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"Customer Reviews or Vlogger Reviews?" The Impact of Cross-Platform UGC on the Sales of Experiential Products on E-Commerce Platforms

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Abstract: User-generated content (UGC) from e-commerce platforms and third-party platforms can impact customer-perceived risk and influence product sales in online stores. However, the understanding of UGC from which platform type yields a stronger effect on product sales and how the effects interact across the platforms remains limited. This limitation arises from the complexity of consumer purchasing behavior and information processing, as well as the heterogeneity of UGC features across different platforms and the uncertainty surrounding causal relationships. This study constructs a novel cross-platform framework using the elaboration likelihood model (ELM) to investigate the underlying mechanism of how cross-platform UGC affects online sales of experiential products. Additionally, it examines the mediating effect of purchase intention in the relationship between cross-platform UGC and product sales, as well as the moderating effect of product price. Taking the e-commerce platform Tmall and third-party platform Bilibili as a cross-platform example, we analyzed customer reviews on Tmall and vlogger reviews on Bilibili for 300 cosmetic products, using text sentiment analysis and multiple regression. Results show that the number of product evaluations from third-party platforms positively impacts sales, but this impact is weaker compared to the influence of UGC originating from e-commerce platforms on sales. The underlying mechanism refers to the process by which UGC on an e-commerce platform directly impacts sales and also influences sales through purchase intention. In contrast, UGC on third-party platforms only influences sales through purchase intention. Furthermore, the product price has no significant moderating effect on the positive relationship between review length and sales. This study provides a cross-platform UGC research framework that can guide effective cross-platform marketing management by shedding light on the role of UGC in reducing customer-perceived risk and its impact on online sales of experiential products.

Keywords: cross-platform UGC; sentiment analysis; elaboration likelihood model; product sales; text mining

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1. Introduction

Online shopping offers consumers the convenience of shopping from anywhere at any time without the need to visit physical stores. However, it also poses challenges for consumers who cannot physically inspect products before buying, leading to greater pre-purchase uncertainties and risks, particularly for experiential products. Experiential products are products like cosmetics, skincare, and clothes, which often lack clear and specific quality evaluation standards, making it difficult to compare their intrinsic product characteristics [1]. Experiential products have high information acquisition costs [2–4], and shoppers often rely on subjective or personal experiences to determine perceived quality [5]. To mitigate such perceived risks, online shoppers seek additional information [6], with user-generated content (UGC) being an important source of such information. UGC, which refers to any content created by users and primarily distributed on the Internet [7], is becoming increasingly prevalent [6,8,9] and can help reduce pre-purchase uncertainties and risks associated with experiential products.

UGC, in the form of product evaluations, can be classified into two types based on their sources. The first type is online reviews generated by other buyers that can be found on the seller's e-commerce platform. This type of review is a relatively passive source of information that online shoppers can easily obtain. The second type of UGC is product evaluations that are hosted on third-party platforms [10–13], such as blogs, vlogs (video-blogs), which need to be actively sought out by consumers. Bilibili, TikTok, Consumer Reports, and TechRadar are examples of popular third-party platforms that provide consumers with the second type of UGC to aid in making online purchase decisions.

While existing literature has explored the impact of UGC from both e-commerce and third-party platforms (i.e., cross-platform) on product sales [14–16], there is a discrepancy in the research findings regarding the influence of UGC on product sales between these platforms. There is still no consensus on which platform's UGC has a stronger impact. On the one hand, some studies suggest that product reviews posted on non-commercially affiliated platforms (i.e., third-party platforms) are perceived as more credible than those on seller-affiliated platforms (i.e., e-commerce platforms), consequently having a greater impact on consumer decision-making [15,17]. In particular, some studies have indicated that, compared to their counterparts on e-commerce platforms, third-party platform UGC has a higher impact on the sales of high-involvement products [18]. For example, Gu et al. [15] compared UGC from Amazon (e-commerce platform) to that from three third-party platforms (CNET, DpReview, and Epinions) and found that third-party UGC had a significant impact on the sales of digital cameras, while UGC on the e-commerce platform did not exhibit a similar effect. On the other hand, some scholars have pointed out that the accessibility of information can affect consumers' judgments of its usefulness, where information received earlier or easier is perceived to be more useful [19,20]. For example, Song et al. [16] confirmed that the enterprise microblogging UGC has stronger predictive power for movie box office revenue than the UGC on Douban! Movies, which is a third-party platform, as it is easier for customers to receive the former information earlier. Their study also considered the influence of marketer-generated content (MGC) on movie box office performance, which is beyond the scope of our research.

However, despite these divergent insights, the existing literature has not thoroughly examined the underlying mechanism that influences the impact of cross-platform UGC, encompassing UGC from both e-commerce platforms and third-party platforms, on product sales. Specifically, the reasons for the varying effects of UGC across platforms have yet to be fully elucidated, making it challenging for businesses to directly apply the findings of relevant research in their marketing practices. In order to address gaps in the current body of research, we propose two primary research questions:

- Which of the following influences experiential product sales more: e-commerce platform online reviews or third-party platform product evaluations?
- What are the mechanisms that lead to differential impacts of cross-platform UGC on sales of experiential products?

The resolution of these issues is confronted with certain challenges. Firstly, during online shopping, consumer attitudes, and purchasing behaviors are susceptible to numerous external factors, involving neural and physiological responses [21,22]. The underlying mechanisms of this process are highly intricate. Secondly, the emergence of cross-platform UGC has intensified the heterogeneity of UGC features across various platforms, thereby introducing new challenges in comprehending its impact on consumer purchase intention and product sales. Lastly, due to the complexity of consumer buying behavior, there remains uncertainty surrounding the causal relationships within the aforementioned influences. To address these questions, we propose a comprehensive research framework based on a cross-platform perspective and ELM theory. Utilizing cross-platform UGC data, we employ text sentiment analysis and multiple regression to analyze and compare the effects of UGC from different platforms on consumers' purchase intention and product sales. Our study aims to reveal the underlying mechanism of the differential impacts of cross-platform UGC on product sales. To the best of our knowledge, we are the first to investigate the mechanisms that lead to differential impacts of cross-platform UGC on sales of experiential products. This study makes three main contributions:

- Integrating a cross-platform perspective and ELM theory. Through this integration, we develop a novel model that examines the underlying mechanisms influencing the impact of cross-platform UGC on product sales. This integration offers a new theoretical framework for understanding the persuasive effects of UGC in a multi-platform environment.
- Investigating the intrinsic mechanisms underlying the differential impact of cross-platform UGC on product sales. Through empirical analysis of cross-platform UGC data, this study explores the differential effects of e-commerce platform UGC and third-party platform UGC on product sales, along with the underlying causes for such differences, which were not clear in previous literature. By delving into this mechanism, our study enhances the understanding of how different types of UGC can vary in their effects on sales, with a specific focus on the influence of cross-platform UGC in the context of e-commerce. This study extends the existing literature in the intersecting domain of ELM and UGC by considering the diversified influence of cross-platform UGC on consumer information processing paths within the ELM process.
- Unveiling valuable insights for effective sales promotion strategies through cross-platform UGC utilization. We explore the moderating role of price in the relationships between cross-platform UGC and product sales. Furthermore, this research offers valuable insights to practitioners regarding sales promotion strategies through effective management practices of cross-platform UGC.

The subsequent sections of this paper are structured as follows. In Section 2, we present a literature review. Research model development and hypotheses are presented in Section 3. Next, the methodology and data collection methods employed in this study are delineated in Section 4. Section 5 presents the process of data analyses and results. A discussion of the results is presented in Section 6, and the conclusions and implications are presented in Section 7. Finally, the limitations and future directions of this research are described in Section 8.

2. Relevant Literature

A few streams of research are related to this study: the impact of UGC on product sales, consumers' information processing, and decision-making behaviors.

