Uncovering the Voice of Consumers in New Media: A Comparative Sentiment Analysis of Anker Product Reviews on Xiaohongshu and Amazon

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Abstract: In the context of the new media economy, user-generated content (UGC) on different digital platforms reflects distinct consumer sentiment structures and expression logic. This study conducts a comparative sentiment analysis of user reviews for Anker power banks on Xiaohongshu, a representative Chinese social commerce platform, and Amazon, a global centralized e-commerce platform. Using SnowNLP for Chinese text sentiment classification and TextBlob for English reviews, combined with a keyword-based thematic analysis, the study examines 600 valid user reviews (300 from each platform). The findings reveal that while both platforms show generally positive attitudes toward the product, significant differences exist in sentiment distribution and thematic focus. Xiaohongshu users exhibit an "inverted pyramid" sentiment structure, characterized by authentic, diverse, and emotionally expressive content, with a strong focus on product appearance and usage scenarios. In contrast, Amazon users demonstrate a polarized sentiment pattern dominated by neutral and positive reviews, emphasizing performance metrics and durability. Grounded in the Stimulus-Organism-Response (S-O-R) framework, this study interprets these differences as outcomes of platform-specific environmental stimuli shaping users' internal emotional states and behavioral responses. The findings provide empirical support for cross-cultural marketing strategies and platform-specific brand communication, highlighting the need for aesthetic and scenario-oriented marketing on Xiaohongshu and function-driven, trust-based communication on Amazon.

Keywords: New Media Economy; Cross-Cultural Marketing; Consumer Sentiment; SnowNLP; Xiaohongshu; Amazon

1. Introduction

As digital technologies become increasingly widespread and continue to evolve, consumer demands grow more diverse and context-dependent. In this process, digital platforms have emerged as a key force reshaping traditional consumption patterns. In the big data era, user-generated content (UGC) has become an important source of information that influences purchasing decisions. High-quality online reviews, when effectively filtered and utilized, not only serve as a crucial reference for consumers but also offer valuable opportunities for e-commerce platforms and merchants to unlock potential commercial value [1]. Consequently, research on the sentiment, information quality, and perceived usefulness of online reviews has drawn growing academic interest.

Amazon, as the world's most representative centralized e-commerce platform, relies on its large user base and well-established operational systems to create a standardized mechanism for ratings and credit management. Such a mechanism helps reduce information asymmetry and encourages users to make rational decisions based on functional attributes and practical value [2]. In contrast, platforms like Xiaohongshu, a typical social content platform, operate on a logic of "social interaction first, purchasing decision second". Through an integrated loop of content creation, community engagement, and consumption conversion, Xiaohongshu fosters trust among users within community interactions, thereby subtly shaping purchase behavior [3,4].

What appears at first glance as a difference in platform design actually reflects a deeper divergence in user psychology. Drawing on the Stimulus- Organism- Response (S-O-R) framework [5], the algorithmic logic and content environment of each platform can be viewed as distinct external stimuli. On Amazon, which prioritizes rationality, users are more inclined toward functional cognitive processing; on Xiaohongshu, where emotional expression dominates, users tend to experience stronger emotional reactions. These two different psychological states ultimately lead to observable differences in behavioral responses, especially in terms of emotional expression and thematic focus in review texts [6].

By selecting Xiaohongshu and Amazon as representative cases, this study aims to explore how platform attributes shape user expression in distinct ways. Through a comparative analysis of sentiment polarity and thematic concentration in user reviews across these two heterogeneous e-commerce ecosystems, we seek to provide empirical insights into cross-platform consumer behavior and the mechanisms underlying trust formation.

2. Literature Review

2.1 New Media and Consumer Behavior

Trust mechanisms play a central role in digital consumption, influencing both consumer decision-making and the generation of word-of-mouth. Different e-commerce models, shaped by their platform characteristics, have developed distinct approaches to building trust. Traditional centralized e-commerce platforms prioritize institutional and algorithm-based trust. They reduce information asymmetry through standardized rating systems, real-name authentication, and verified purchase mechanisms. Amazon exemplifies this approach: it relies on uniform scoring, objective functional feedback, and big data algorithms to create a utility- and efficiency-oriented trust structure. As a result, users tend to base their judgments on quantitative indicators and institutional endorsements [7].

