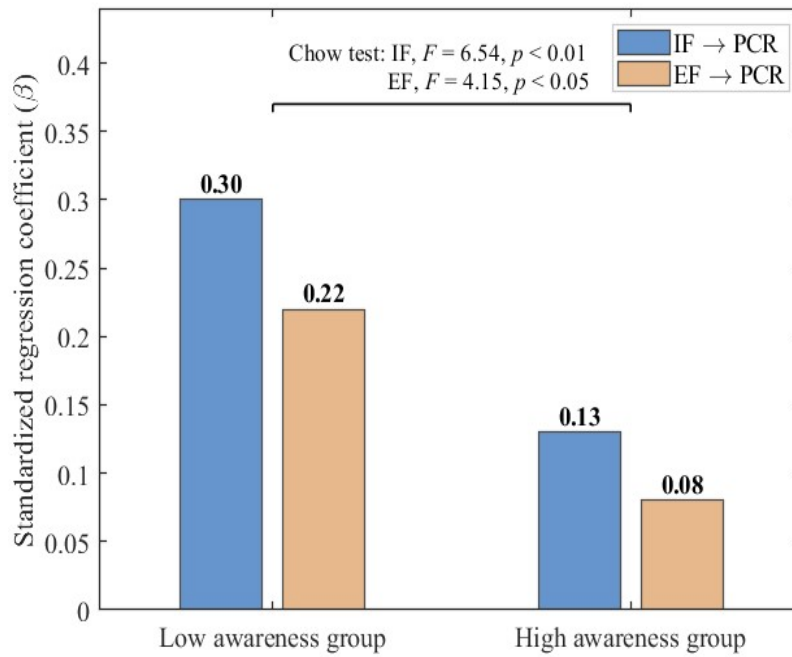


Fig. 4 Moderating Effect of Brand Awareness on Content Features→PCR

4.3. Robustness Checks

To verify these findings, four complementary robustness checks were conducted - alternative dependent variable, link-embedded subsample, bias-corrected bootstrap, and category subsample regressions - as detailed in Table 4.

Table 4. Robustness Check Results

Test	H1 (IF→PCR)	H2 (EF→PCR)	H3a (IF × INT)	H4a (IF × BA)	H4b (EF × BA)
Alternative DV (save rate)	0.21***	0.13**	0.08*	-0.10**	-0.07*
Link subsample (n = 908)	0.26***	0.14**	0.11*	-0.13**	-0.08*
Bootstrap 95% CI	[0.15, 0.31]	[0.07, 0.25]	[0.01, 0.19]	[-0.21, -0.04]	[-0.18, -0.01]
Beauty subsample	0.25***	0.19**	0.12*	-0.14**	-0.11*
Food subsample	0.22**	0.15*	0.09†	-0.11*	-0.08†
Home subsample	0.20**	0.10†	0.07 n.s.	-0.10*	-0.06 n.s.

Note: †p < 0.10. All robustness models estimated with the full specification (including INT and BA main effects) and brand-level cluster-robust standard errors. Bootstrap resampling N = 5,000; 95% CI = bias-corrected confidence interval. The link-embedded subsample uses raw click-through rate (link clicks ÷ page views) as the dependent variable without z-score pooling.

These tests demonstrated the stability of the main conclusions made by the study from four different angles. With respect to measurement sensitivity, replacing the dependent variable with save conversion rate (saves ÷ page views) yielded consistent coefficient directions and significance levels across all hypotheses in terms of both sign and significance of coefficients for all hypotheses tested. For the construction of the dependent variable, the subsample including embedded links (n = 908) produced similar coefficients in both sign and significance of coefficients compared to the full sample (Table 4). In terms of statistical inference, Bootstrap analysis of 5,000 replications indicated that none of the hypothesized relationships found support had zero coefficients at the 95% confidence level. With regard to external validity, the subsample analysis by product category demonstrated that, although informational features

(H1) had significant effect for all product types, emotional features (H2) reached only marginal significance in the home and living category ($p = 0.07$). The same applied to the interaction moderation effect (H3a).

5. Conclusion

The current study explores the impact of seeding content characteristics on the purchase conversion rate of new consumer brands on Xiaohongshu using an analysis of 2,200 notes from a theoretical perspective based on the Dual-Routes concept of the Elaboration Likelihood Model. The empirical findings suggest that informational characteristics drive purchase conversion with a higher effect than the emotional ones, the influence of which asymmetrically interacts with the interaction level of users – increasing the influence of informational characteristics without any effect on the emotional route, and that brand awareness plays a boundary role, with low-awareness brands more responsive to high-quality content. Thus, this study extends the theory by demonstrating the dominant impact of the central route on social media-based seeding of new products, even on visually-oriented communities, and proves that engagement in comments occurs through information validation rather than emotional resonance. Practically, the study provides a number of useful insights regarding the focus on the density and precision of content related to information, and the active engagement in discussion sections, especially for new consumer brands that need to prioritize content quality rather than the blogger audience scale. However, there are several limitations to be taken into account: the conversion metric was based on proxies rather than transactional data, the 15 sampled brands were top-ranked by note volume within each category and further applicability needs to be tested in other contexts, the sentiment measurement approach might be limited in capturing colloquial seeding content language, and the cross-sectional study design leaves open the possibility of reverse causality.

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