2.1. Effect of User-Generated Content on Online Sales

User-generated content (UGC) refers to media content created by the general public rather than paid professionals, and it is primarily distributed online. UGC is easily accessed by users in real-time via the Internet [7,23]. UGC takes various forms, including Twitter tweets, Facebook status updates, YouTube videos, and consumer-generated product reviews, among others [24]. A closely related concept frequently discussed in the literature is electronic word-of-mouth (eWOM), which refers to consumption-related statements posted on the Internet by potential, actual, or former customers about a product or company [25–27]. As eWOM is also user-generated, it is a form of UGC, and the two concepts share the same meaning within the e-commerce context [26]. Consequently, in our literature review on UGC, we include studies on eWOM in the e-commerce context without making any conceptual distinctions.

UGC is influential in reducing customer perceived risk and increasing online store sales, and has therefore garnered widespread attention from scholars [17,28–30]. Furthermore, online reviews on e-commerce platforms are one of the most prevalent types of UGC, consisting primarily of customer textual reviews. These are assessments and descriptions of a product or company, generated and shared by current or former consumers, conveying positive or negative feedback in e-commerce platforms [31]. Amazon, eBay, Tmall, and JD are renowned e-commerce platforms that attract numerous users and offer diverse product selections, resulting in a significant amount of UGC [23]. Consumers generally perceive such reviews as crucial and trustworthy sources of information that significantly influence their purchasing behavior [32,33]. Additionally, 70% of customers rely on online reviews when making their purchasing decisions [34].

Consumers rely on UGC from diverse sources to gather information about product attributes and quality, especially when considering experiential products [16]. Xiao and Benbasat [35] pointed out that consumers rely more on their own information when purchasing search-based products. Still, they refer to other consumers' choices when buying experiential products [17]. Park and Lee [36] also found that compared to search-based products, UGC effects are more significant for experiential products. Additionally, online reviews provide new information from the perspective of customers who have purchased and used the product. The customers share their experiences, evaluations, and opinions on e-commerce platforms [37], and this user-centric information about a product or service becomes part of the UGC [31].

The measurement of the impact of UGC mainly revolves around three key elements: valence, volume, and dispersion [38]. While research on valence has produced relatively consistent findings, there is significant controversy surrounding the influence of volume and dispersion on product sales. On the one hand, the impact of review length, which is also a form of UGC volume, on sales is controversial. Intuitively, it is generally believed that the length of reviews represents the popularity of products and positively impacts sales. However, some studies have suggested that when review length exceeds a certain threshold, excessively long reviews will increase consumers' cognitive load, reducing the usefulness of reviews [33,39,40]. Therefore, to fully capture the economic impact of UGC, it is important to understand how consumers process the information embedded in UGC [41]. On the other hand, there is also considerable controversy regarding the impact of UGC dispersion on product sales [42,43]. From the accessibility-diagnosticity theory perspective, rating bias leads to information ambiguity, reduces information diagnosticity, and makes it difficult for consumers to judge product quality [44]. However, some scholars have pointed out that the information content of dispersion indicators is greater, and they have introduced entropy of review sentiment polarity into the model [45]. The results show that these indicators significantly impact product sales, but there is no consistent conclusion on the impact direction.

On e-commerce platforms, online reviews generally refer to the reviews made by buyers and typical measurement attributes of online reviews besides review length include numerical rating and review text. A numerical rating is a quantitative summary of consumers' experience, attitude, opinion, or emotion towards a purchased product or service, typically represented by the number of stars, while review text is an open qualitative description of reviewers' opinions and emotions about products or services in the form of text [5]. Although review text is one of the important factors influencing sales, most previous studies have focused on star ratings, with a relatively less in-depth exploration of review text information [46]. Furthermore, scholars have also paid attention to the impact of third-party platform reviews on product sales. For example, Wu et al. [18] established a log-linear regression model to study the different effects of third-party website reviews and retailer website reviews on product sales but did not reveal the underlying impact mechanisms. In summary, while there is already a wealth of research on the impact of UGC on product sales, there are still some controversies and deficiencies in the measurement of UGC impact, requiring further exploration in combination with UGC from various sources and text information analysis tools.

2.2. Elaboration Likelihood Model

The elaboration likelihood model (ELM), originally proposed by renowned psychologists Petty and Cacioppo [47], is commonly used in social psychology to explain the internal mechanisms of attitude change when individuals are faced with persuasive information. The ELM suggests that both the central and peripheral paths, which are viewed as two relatively distinct paths to persuasion [48], influence individual information processing and attitude change. When an individual's information processing ability and motivation to participate are high, the central path plays a dominant persuasive role. At this time, the individual is inclined to think deeply about the main points of the information and pay more attention to the quality of the information itself. When an individual's information processing ability and motivation to participate are low, the peripheral path plays a dominant persuasive role. At this time, the individual is inclined to rely on environmental factors and heuristic cues and pay more attention to the credibility of the information source [32,49].

The ELM has been widely applied in e-commerce to analyze changes in consumer attitudes and behaviors [50]. Although users can process information through either the central or peripheral path, in reality, they tend to use both paths together. Moreover, Park and Kim [51] used the ELM to study the impact of online reviews' type, quantity, and consumers' expertise on the usefulness of online reviews and their purchase intention. Lee et al. [49] analyzed, using the ELM, the attention paid by consumers to negative online reviews of products with different levels of involvement and found that for negative reviews, high involvement consumers are more concerned about the quality of the review. In contrast, low-involvement consumers focus more on the views and attitudes expressed in the review. Furthermore, ELM-related studies indicate that when making purchase decisions, consumers often have incomplete information about product quality, seller reputation, and other factors. Therefore, they need to reduce uncertainty through information search [52].

From the ELM perspective, researchers have also studied the impact of UGC information from different sources on consumer purchase decisions and product sales. For example, Liao and Huang [53] focused on Weibo (a popular micro-blogging platform in China) and used ELM to investigate the impact of different Weibo marketing channels on movie sales using secondary data. However, they did not examine the effect of Weibo UGC with different emotional tones on consumers. Instead, the number of Weibo posts was used as one of the independent variables for data analysis. Additionally, the impact of cross-platform UGC on consumers and sales has not been investigated.

In existing research exploring the impact of UGC from both e-commerce and third-party platforms on product sales, the ELM model has been utilized and provides a theoretical foundation for future studies. However, there are still some shortcomings in the literature that deserve attention, including (1) existing research has primarily focused on the impact of cross-platform UGC on product sales to determine which platform's UGC has a greater influence. However, these studies have overlooked the potential mechanisms through which UGC from different types of platforms may have differential effects on product sales. Furthermore, (2) few studies have integrated text sentiment analysis to explore the impact of cross-platform UGC on product sales, despite sentiment analysis being a powerful tool in UGC analysis [54–56]. Table 1 summarizes the most relevant studies in literature, highlighting the distinctive aspects of our work in comparison to theirs.

Table 1. Comparison of the related studies.

Study	Platform Type		Content Type		Sentiment Analysis	Mechanism
	EP	TP	MGC	UGC		
Song et al. [16]	✓	✓	✓	✓	-	-
Gu et al. [15]	✓	✓	-	✓	-	-
Chung et al. [57], Zhou and Guo [19]	-	✓	-	✓	-	-
Chen et al. [58]	✓	-	-	✓	✓	-
Goh et al. [59], Liao and Huang [53]	-	✓	✓	✓	-	-
Yi et al. [17], Alzate et al. [20], Li et al. [28]	✓	-	-	✓	-	-
Our study	✓	✓	-	✓	✓	✓

Note: EP = e-commerce platform; TP = third-party platform; MGC = marketer-generated content; Mechanism = The process or reasons behind the differential impact of cross-platform UGC on experiential product sales.