In contrast, social e-commerce platforms are grounded in emotional and community-based trust. Xiaohongshu, for instance, leverages its “content + social” ecosystem to foster trust through interpersonal interaction, experience sharing, and emotional resonance. Users mitigate purchase risks by drawing on the authentic experiences of key opinion leaders (KOLs) and key opinion consumers (KOCs), as well as community word-of-mouth. This shifts the source of trust from institutional validation to peer affirmation [8]. Within such platforms, content sharing and product recommendations constitute a form of emotional labor: users construct their identities and form emotional bonds through sharing, which further reinforces community trust [9].

Online reviews serve as a crucial vehicle for conveying trust. In traditional e-commerce, reviews focus on functionality, performance, and objective utility, thereby strengthening institutional trust [10]. Social e-commerce reviews, however, pay more attention to usage scenarios, aesthetics, and emotional expression, which helps solidify emotional trust. To summarize, traditional centralized e-commerce builds “weak-tie trust” based on algorithms and institutional frameworks, with the primary goal of reducing transaction costs and risks. Social e-commerce platforms, on the other hand, cultivate “strong-tie trust” through interaction and emotional resonance, centered on the exchange of emotional value. This fundamental divergence in trust logic inevitably leads to differences in how users screen information and the intensity of emotional expression in their reviews. Nevertheless, most existing studies focus on trust-building pathways within a single platform, and there remains a lack of comparative research examining how cross-platform heterogeneity in trust logic specifically shapes the emotional polarity and thematic focus of user comments.

In short, traditional e-commerce pursues efficiency through institutional and algorithmic trust, while social e-commerce promotes user stickiness through emotional and community trust. These differences provide theoretical support for the cross-platform comparison of sentiment and thematic focus undertaken in this study.

2.2 Consumer Sentiment and Purchase Intention: The S-O-R Framework

Consumers’ emotional tendencies play a key mediating role in the purchasing process. The Stimulus-Organism-Response (S-O-R) theory offers a classic lens for analyzing how environmental factors evoke emotions and subsequently drive consumer behavior [5]. According to this theory, external environmental stimuli (S) affect an individual’s internal psychological state (O), which in turn leads to specific behavioral responses (R). In the context of new media consumption, this framework is widely used to examine how platform environments and content-based stimuli ultimately shape users' behavioral intentions through both cognitive and emotional pathways [11]. In social e-commerce scenarios, the platform environment and user-generated content (UGC) constitute the primary external stimuli (S).

Previous research indicates that the content formats, interactive features, and community attributes of social media significantly influence users' perceptions and engagement behaviors [12,13]. These stimuli act on the user's internal state (O), which includes emotions, cognitive evaluations, and perceived experiential value [14,15]. Among these, emotional value serves as a key intermediary linking stimulus and behavior [16], ultimately triggering behavioral responses such as information sharing and purchase intention (R) [16, 17]. Meanwhile, the quality and credibility of online reviews directly affect user trust and risk perception, thereby influencing consumption decisions [18].

Building on this, the present study operationalizes the S-O-R framework as a working model for cross-platform sentiment analysis. Specifically, platform attributes such as interface design, recommendation algorithms, and community norms, are treated as external "stimuli" (S). The emotional tendencies (positive or negative) and cognitive evaluations expressed by users in their reviews are regarded as internal "organism" states (O). Finally, the resulting textual features of reviews, including topic focus and linguistic style, are considered observable "responses" (R). This logical mapping not only helps clarify the black box of how platform environments affect user psychology but also provides a solid micro-level theoretical foundation for comparing emotional expression across heterogeneous platforms.