3. Model Development and Hypothesis

3.1. Theoretical Model

This study focuses on the impact of cross-platform UGC on experiential product sales, specifically examining the differential effects between UGC on e-commerce platforms and UGC on third-party platforms. The underlying mechanism behind these differences is explored. Our focus is on cosmetic products, which represent a typical experiential product. When consumers select cosmetic products on e-commerce platforms, they primarily encounter two different types of UGC (i.e., cross-platform UGC):

- E-commerce platform UGC: online reviews on mainstream e-commerce platforms (such as Tmall, JD, and Amazon), primarily comprise detailed textual product reviews shared by users who have previously made purchases. These reviews are accompanied by high-quality evidence directly linked to the transactions.
- Third-party platform UGC: product evaluations on third-party platforms (such as Bilibili, TikTok, and TechRadar), which provides users with peripheral clues about products and is considered a more reliable source [15,17], encompassing various formats such as video blogs and images.

In the given scenario, which type of UGC would have a greater impact on consumers' purchase decisions? Furthermore, why do different platforms show variations in the influence of UGC on consumers' purchase decisions? These questions are the focal point of this article since consumers' purchase decisions ultimately manifest as sales on e-commerce platforms. The ELM is a dual-process theory, which is often used to explain people's cognitive processes and decision-making mechanisms when accepting and processing information [60,61]. ELM theory suggests that external information (such as, but not limited to UGC) is a significant factor in driving attitude change and subsequent behavior change [57,62]. The core idea of ELM is that individuals employ two different processing paths, namely the *central path* and the *peripheral path* when making decisions. The central path refers to the process of carefully considering the *argument quality* and evaluating it. Argument quality refers to an individual's perception of the strength and soundness of the arguments presented in a message, as opposed to weak and deceptive ones. On the other hand, the peripheral path involves drawing conclusions based on heuristics or relying on cues such as source credibility (i.e., *peripheral cues*), without critically evaluating the actual merits of the argument [60,63]. Based on the principles of the ELM and the characteristics of cross-platform UGC in e-commerce platforms, it is suggested that UGC on the e-commerce platform, which is associated with argument quality, should be processed through the central path. On the other hand, third-party platform UGC, which is primarily related to peripheral cues, should be processed through the peripheral path. Furthermore, individuals who choose the peripheral path typically either lack the desire or are unable to invest the cognitive effort required for elaboration [64].

The ELM offers a conceptual basis for investigating attitude and persuasion [64]. According to the ELM, recipients of information vary in their ability and motivation to engage in elaboration, which influences the path they use to process information, subsequently affecting the formation or change of their attitudes. The ELM captures this variation in ability and motivation through the construct of elaboration likelihood [62].

Therefore, adopting ELM as a theoretical framework aligns with the research question of this paper. It allows for a comparison of different types of UGC and a clearer determination of the role (i.e., argument quality or peripheral cues) each type plays in persuasive information processing. Ultimately, this approach will uncover the mechanisms through which different types of UGC influence product sales. Specifically, we utilize ELM theory as our theoretical framework for the following reasons: Firstly, ELM is widely recognized and extensively used in the field of persuasion and information processing [53,57,65]. It provides a comprehensive understanding of how individuals process and evaluate persuasive messages, considering both central and peripheral paths of information processing. Secondly, ELM is a quintessential dual-process model [60,61,63], and it is particularly suitable for our research focus on electronic commerce and the influence of cross-platform UGC on product sales. ELM helps us analyze the impact of UGC on consumer decision-making in different scenarios, such as e-commerce platforms and third-party platforms. By employing ELM, we can compare and contrast the effects of different types of UGC and gain insights into the underlying mechanisms behind their influence on product sales. Lastly, ELM offers a systematic framework to examine the role of factors such as motivation, cognitive abilities, and message characteristics in information processing. This allows us to investigate why different types of UGC may have varying effects on product sales. By leveraging ELM, we aim to provide a comprehensive explanation of the differential impacts of UGC in cross-platform scenarios.

In our research, according to the ELM, when faced with cross-platform UGC, customers may employ different processing paths, namely the central path and the peripheral path, based on their motivation and elaboration ability to process information. These differential processing strategies are expected to influence customers' attitudes, which in turn will impact their purchase decisions. The conceptual model of our research, which is based on the cross-platform UGC perspective and ELM theory [60,62], is illustrated in Figure 1.

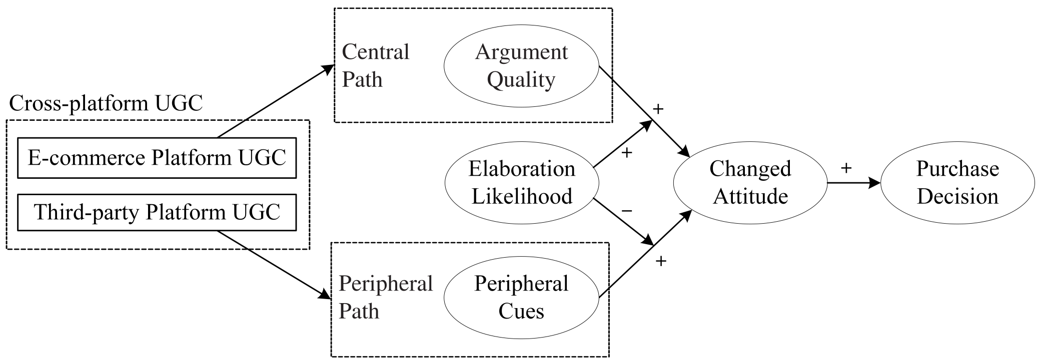

Figure 1. Conceptual model.

Although online reviews on e-commerce platforms and product evaluations on third-party platforms both belong to UGC, they come from platforms of different natures and have different impact paths on consumers under the ELM framework. As an important form of UGC, online reviews significantly impact consumer purchase decisions and product sales [32]. When judging the usefulness of online reviews, consumers usually consider the extremity and depth of the reviews [66], which can be measured by review inconsistency [14] and review length [67], respectively. In addition to online reviews on e-commerce platforms, consumers can also obtain product evaluation information from third-party platforms to guide their consumption decisions. However, it is difficult for consumers to directly use the length and inconsistency of online reviews on e-commerce platforms as a reference for their decisions. The length and inconsistency of online reviews on e-commerce platforms can only be processed when consumers have sufficient motivation and sophisticated information processing capabilities, during which the central path assumes a dominant persuasive role. Therefore, the length and inconsistency of online reviews, which belong to the e-commerce platform UGC, tend to be processed through the central path. On the other hand, third-party platforms are relatively more objective and neutral. User-generated product evaluations on third-party platforms are mainly presented in the form of videos, which contain richer and more intuitive information. Consumers do not need a high level of information processing capability and are more likely to resonate emotionally with the content creators, which can lead to purchase decisions. Moreover, the more evaluation videos on the product, the easier it is for consumers to obtain its experiential information. Therefore, the number of product evaluation videos, which belong to the third-party platform UGC, tends to be processed through the peripheral path.

To clarify how cross-platform UGC affects consumer purchase decisions and sales for experiential products, this study builds a research model based on the conceptual model in Figure 1, and the research model is illustrated in Figure 2. The central path focuses on the impact of online review length and online review inconsistency on product sales on e-commerce platforms. The peripheral path investigates the impact of the number of product evaluation videos on third-party platforms on product sales. Additionally, cross-platform UGC may influence sales by affecting consumers' purchase intentions [53], which are highly responsive to pricing [28,58]. For instance, Monroe [68] demonstrated that customers have absolute thresholds for prices, and when a price surpasses these upper or lower thresholds, customers will decline the purchase due to the price. Therefore the model explores the mediating effect of purchase intention and the moderating effect of the product price on the relationship between cross-platform UGC and product sales. Moreover, store rating is included as a control variable to eliminate the influence of store dimensions on product sales, as consumers often use store rating as an important reference for consumption decisions [69,70].

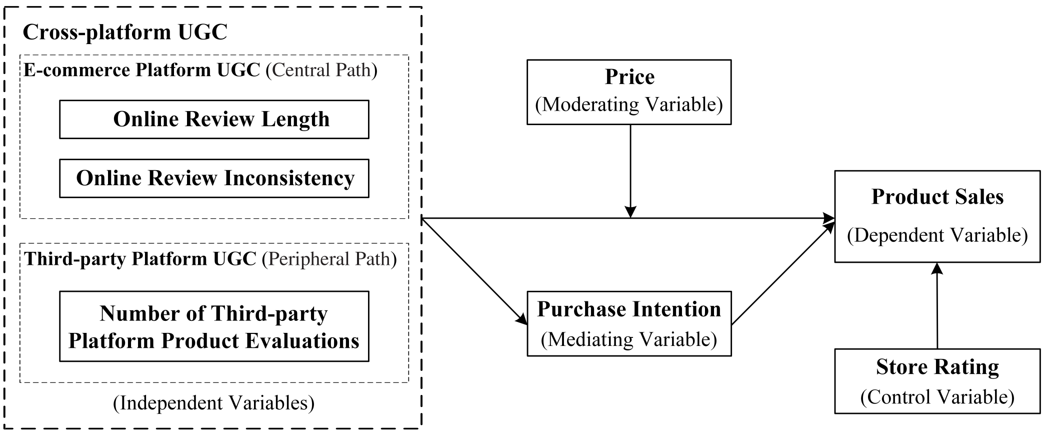

Figure 2. Research model.

3.2. Hypothesis

3.2.1. Impact of Central Path UGC on Product Sales

Online review length can impact product sales in two ways. Firstly, the length of online reviews can be measured by the total number of words or characters in the review [71,72]. The longer the average review length, the more detailed information about the product or service it contains, and the more useful consumers perceive it [73]. This can help consumers better understand the product or service, positively impacting product sales. Secondly, experiential products have significant individual differences in user experience and effects. Consumers tend to pay more attention to online reviews rich in content and detail. Longer reviews convey more information, which makes it easier for consumers to reduce the risk of purchasing errors due to a lack of product user experiences. Consumers are more likely to uncover omitted details in longer reviews [72]. This notion is supported by Bosman et al. [74], who confirmed that the length of reviews is a dependable gauge of their credibility. Based on these, this paper proposes the following hypothesis:

Hypothesis 1 (H1): *The length of online reviews positively influences product sales.*

Review inconsistency refers to the extent of sentiment consensus among reviewers on product evaluation, with lower consensus leading to higher review inconsistency [75]. In particular, when consumers are extremely satisfied or dissatisfied, they are more likely to post reviews online, resulting in a bimodal distribution of user ratings [76]. When faced with reviews with high levels of inconsistency, most consumers attribute it to unstable product quality, particularly for experiential products. Consumers tend to be more cautious in purchase decisions. In addition, the inconsistency of online review information can also exacerbate the uncertainty of online shopping environments, leading to a reduced likelihood of product purchasing behavior [77]. For experiential products, the inconsistency of consumer evaluations expressed in reviews can have a negative impact on product sales [78]. Therefore, inconsistent online reviews can increase consumers' risk perception and reduce product sales. Based on these, this paper proposes the following hypothesis:

Hypothesis 2 (H2): *The inconsistency of online reviews negatively influences product sales.*

3.2.2. Impact of Peripheral Path UGC on Product Sales

User-generated content often expresses users' attitudes toward a product. It can help shape other consumers' perceptions of product quality, which influences their purchase intentions and decisions, known as the recommendation effect [79]. For consumers, third-party UGC platforms can provide more important information about products or brands that cannot be directly observed. Consumers tend to purchase products that attract numerous reviews [80]. For example, marketers can use YouTube beauty channels to provide alternative experiences (i.e., product evaluations) for cosmetic consumers, thereby reducing consumers' perceived risks and enhancing their purchase intentions [81]. On the other hand, the products with many reviews on third-party platforms indicate their popularity among consumers or a large user base. This suggests that the product is reliable and of good quality, which can stimulate potential buyers' demand [82]. In addition, vloggers on third-party platforms are more willing to show their pleasant usage experiences and high-quality products to audiences to gain more collections, follows, and shares. Therefore, the number of third-party platform product evaluations also represents consumers' affirmation of the quality and usage experience of the product to some extent, and products with more third-party platform product evaluations are more likely to be purchased by consumers. Based on the above, we propose the following hypothesis:

Hypothesis 3 (H3): *The number of third-party platform product evaluations positively influences product sales.*

3.2.3. Mediating Effect of Purchase Intention

The consumption behavior of individuals is a series of reactions in which individuals, influenced by external stimuli, including information, undergo a series of difficult-to-measure psychological changes, resulting in a willingness to purchase and a series of corresponding purchase behaviors. Consumer purchase intention represents the likelihood of an individual purchasing a particular product, with high purchase intention indicating a high likelihood of purchase and low purchase intention indicating a low likelihood of purchase. UGC for experiential products serves as sensory cues that can be used as external stimuli to induce audience engagement, increase their purchase intention [83,84], and increase the likelihood of consumers making purchase decisions when their purchase intention is high enough.

Specifically, informative and commendable online reviews, typically characterized by lengthier reviews, serve to mitigate shopping uncertainty and bolster consumer purchase intention, thereby playing a crucial role in increasing market demand or product sales [51]. In addition, the sentiments expressed in product evaluations, which mainly affect consumers' purchase intention, significantly impact the future sales performance of the product [85–87]. Hence, review inconsistency can potentially escalate consumers' perceived risk, impede their purchase intention, and subsequently lower product sales. On the other hand, the greater the number of UGC on third-party platforms for a product, the more consumers trust the quality of the product, and the increased trust leads to a stronger intention to purchase, which in turn increases the likelihood of making a purchase decision [80,82]. Based on the above, we propose the following hypothesis:

Hypothesis 4a (H4a): *Purchase intention plays a mediating role in the impact of review length on sales.*

Hypothesis 4b (H4b): *Purchase intention plays a mediating role in the impact of review inconsistency on sales.*

Hypothesis 4c (H4c): *Purchase intention plays a mediating role in the impact of the number of third-party platform evaluations on sales.*

3.2.4. Moderating Effect of Product Price

Previous research suggests that product price positively moderates the relationship between online reviews and product sales, primarily through its promotional function and use as a signal of quality [88,89]. Generally, prices can act as a promotion tool, with low prices stimulating consumer willingness to purchase and high prices suppressing it [90,91]. However, prices can also convey a product's quality signal. Higher prices potentially indicate that the product has better quality compared to similar products, thereby enhancing consumer willingness to purchase. The quality signaling function of price contributes to reinforcing the impact of UGC on sales to a certain extent. For example, the longer online reviews of high-priced products may lead consumers to perceive the product as popular and of high quality, thereby positively influencing product sales.

Compared to purchasing low-priced products, consumers who purchase high-priced experiential products tend to have a higher perception of product risk, which may result in a greater perceived loss. Campbell and Goodstein [92] found that as perceived risk increases, consumers tend to become more cautious and pay greater attention to risk avoidance strategies. Therefore, when it comes to higher-priced products, consumers tend to be more cautious in their purchase decisions and are more sensitive to inconsistent online reviews. As a result, sellers can mitigate the negative impact of inconsistent reviews on sales by offering price reductions. The promotional effect is expected to offset the adverse effects of unfavorable reviews [89].