2.3 SnowNLP Technology: A Functional Introduction

Given the unstructured nature and semantic complexity of Chinese review texts, this study adopts the SnowNLP (Simple Natural Language Processing) library as a tool for quantifying sentiment in Chinese reviews. SnowNLP is a Python-based natural language processing library specifically designed for Chinese text, with its core algorithm built on a Naive Bayes classifier. A key advantage of this tool is that it performs sentiment analysis by directly loading pre-trained models, eliminating the need to construct complex neural network architectures. This allows researchers to focus on mining and interpreting textual semantics rather than fine-tuning algorithmic parameters [19].

From a technical standpoint, SnowNLP's sentiment analysis module is primarily based on the Naive Bayes classification algorithm [20]. The basic workflow is as follows: first, a pre-labeled sentiment corpus containing a large volume of Chinese texts marked as positive or negative is constructed; then, a classification model is trained on this corpus. When processing new text, the system performs Chinese word segmentation and calculates the probability that the text belongs to the positive or negative category based on Bayes' theorem [2,20], ultimately outputting a sentiment score between 0 and 1. Generally, a score above 0.5 indicates positive sentiment, a score below 0.5 indicates negative sentiment, and scores between 0.4 and 0.5 can be considered neutral [2]. The model also incorporates a built-in sentiment lexicon and performs weighted calculations that take into account contextual factors and degree adverbs, thereby improving judgment accuracy [19].

Owing to its ease of use and basic Chinese semantic analysis capabilities, SnowNLP has been validated and applied across multiple research domains, including tourist sentiment mining in cultural tourism contexts [2], user satisfaction analysis in e-commerce [21,22], and online public opinion monitoring [23]. However, it must be noted that the effectiveness of SnowNLP is highly dependent on the distribution characteristics of its training corpus. The underlying corpus of the model is derived mainly from early e-commerce reviews, and its logic for determining sentiment polarity is relatively simplistic. In light of this, the present study positions SnowNLP as a "pre-screening tool", using its high efficiency to perform preliminary sentiment classification on large-scale Chinese reviews, while supplementing the results with subsequent manual verification and correction to ensure the reliability and validity of the analysis.

2.4 TextBlob Technology: An Adaptation for English Text

To meet the needs of cross-lingual comparative analysis, this study selected the TextBlob library as the sentiment analysis tool for processing English reviews from the Amazon platform. TextBlob is a widely used natural language processing library in the Python ecosystem, specifically designed for English text. Its sentiment analysis module inherits the core algorithms of the Pattern library [24]. Unlike SnowNLP, which relies on probabilistic classification, TextBlob adopts a dictionary-based and syntactic rule-based paradigm [25]. It identifies emotion-bearing words such as adjectives and adverbs, in the text and combines them with grammatical rules (e.g., negations and degree modifiers) to perform weighted calculations, ultimately outputting two dimensional indicators: polarity and subjectivity [26]. This rule-based approach offers high accuracy and stability when dealing with short, structurally standardized review texts [27].

Technically, TextBlob's sentiment analysis primarily depends on its built-in sentiment lexicon, which contains approximately 2,900 English words [28]. The algorithm then parses the text sentence by sentence, identifies modifier relationships and negation scopes, and computes the overall sentiment orientation through cumulative weighted calculations [25]. This tool can be applied directly to new text without the need for pre-training models, providing excellent flexibility and scalability when processing large-scale, cross-domain English reviews [29] Additionally, TextBlob supports auxiliary functions such as part-of-speech tagging and noun phrase extraction, which help researchers conduct more detailed semantic mining of the text [24].

TextBlob has been widely used in academic research for English sentiment analysis in fields such as cross-border e-commerce review analysis and social media sentiment monitoring [30]. Its open-source nature and simple API interface enable researchers to efficiently perform sentiment quantification on large-scale English texts [29]. To ensure comparability with the Chinese sentiment scores generated by SnowNLP, this study linearly maps the polarity scores produced by TextBlob (originally ranging from -1 to 1) to the 0-1 interval, thereby establishing a unified cross-platform sentiment analysis framework [26]. This processing allows for subsequent quantitative comparison of sentiment between Xiaohongshu and Amazon reviews.