Perceived product risk, which comes from the decision to purchase high-priced products, can promote risk-avoidance behavior in online consumers. This may result in them spending more time referring to the product information provided by information retrieval systems or third-party platforms [93]. Therefore, when consumers are faced with high-priced products, they are more motivated to refer to product evaluations on third-party platforms, in addition to online reviews on e-commerce platforms, and to synthesize cross-platform UGC generated from central and peripheral paths in order to facilitate the formation of purchase decisions and strengthen the impact of third-party platform UGC on sales. Moreover, a higher quantity of UGC on third-party platforms for a product indicates that additional information about the product is more easily accessible to consumers. As price serves as a signal of quality, consumers are more likely to trust the quality of high-priced products. Hence, the impact of the quantity of third-party platform UGC on the sales of high-priced products is more significant. Based on the above analysis, we have formulated the following hypothesis:

Hypothesis 5a (H5a): *Product price has a positive moderating effect on the relationship between online review length and product sales.*

Hypothesis 5b (H5b): *Product price has a positive moderating effect on the relationship between online review inconsistency and product sales.*

Hypothesis 5c (H5c): *Product price has a positive moderating effect on the relationship between third-party platform review quantity and product sales.*

4. Research Methodology

4.1. Variable Definition and Measurement

The current study investigates the impact of several variables on product sales (*Sales*) in the cross-platform context. Specifically, it examines the influence of online review length (*Char*), online review inconsistency (*Svar*), and the number of third-party platform product evaluations (*Tugc*) as independent variables. Additionally, this study considers purchase intention (*Pintent*) as a mediating variable, product price (*Price*) as a moderating variable, and controls for store rating (*Store*). The dependent variable of interest is product sales (*Sales*). The specific variables and their measurement methods are presented in Table 2.

Table 2. Variable description and measurement methods.

Variables	Symbols	Path	Variable Type	Measurement	Data Source
Online Review Length	*Char*	Central Path	Independent	Average character count of consumer online reviews for each product [72,73]	E-commerce Platform
Online Review Inconsistency	*Svar*		Independent	Sentiment variance of consumer online reviews for each product [14]	E-commerce Platform
Number of Third-party Platform Product Evaluations	*Tugc*	Peripheral Path	Independent	Number of product evaluations published on the third-party platform [16,72]	Third-party Platform
Purchase Intention	*Pintent*	-	Mediating	Number of users who add the product into their favorites [28,94]	E-commerce Platform
Product Price	*Price*	-	Moderating	Product's price in RMB yuan	E-commerce Platform
Product Sales	*Sales*	-	Dependent	Monthly sales volume of the product	E-commerce Platform
Store Rating	*Store*	-	Control	Average of store description, service, and logistics ratings [95]	E-commerce Platform

4.2. Sample Selection and Data Collection

In terms of sample category selection, this study focuses on a representative experiential product category in the cosmetic industry: liquid foundation. Liquid foundation stands out among cosmetic products due to its distinctive characteristics, including frequent product introductions, diverse sub-categories, and a wide price range. It holds a significant position in the market, commanding a substantial market share and capturing the interest of consumers. In addition, a considerable amount of UGC specifically related to liquid foundations is available on both e-commerce platforms and third-party ones, providing consumers with abundant reference information to guide their purchasing decisions. Considering these factors, liquid foundation serves as an ideal representative for conducting a comprehensive analysis of the impact of cross-platform UGC on experiential product sales.

When selecting e-commerce platforms and third-party platforms, this study chose (1) Tmall (https://www.tmall.com, accessed on 28 November 2021), one of China's most active and strongest business to customer (B2C) e-commerce platforms, and (2) Bilibili (https://www.bilibili.com, accessed on 28 November 2021), one of China's most popular video sharing platforms, which is often referred to as the counterpart of Youtube in China. Tmall and Bilibili were selected due to their platform scale, influence, and relevance to our study. Specifically, Tmall has accounted for more than 50% of the sales share of comprehensive cosmetic products in both 2019 and 2020. Bilibili has gathered many high-quality UGC, and it is also one of the cosmetic product evaluation-sharing platforms with the highest active penetration rate among makeup consumers, according to the "2020 China Internet Annual Report" published by QuestMobile. Therefore, Tmall and Bilibili are good representatives of e-commerce platforms and third-party platforms, respectively.

We analyzed the hypotheses in Section 3.2 using the e-commerce platform UGC from Tmall and the third-party platform UGC from Bilibili. All data were collected from 28 November to 23 December 2021. The data collection procedure involved several steps. First, we selected the liquid foundation products to be included in the sample. We searched for liquid foundation products on Tmall using the keywords "liquid foundation" and the platform gave the results and presented a comprehensive ranking of related products based on the input keywords. This study collected data on the top 400 liquid foundation products based on the comprehensive ranking, which was employed to minimize sample selection bias. Second, we collected e-commerce platform UGC data of the 400 products from the Tmall platform. For each product, we collected the following pieces of information (all of which were visible on Tmall): the title of the product, the product price (*Price*, in RMB yuan), the monthly sales volume (*Sales*), the number of bookmarks (*Pintent*), the store rating (*Store*), as well as the top 100 reviews (or all reviews if the total number is less than 100) used to calculate the online review inconsistency (*Svar*) through text sentiment analysis. We selected the first 100 reviews on Tmall based on their posting time, giving priority to recent reviews that have a significant impact on consumer decision-making. This subset is considered representative as it acknowledges consumers' limited capacity to read through multiple reviews, with browsing 100 reviews requiring navigation through five pages on Tmall's platform. After deleting 29 products that were off the shelves at the time of data collection, 371 liquid foundation products on Tmall's platform were obtained. Third, we manually collected third-party platform UGC data of the 371 products from the Bilibili platform. For each product, using the "brand name + modifier + product category" as keywords (e.g., "Maybelline + Super Stay + Foundation"), we searched on the Bilibili platform to obtain the number of product evaluation videos, which were visible on Bilibili, as the third-party platform UGC. Fourth, we additionally excluded the samples that did not meet the following criterion: neither the number of Bilibili evaluation videos nor the number of online reviews is zero. Consequently, 71 samples were eliminated. Finally, objective data from 300 Tmall liquid foundation products (corresponding to 29,557 online reviews) and their corresponding Bilibili UGC data (corresponding to 73,924 product evaluation videos) were obtained and stored in structured Excel spreadsheets for subsequent analysis. The collected liquid foundation samples cover multiple brands, such as L'Oreal, Estee Lauder, Lancome, and Shiseido. To verify whether the sample size of 300 is adequate, we performed post-hoc statistical power analysis using the G*power software package (version 3.1.9.7) [96,97]. The input parameters were set based on the characteristics of the main effects regression model, including two-tailed t-tests, an α error probability of 0.05, and a total of four predictors. The partial R^2 values for *Char*, *Svar*, and *Tugc* were found to be 0.139, 0.101, and 0.041, respectively. The results revealed that the statistical power of our sample size reached 0.99, 0.99, and 0.95, respectively. These values exceed 0.80, indicating that our proposed model possesses a sufficient sample size.

Specifically, we can utilize the collected data to determine the values of the variables. Firstly, as previously stated, we could obtain the value of *Tugc*, *Price*, *Sales*, and *Store* directly from Tmall and Bilibili platforms. Additionally, as shown in Table 2, we define the average character count of each product's online reviews as the online review length (*Char*). This value can be computed by calculating the average character count of the online reviews collected from the Tmall platform. Regarding the measurement of purchase intention (*Pintent*), we represent purchase intention by the number of times a product has been favorited by customers [94], which can be obtained from Tmall. The online review inconsistency (*Svar*) is measured based on the sentiment variance of the comments, as shown in Table 2. Furthermore, sentiment variance is determined through text sentiment analysis and an inconsistency calculation, which is detailed next in Section 4.3.

4.3. Online Review Inconsistency and Text Sentiment Analysis

Sentiment analysis is a branch of natural language processing (NLP) that involves automatically classifying text based on its sentiment or emotional tone using valence or polarity. The present study utilizes text sentiment analysis to investigate the underlying emotional state of online reviews and assess consumers' emotional attitudes using a polarity score for each word. We next explain the sentiment polarity analysis and how that can be used to compute the tone of a review text. Finally, we'll show how the tone is used to derive online review inconsistency, *Svar*.

4.3.1. Sentiment Polarity Analysis

To avoid manually annotating the training data, this study utilized the SnowNLP library for adaptive sentiment annotation to build the corpus. Sentiment words that SnowNLP judges to have a score greater than 0.8 are labeled as 1 (positive sentiment), and those with a score less than 0.2 are labeled as 0 (negative sentiment). Sentiment words scoring within the range of (0.2, 0.8) indicate ambiguous sentiment and are not further processed. The specific steps for sentiment polarity analysis of online review data using Python have presented in Table A1 in Appendix A.

4.3.2. Tone and Online Review Inconsistency Measures

The level of discrepancy in sentiment orientation within online reviews increases with higher sentiment variance, indicating greater inconsistency among the reviews. Therefore, this study employs sentiment variance as a metric to measure the level of inconsistency in reviews. After conducting sentiment polarity analysis on online review texts, the sentiment orientation of each review text can be calculated. To further comprehensively evaluate the overall sentiment orientation of each product expressed by consumers, it is necessary to integrate the sentiment orientation of each review. To calculate the comprehensive sentiment orientation of each product, this study adopts the definition of text-based sentiment value by Davis et al. [98], as shown in Equation (1):

$$Tone\_i = \frac{PosSent_i - NegSent_i}{TotalSent_i} \tag{1}$$

The variable $Tone\_i$ represents the sentiment value of a certain product's i-th review texts. $PosSent_i$ denotes the number of positive evaluation texts in the i-th review, $NegSent_i$ represents the number of negative evaluation texts in the i-th review, and $TotalSent_i$ is the total number of evaluation texts in the i-th review.

To scale the processed data to the range of [0, 1], which is more suitable for subsequent analysis in this paper, we applied a linear adjustment, as shown in Equation (2). The specific method for calculating the inconsistency of reviews is shown in Equation (3).

$$Tone_i = \frac{Tone\_i + 1}{2} \tag{2}$$

$$Svar = \frac{\sum_{i=1}^{n} \left(Tone_i - \overline{Tone}\right)^2}{n-1} \tag{3}$$

Here, $\overline{Tone}$ denotes the mean sentiment value of all reviews for the product, assuming the total number of product reviews in the sample data is n. The $n-1$ (instead of n) in the denominator is because we are using sample data.

5. Data Analysis and Results

5.1. Descriptive Statistics and Correlation Analysis

The descriptive statistics of the raw sample data are presented in Table 3 (using R version 4.2.2 for all subsequent data analysis). Based on the descriptive statistics in Table 3, it can be observed that there are significant differences in the magnitudes of the various observed variables due to differences in the measurement scales. To minimize the potential bias in the analysis results caused by these differences in magnitudes, all subsequent data analyses were conducted by adding 1 to the raw data and then applying a natural logarithm transformation [38,99]. The widely used Pearson correlation test [100] was employed to analyze correlations between variables, and the results are presented in Table 4.

Table 3. Descriptive statistics of the raw sample data.

Variables	Maximum	Minimum	Mean	SD	Median
Sales	100,000.00	142.00	3432.09	9280.58	782.50
Char	118.94	17.33	41.43	16.77	36.95
Svar	0.21	0.00	0.07	0.04	0.07
Tugc	1000.00	1.00	246.41	308.26	102.50
Pintent	5,426,310.00	312.00	248,902.22	663,702.37	48,441.50
Price	2300.00	29.90	226.81	243.33	139.00
Store	4.90	4.60	4.81	0.04	4.80

Note: SD = standard deviations.

Table 4. Correlation coefficients.

Variables	Mean	SD	1	2	3	4	5	6
1. *Sales*	6.92	1.43						
2. *Char*	3.68	0.35	0.41 **					
3. *Svar*	0.07	0.04	−0.39 **	−0.37 **				
4. *Tugc*	4.48	1.70	0.21 **	−0.06	−0.08			
5. *Pintent*	10.79	1.91	0.62 **	0.24 **	−0.27 **	0.27 **		
6. *Price*	5.08	0.78	−0.11	0.06	0.24 **	0.08	0.10	
7. *Store*	1.76	0.01	−0.11	0.11	−0.00	−0.07	−0.02	0.33 **

Note: $N = 300$, ** $p < 0.01$ (two-tailed); SD = standard deviations.

As shown in Table 4, the correlation coefficient between purchase intention (*Pintent*) and product sales (*Sales*) is 0.62, indicating a significant but not unreasonably high correlation. The correlation coefficients between the three independent variables, namely, review length (*Char*), review inconsistency (*Svar*), third-party platform product evaluations count (*Tugc*), and the dependent variable, product sales (*Sales*), are 0.41, −0.39, and 0.21, respectively, indicating no strong correlation. However, correlation coefficients cannot reflect causal relationships between variables or mediating and moderating effects, and thus, hypothesis testing requires the combined use of regression analysis and path analysis methods.

5.2. Main Effect Analysis

To further determine whether there is multicollinearity in the regression model, this paper reports the variance inflation factor (VIF) index in the regression analysis. We found no evidence of significant multicollinearity issues since none of the VIFs in our study is much greater than 1 [101]. When conducting main effect analysis, three regression models were constructed, respectively shown in Equations (4)–(6), where β_0 represents the intercept, β represents the variable coefficient, ε represents the random error term, and other variables have been defined in Section 4.1.

$$Sales = \beta_0 + \beta_1 Char + \beta_2 Svar + \beta_3 Store + \varepsilon \quad (4)$$

$$Sales = \beta_0 + \beta_1 Tugc + \beta_2 Store + \varepsilon \tag{5}$$

$$Sales = \beta_0 + \beta_1 Char + \beta_2 Svar + \beta_3 Tugc + \beta_4 Store + \varepsilon \tag{6}$$

Equation (4) represents the analysis of the regression model M1 for the central path (including *Char*, *Svar*), Equation (5) represents the analysis of regression model M2 for the peripheral path (including *Tugc*), and Equation (6) represents the analysis of the comprehensive regression model M3 for the central and peripheral paths, with specific results shown in Table 5.

Table 5. Parameter results of the main effects model.

Variables		*Sales*					
		M1		M2		M3	
		Coefficient	**VIF**	**Coefficient**	**VIF**	**Coefficient**	**VIF**
Independent Variable (Central Path)	*Char*	1.360 ***	1.170			1.437 ***	1.179
	Svar	−10.393 ***	1.156			−9.536 ***	1.168
Independent Variable (Peripheral Path)	*Tugc*			0.169 ***	1.005	0.169 ***	1.019
Control Variable	*Store*	−29.777 **	1.013	−19.497	1.005	−27.265 **	1.017
Adjusted R^2		0.25		0.05		0.29	
F-value		34.4 ***		8.2 ***		31.3 ***	

Note: $N = 300$, *** $p < 0.001$, ** $p < 0.01$ (two-tailed).

First, check whether the regression model has statistical significance, mainly from two aspects: whether it meets the significance requirements and whether it has multicollinearity. From the results of the three main effect regression models in Table 5, it is evident that the F-values of the three models M1, M2, and M3, all meet the 0.1% level of significance, reaching the significance requirement, indicating that the constructed model has statistical significance. In addition, the VIF coefficients of the M1, M2, and M3 models are very close to 1, indicating that they do not have obvious multicollinearity problems.