3. Research Methods

3.1 Data Collection

This study adopts a cross-platform comparative design, using user reviews of the same product to investigate differences in emotional expression and thematic focus between Chinese and foreign consumers within distinct new media environments. Chinese review data were collected from Xiaohongshu, a platform widely recognized as China's most influential lifestyle sharing and consumption decision-making community among young users. Xiaohongshu functions not only as a tool for purchase decisions but also as a social space where users express themselves and share personal experiences. On this platform, users tend to post authentic, subjective, and emotionally rich content, which makes the reviews highly credible and valuable for sentiment analysis. Foreign-language review data were sourced from Amazon US. As the world's largest comprehensive e-commerce platform, Amazon's user review system reflects typical features of Western consumer culture, with an emphasis on post-purchase practical usage experiences, functional evaluations, and objective feedback.

To ensure data comparability, this study selected Anker power banks of the same models (the 3-in-1 10,000mAh and 25,000mAh portable power banks) as the target products, thereby eliminating interference caused by model differences. The data collection period spanned from September to December 2025. Reviews were obtained through a combination of targeted searches and manual screening. After data cleaning, deduplication, and removal of invalid content, a total of 300 valid reviews from Xiaohongshu and 300 valid reviews from Amazon were retained, yielding a final sample of 600 reviews. This sample size meets the basic requirements for sentiment analysis and comparative research.

3.2 Data Preprocessing

Raw review data contain substantial amounts of extraneous information. To improve the accuracy of subsequent analyses, this study performed a series of standardized cleaning and preprocessing steps in sequence.

Denoising: Emojis, hyperlinks, special characters, and redundant punctuation were removed from the review texts, retaining only plain text content.

Stop word filtering: For Chinese data, auxiliary words lacking emotional meaning (e.g., “de”, “le”, “ne”) were removed. For English data, high-frequency function words (e.g., “and”, “the”, “is”) were eliminated. This study referred to the Harbin Institute of Technology stopword list and the SnowNLP stopword list to ensure filtering effectiveness.

Text normalization: Case was unified, common abbreviations were standardized, and invalid texts that were too short (fewer than five characters) or lacked substantive meaning (e.g., simple emoticons) were discarded.

3.3 Sentiment Analysis Process

This study employed a dictionary-based sentiment analysis method to quantitatively evaluate the preprocessed text data. For Chinese reviews, the SnowNLP model was used to calculate sentiment scores. For English reviews, TextBlob, a tool more suitable for English contexts, was adopted for analysis. The scores from both tools were uniformly mapped to the [0,1] interval to enable cross-platform comparison. In this scheme, 0 represents extremely negative sentiment, 1 represents extremely positive sentiment, and higher scores indicate more favorable user attitudes.

In line with the Stimulus-Organism-Response (S-O-R) theoretical framework and to ensure result interpretability, this study established clear sentiment classification thresholds: negative sentiment for scores in [0,0.35), neutral sentiment for [0.35,0.65], and positive sentiment for [0.65,1]. Based on these thresholds, the average sentiment score, sentiment distribution ratio, and positive review rate were calculated for each platform to comprehensively characterize user attitudes.

3.4 Thematic Analysis Method

This study adopts an automated topic classification method based on keyword matching. First of all, according to the research objectives and product attributes, four theme dimensions are defined in advance:

(1) Appearance: Related to appearance, color, design, texture, and aesthetics;

(2) Scenario: Usage scenarios such as travel, business trips, commuting, travel, and emergencies;

(3) Performance: Charging speed, power, capacity, compatibility, battery life, etc.;

(4) Durability: Materials, lifespan, failure rate, after-sales service, etc.

After data cleaning, automatic classification is implemented using Python’s Pandas and regular expressions. The model processes each cleaned text entry to determine whether it contains corresponding thematic keywords and automatically assigns a Theme label accordingly. The final output is a structured data table containing Raw-Text, Clean-Text, Sentiment-Score, Sentiment-Label, and Theme, providing a foundation for subsequent statistical analysis and visualization.