The adjusted R^2 values of models M1, M2, and M3 are 0.25, 0.05, and 0.29, respectively, as shown in Table 5. The results indicate that the central path has a higher degree of explanation for product sales compared to the peripheral path. Furthermore, when both paths are included in model M3, the adjusted R^2 value increases to 0.29, indicating a higher degree of explanation by the comprehensive central and peripheral paths. Moreover, we calculated the standardized regression coefficients of *Char*, *Svar*, and *Tugc* in model M3, which were 0.352, −0.245, and 0.201, respectively. These results suggest that the impact of UGC on sales is greater for e-commerce platforms than for third-party platforms, which is inconsistent with the research conclusions of some existing literature, such as refs. [15,17,18].

In the comprehensive model, online review length, online review inconsistency, and third-party evaluation count are all significant at the 0.1% level. Except for online review inconsistency, they all positively promote product sales. We conclude that hypotheses H1–H3 are supported.

5.3. Analysis of the Mediating Effects of Purchase Intention

To explore the reasons and mechanisms behind the greater influence of UGC on sales in e-commerce platforms compared to third-party platforms, we conducted a mediation analysis of purchase intention. The regression models M4 and M5 were constructed as shown in Equations (7) and (8), respectively. The mediating effect model results were obtained and presented in Table 6. From Table 6, it can be seen that the VIF values for the corresponding variables in models M4 and M5 are close to 1, indicating that there is no obvious problem of multicollinearity.

$$Pintent = \beta_0 + \beta_1 Char + \beta_2 Svar + \beta_3 Store + \beta_4 Tugc + \varepsilon \tag{7}$$

$$Sales = \beta_0 + \beta_1 Char + \beta_2 Svar + \beta_3 Store + \beta_4 Tugc + \beta_5 Pintent + \varepsilon \quad (8)$$

Table 6. Parameter results of the mediating effects model.

Variables		*Pintent*		*Sales*	
		M4		M5	
		Coefficient	VIF	Coefficient	VIF
Independent Variable (Central Path)	*Char*	1.074 ***	1.179	1.036 ***	1.226
	Svar	−9.433 **	1.168	−6.010 ***	1.208
Independent Variable (Peripheral Path)	*Tugc*	0.305 ***	1.019	0.055	1.108
Control Variable	*Store*	−6.299	1.017	−24.911 **	1.018
Mediating Variable	*Pintent*			0.374 ***	1.208
Adjusted R^2		0.16		0.51	
F-value		15.37 ***		59.99 ***	

Note: $N = 300$, *** $p < 0.001$, ** $p < 0.01$ (two-tailed).

This paper employs the Bootstrap mediation test method to examine the mediating effect of purchase intention, and the number of resamples is set to 5000. The mediating effect is considered significant if the confidence interval does not include 0. As shown in Table 7, *Char* has a significant positive indirect effect on *Sales* through *Pintent* (coefficient = 0.401, 95% CI = [0.144, 0.680]), *Svar* has a significant negative indirect effect on *Sales* through *Pintent* (coefficient = −3.525, 95% CI = [−5.704, −1.340]), and *Tugc* has a significant positive indirect effect on *Sales* through *Pintent* (coefficient=0.114, 95% CI = [0.070, 0.160]).

Table 7. Summary of mediating effects of purchase intention.

Route Description	Coefficients	95% CI	*p*-Value
Char → *Pintent* → *Sales*	0.401	[0.144, 0.680]	0.0024 **
Svar → *Pintent* → *Sales*	−3.525	[−5.704, −1.340]	0.0024 **
Tugc → *Pintent* → *Sales*	0.114	[0.070, 0.160]	$<2 \times 10^{-16}$ ***

Note: $N = 300$, *** $p < 0.001$, ** $p < 0.01$ (two-tailed).

Furthermore, we examined the significance of the coefficients of the independent variables in model M5 (as shown in Table 6). It is evident that the coefficients of *Char* and *Svar* in model M5 (1.036 and −6.010, respectively) are both significant at the 0.1% level, and their absolute values are smaller than those in model M3 (1.437 and −9.536, respectively). However, the coefficient of *Tugc* is not significant. Therefore, we can conclude that *Pintent* has a significant partial mediating effect on the relationship between *Char*/*Svar* and *Sales*, and a significant complete mediating effect on the relationship between *Tugc* and *Sales*. The mediating effect of purchase intention in the process whereby the number of third-party platform product evaluations influences product sales is complete, indicating that the number of third-party platform product evaluations positively influences product sales solely through its impact on purchase intention. In contrast, UGC on e-commerce platforms not only directly impacts sales but also affects them through purchase intention. In our view, this is a significant reason why UGC on e-commerce platforms has a more substantial impact on the sales of experiential products than UGC on third-party platforms.

In summary, the above analysis shows that purchase intention significantly mediates the impact of review length, review inconsistency, and the number of third-party platform product evaluations on product sales, which supports research hypothesis H4.

5.4. Analysis of the Moderating Effects of Product Price

After conducting the main effects and mediating tests, the moderating effects test of the central and peripheral paths was performed. Before conducting the moderating analysis, we centered the independent variables and moderator. The specific expressions of models M6, M7, and M8 for the moderating effects test are shown in Equations (9)–(11).

$$Sales = \beta_0 + \beta_1 Char + \beta_2 Svar + \beta_3 Tugc + \beta_4 Store + \beta_5 Price + \beta_6 Char \times Price + \varepsilon \quad (9)$$

$$Sales = \beta_0 + \beta_1 Char + \beta_2 Svar + \beta_3 Tugc + \beta_4 Store + \beta_5 Price + \beta_6 Svar \times Price + \varepsilon \quad (10)$$

$$Sales = \beta_0 + \beta_1 Char + \beta_2 Svar + \beta_3 Tugc + \beta_4 Store + \beta_5 Price + \beta_6 Tugc \times Price + \varepsilon \quad (11)$$

The moderation effects test was conducted using the independent variable, control variable, moderating variable, and interaction terms according to Equations (9)–(11). The results are shown in Table 8, and the corresponding VIFs are close to 1, indicating no significant multicollinearity issue in models M6-M8 after introducing the interaction terms.

Table 8. Parameter results of the moderating effect model.

Variables		*Sales*					
		M6		M7		M8	
		Coefficient	VIF	Coefficient	VIF	Coefficient	VIF
Independent Variable (Central Path)	*Char*	1.443 ***	1.370	1.566 ***	1.233	1.484 ***	1.206
	Svar	−8.837 ***	1.290	−8.341 ***	1.294	−8.776 ***	1.284
Independent Variable (Peripheral Path)	*Tugc*	0.175 ***	1.042	0.176 ***	1.042	0.177 ***	1.043
Control Variable	*Store*	−23.187 *	1.176	−24.576 *	1.152	−21.280 *	1.164
Moderating Variable	*Price*	−0.106	1.302	−0.047	1.293	−0.120	1.261
Moderating Items	*Char* × *Price*	−0.103	1.236				
	Svar × *Price*			−6.783 **	1.077		
	Tugc × *Price*					0.124 *	1.015
Adjusted R^2		0.29		0.31		0.30	
F-value		21.01 ***		23.05 ***		22.19 ***	

Note: $N = 300$, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ (two-tailed).

From the regression results of models M6–M8 in Table 8, it can be observed that after adding moderating variables and interaction terms, the adjusted R^2 values have improved to a certain extent (compared to the adjusted R^2 of the main effects of 0.29), but to varying degrees. Model M7 shows the greatest improvement, indicating that the overall explanatory power of the model has increased after introducing the moderating variables and interaction terms. Moreover, the F-values of models M6–M8 all meet the significance requirement at the 0.1% level, indicating the practical significance of the constructed models.

Additionally, the coefficient of the moderating variable *Price* is insignificant, indicating that the product price does not have a substitution effect but only has a moderating effect. In models M6–M8, the coefficients of the independent variables are all significant at the 0.1% level. Among the three interaction terms, the coefficient of *Char* × *Price* is insignificant, and hypothesis H5a is not supported.