Table 1. Sentiment Distribution Statistics of Xiaohongshu and Amazon

Platform	Percentage of Negative Comments	Percentage of Neutral Comments	Percentage of Positive Comments	Average Sentiment Score
Xiaohongshu	19.10%	16.10%	64.50%	0.686
Amazon	0.60%	44.40%	55.00%	0.678

4. Data Analysis and Discovery

4.1 Comparative Analysis of Overall Sentiment

Sentiment analysis results show that users on both platforms have a generally positive attitude toward Anker power banks, but there are significant differences in the sentiment structure. To illustrate this difference visually, this study categorizes sentiment scores into three intervals for statistical analysis: negative (0-0.35), neutral (0.35-0.65), and positive (0.65-1).

As shown in Table 1, Xiaohongshu and Amazon exhibit distinct patterns in sentiment distribution. Xiaohongshu’s sentiment distribution follows an “inverted pyramid” structure, with negative reviews accounting for 16.7%, neutral reviews for 18.1%, and positive reviews for 65.2%. This indicates that Xiaohongshu users tend to actively express their genuine feelings; their reviews contain both praise and criticism and are expressed directly, reflecting the typical “product recommendation” sharing characteristics of a social platform. In contrast, Amazon’s sentiment distribution exhibits a more polarized pattern, with negative reviews accounting for only 0.6%, neutral reviews as high as 44.4%, and positive reviews at 55.0%. The vast majority of Amazon user reviews are positive, while the few negative reviews are concentrated on extremely serious product defects.

To uncover the semantic features underlying sentiment scores, this study selected and analyzed representative reviews from various platforms. Among the positive reviews on Xiaohongshu, one user wrote: “The Anker 3-in-1 power bank looks so stylish! The pink color is super soft, it’s super convenient to slip into my bag when traveling for work, and with dual-port fast charging, I never have to carry extra cables, a must-have for travel!” (Sentiment score: 0.97). In contrast, a negative review stated: “The charging speed is incredibly slow, it only reaches 60% after a full day and it gets hot. The quality is too unreliable.” (Sentiment score: 0.17). On Amazon, positive reviews included: “This power bank charges my laptop and phone fast; the 10,000mAh capacity is perfect for travel; it has a sturdy build and is reliable.” (Sentiment score: 0.72); while negative reviews include: “The built-in cable stopped working after 2 months; poor durability and slow charging.” (Sentiment score: 0.33). These typical examples vividly illustrate the differences in emotional expression and focus between users on the two platforms. This study found that such differences in emotional structure cannot be attributed solely to the products themselves; the deeper cause lies in the differences in platform mechanisms and cultural attributes. As a lifestyle-sharing community, Xiaohongshu’s core logic is “authentic sharing”. Users’ motivations for commenting are primarily to document their lives, seek resonance, or vent frustrations to warn others. In this process, users not only evaluate products but also discuss “corporate social responsibility” and “consumer rights,” which aligns with the pathway in SOR theory where “social environmental stimuli” trigger “emotional responses.” Consequently, the platform encourages diverse expressions; whether praise or criticism, both hold high social value, leading to a widespread phenomenon of “daring to criticize.” In contrast, as a transaction-oriented platform, Amazon’s review system is fundamentally based on a filtering mechanism. Users typically leave reviews only when they encounter serious issues or when their experience far exceeds expectations. Data shows that negative reviews account for an extremely low percentage on Amazon, confirming the “selective silence” mindset among Western consumers in non-extreme situations. Furthermore, Amazon’s exceptionally high rate of positive reviews (99.4%) does not imply that products are absolutely perfect; rather, it is a result of the platform’s review culture, where users generally tend to leave positive reviews on e-commerce platforms, while those with neutral or mildly negative experiences tend to remain silent.

Although Amazon’s average sentiment score (0.678) is slightly higher than Xiaohongshu’s (0.612), the differences in sentiment structure and topic preferences are significant, indicating that differences stemming from platform culture and user behavior are more important than satisfaction levels themselves. Xiaohongshu exhibits a characteristic of “authentic expression coexisting with diversity”, with a valid positive review rate of 64.5%, meaning a significant proportion of users are willing to express negative or neutral opinions. In contrast, Amazon displays a “predominance of positive reviews”, with a valid positive review rate as high as 99.4%, but valid emotional reviews accounting for only 55.6%. This shows that differences in sentiment structure reflect genuine user attitudes more accurately than average scores.

4.2 Feature Analysis Based on Theme

To quantify the sentiment trends associated with different topics of interest, this study developed a table comparing sentiments across topics (Table 2). As can be seen, although the two platforms focus on entirely different topics, users assigned high sentiment scores to the core areas of interest on each platform.

Comments from Xiaohongshu users primarily focus on appearance, usage scenarios, and overall experience. Among these, comments driven by appearance account for 24.1% of the total, with an average score as high as 0.732. Users frequently use terms such as “cute”, “pink”, “pretty” and “good-looking”, indicating that, for Chinese consumers, a product’s appearance is a key factor in forming a first impression. Comments related to usage scenarios accounted for 18.4% of the total, with an average score of 0.603. These comments primarily revolved around specific contexts such as “travel”, “air travel”, “commuting” and “business trips”, emphasizing the emotional value and convenience the product brings in these particular life situations. Comments regarding performance and durability also accounted for a significant proportion, though their emotional scores were relatively lower.

Table 2. Comparison of Thematic Sentiment Scores between Xiaohongshu and Amazon

Theme	Xiaohongshu (Score / Ratio)	Amazon (Score / Ratio)
Appearance	0.732 (24.1%)	0.613 (12.9%)
Scenario	0.603 (18.4%)	0.654(15.5%)
Performance	0.581 (42.6%)	0.682 (68.1%)
Durability	0.521(15.0%)	0.650 (3.1%)

Amazon users focus heavily on product performance metrics and technical specifications. Reviews centered on core performance aspects account for as much as 79.1% of the total, with an average score of 0.667. These reviews primarily revolve around hard metrics such as “charging speed”, “battery capacity”, “output power”, and “compatibility”, with comments like “Charges fast” and “The battery life is outstanding” clearly demonstrating a functional priority and technical orientation. Reviews regarding durability account for 2.0%, involving objective assessments of product lifespan, materials, and long-term value, reflecting consumers’ rational consideration of “value for money”. The remaining 18.9% of reviews primarily concern logistics and packaging experiences, rather than emotional or casual chatter.

These findings validate the core tenets of cross-cultural consumption theory: Eastern consumers tend to prioritize emotional and aesthetic factors, while Western consumers tend to prioritize rational and functional factors. Specifically, consumption decisions among users on the Xiaohongshu platform are driven by emotional factors, with a focus on the visual pleasure and social sharing value that products provide; in contrast, consumption decisions among users on the Amazon platform are driven by rational factors, with a focus on the functional value of products. This difference not only explains the underlying causes of the emotional disparities discussed earlier but also provides a theoretical basis for global brands to formulate localized marketing strategies: in the Chinese market, marketing should focus on “aesthetic marketing” and “scenario-based influence”; in overseas markets, it should focus on “specification comparisons” and “functional validation”.

In summary, the themes of reviews on Xiaohongshu and Amazon exhibit a distinct dichotomous structure. Xiaohongshu users prioritize experience, aesthetics, scenarios, and social sharing, reflecting a typical “emotional consumption culture”; Amazon users prioritize performance, specifications, durability, and practical utility, reflecting a typical “rational consumption culture.” This finding not only enriches empirical research on cross-cultural consumer behavior but also provides data support for brands to implement differentiated marketing strategies across different platforms.

5. Management Insights and Conclusions

5.1 Differentiated Marketing Strategy

Drawing on the sentiment and thematic analysis of user reviews from Xiaohongshu and Amazon, this study reveals notable differences in consumer motivations between Chinese and foreign users. Xiaohongshu users display typical traits of emotional consumption, with a strong emphasis on a product’s aesthetic appeal and usage scenarios. In contrast, Amazon users show a pronounced tendency toward rational consumption, focusing primarily on hard performance metrics and durability. These findings offer important guidance for companies seeking to develop differentiated marketing strategies for global products. Rather than applying a one-size-fits-all marketing plan across different markets, firms should adopt precision marketing approaches tailored to the specific characteristics of each platform.

For Chinese social e-commerce platforms such as Xiaohongshu, marketing strategies should highlight aesthetic appeal and scenario integration. Given that aesthetic appeal receives the highest sentiment score on this platform and resonates most strongly with users, product design and promotional efforts should prioritize visual attractiveness to lower the threshold for purchase decisions. Meanwhile, leveraging the high sentiment scores associated with the scenario dimension, products should be embedded into specific lifestyle contexts, such as travel, business trips, and camping, thereby cultivating their social attributes and making them a natural part of users’ lifestyle expression. Conversely, for traditional e-commerce platforms like Amazon, marketing strategies should revert to a function-oriented approach and empirical specification demonstration. Since users on these platforms place a high value on performance and durability, marketing efforts should focus on transparently presenting technical specifications and providing empirical tests of charging speed and battery capacity. Companies should build trust through detailed data and objective performance comparisons rather than relying solely on emotional appeals. This differentiated strategy effectively aligns with the information needs of consumers from different cultural backgrounds, thereby improving marketing conversion rates.

5.2 Brand Communication Strategy

Beyond product strategy differences, brands must also adapt their communication messages and interaction styles in cross-cultural contexts to match the emotional dynamics of each platform. The data presented in Chapter 4 show that sentiment distribution on Xiaohongshu is characterized by high conflict, with users freely expressing both strong positive and strong negative emotions. Amazon, by contrast, exhibits a high satisfaction pattern, where users are generally rational and restrained, offering negative feedback only when extremely dissatisfied. Therefore, on new media community platforms like Xiaohongshu, brands should adopt empathetic and interactive communication strategies. For positive user reviews, brands can enhance the recommendation experience through active engagement; for negative reviews, brands should maintain high sensitivity and tolerance, promptly offering emotional reassurance and resolving issues. By leveraging the platform's strong interactivity, brands can turn negative word-of-mouth into brand affinity. On traditional e-commerce platforms such as Amazon, however, brand communication should shift toward authoritative and trust-building approaches. Given that users tend to make decisions based on objective metrics, brands should utilize professional Q&A sections, detailed technical specifications, and authoritative certification information to establish a professional image. Moreover, in light of users' significantly increased concern over durability, brands should pay close attention even to rare negative feedback and use it as a core basis for product improvement. By maintaining an exceptionally high rating through uncompromising product quality, brands can build a solid trust barrier in the face of intense market competition.

5.3 Conclusion

Applying Anker power banks as a case study, this research compares user review data from Xiaohongshu and Amazon to conduct an in-depth analysis of differences in emotional expression and thematic focus between Chinese and foreign consumers across distinct new media environments. The results indicate that while users on both platforms hold a generally positive attitude toward the product, there are fundamental differences in sentiment structure and thematic preferences. Driven by an emotional culture, Xiaohongshu users place greater emphasis on a product's aesthetic value and suitability for specific scenarios, exhibiting evaluation characteristics marked by authenticity, diversity, and bold self-expression. In contrast, Amazon users are driven by a rational culture, focusing more on technical performance and durability, and displaying evaluation traits such as objectivity, restraint, and selective silence. This conclusion not only validates the applicability of cross-cultural consumption theory in the digital marketing domain, specifically, that Eastern consumer culture leans toward the emotional and aesthetic while Western consumer culture leans toward the rational and functional, but also provides concrete practical pathways for global brands. Companies must recognize that platform attributes and cultural DNA profoundly shape users' evaluation logic. Future brand globalization and cross-platform operations should not be limited to one-dimensional product exports; rather, they should be grounded in deep insights into the psychology of target market users, implementing cultural adaptation. Through differentiated marketing strategies and precise brand communication, companies can achieve resonance in product value and effectively expand their markets amid the collision of diverse cultures.

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