The regression coefficient of the interaction term *Svar* × *Price* is −6.783, significant at the 1% level. The coefficient of the independent variable *Svar* in the main effects is also significant and negative, indicating that the moderating variable *Price* strengthens the negative effect of *Svar* on *Sales*, as shown in Figure 3. The product price positively moderates the impact of review inconsistency on *Sales*, supporting hypothesis H5b.

The regression coefficient of the interaction term *Tugc* × *Price* is 0.124, significant at the 5% level. The coefficient of the independent variable *Tugc* in the main effects is also significant and positive, indicating that the moderating variable *Price* strengthens the positive effect of *Tugc* on *Sales*, as shown in Figure 4. The product price has a positive moderating effect on the impact of the number of third-party platform product evaluations on product sales, supporting hypothesis H5c.

In summary, based on all the analysis and hypothesis testing results, it can be concluded that research hypotheses H1–H4 are supported, and hypothesis H5 is partially supported, as shown in Table 9.

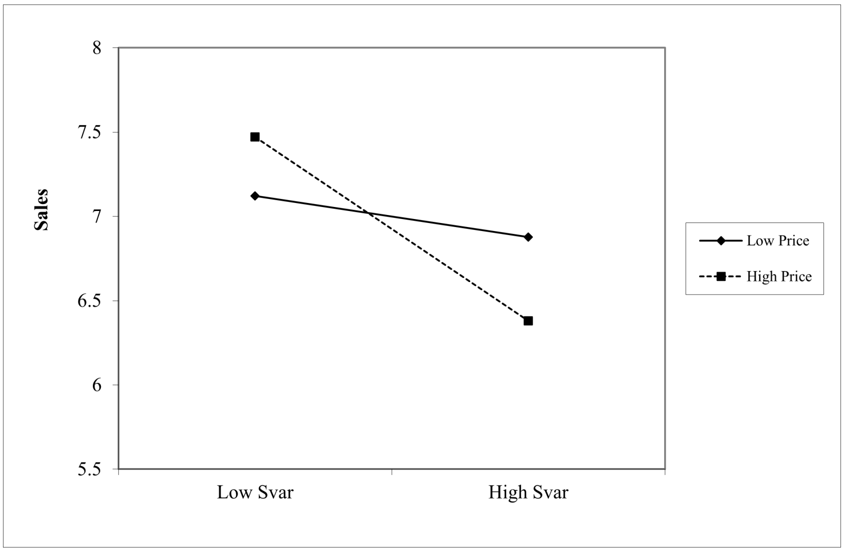

Figure 3. Moderating effect of *Price* on the relationship between *Svar* and *Sales*.

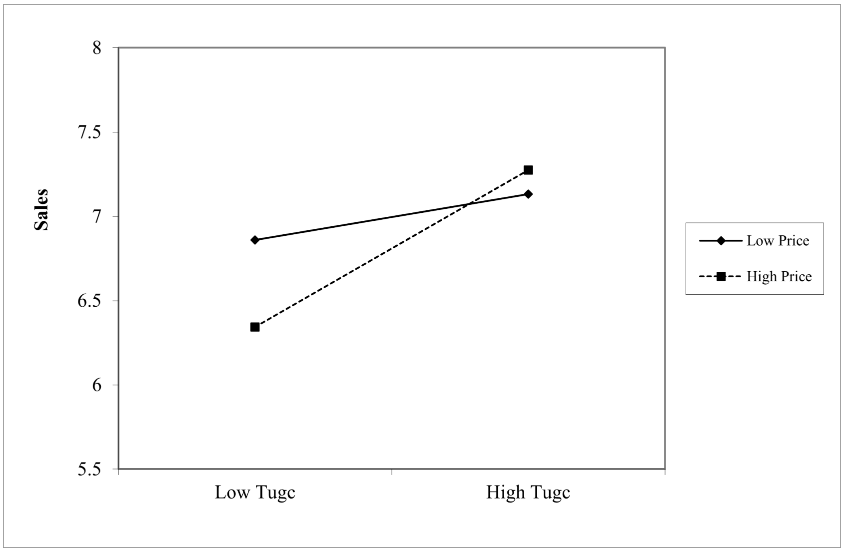

Figure 4. Moderating effect of *Price* on the relationship between *Tugc* and *Sales*.

Table 9. Summary of hypothesis testing results.

Hypothesis Related Questions	Hypothesis	Results
How does the central path of UGC affect sales?	**H1:** The length of online reviews positively influences product sales. **H2:** The inconsistency of online reviews negatively influences product sales.	Supported Supported
How does the peripheral path of UGC affect sales?	**H3:** The number of third-party platform product evaluations positively influences product sales.	Supported
What is the mediating role of purchase intention in the relationship between cross-platform UGC and sales?	**H4a:** Purchase intention mediates the relationship between review length and sales. **H4b:** Purchase intention mediates the relationship between review inconsistency and sales. **H4c:** Purchase intention mediates the relationship between the number of third-party platform product evaluations and sales.	Supported Supported Supported
What is the moderating role of the product price in the relationship between cross-platform UGC and sales?	**H5a:** The effect of review length on sales is positively moderated by product price. **H5b:** The effect of review inconsistency on sales is positively moderated by product price. **H5c:** The effect of the number of third-party platform product evaluations on sales is positively moderated by product price.	Not supported Supported Supported

6. Discussion

In this paper, we propose a novel cross-platform research model to explore the differences in the impact of UGC from different platform sources (i.e., cross-platform UGC) on product sales, as well as the underlying mechanism for these differences. In investigating the relationship between cross-platform UGC and product sales, the model considers differences in consumer information processing based on the ELM theory. We developed this model within the context of online sales of experiential products, using cosmetics as an example. By collecting online reviews of cosmetic products from the e-commerce platforms, as well as the number of relevant product evaluation videos on third-party platforms, we obtained empirical results (as shown in Table 9) through regression analysis and sentiment analysis of the review texts. Our findings demonstrate that when considering cross-platform UGC, the impact of UGC from e-commerce platforms is greater on sales compared to UGC from third-party platforms, and we also reveal the underlying reasons for this outcome. The specific discussion of the results is as follows:

- Both the text features (*Char*, *Svar*) of online reviews from the central path and the third-party platform evaluation quantity (*Tugc*) from the peripheral path significantly impact product sales, with the central path having greater explanatory power. Moreover, online reviews from the central path are the primary source of information for consumers' purchase decisions, which supports previous research findings [16,20]. Additionally, integrating cross-platform information from both paths is advantageous for boosting sales.
- Review length positively impacts sales, while review inconsistency has a negative impact. The quantity of third-party platform product evaluations has a positive impact on sales. An interesting phenomenon is that there is a significant positive correlation between review length and product sales, likely due to the perceived popularity it generates. Moreover, as illustrated in Table 5, third-party evaluations can, to some extent, weaken the negative impact of review inconsistency and enhance the positive effect of review length on sales. This is due to the fact that the number of third-party evaluations in the peripheral path can reduce information asymmetry in the central path and improve product sales.
- Purchase intention mediates the relationship between review length, review inconsistency, the quantity of third-party platform product evaluations, and sales. Moreover, purchase intention fully mediates the relationship between the number of third-party evaluations and sales, indicating that third-party platform UGC can only indirectly affect product sales by influencing consumer purchase intention. However, obtaining third-party platform evaluation information incurs additional costs for consumers. As such, consumers typically only purchase a product when they have a strong purchase intention. Therefore, *Tugc* may be more effective for non-rational or impulsive consumers in facilitating their purchasing decisions.
- Product price positively moderates the relationship between review inconsistency and the number of third-party platform evaluations on sales but not review length and sales. Higher-priced products raise consumers' perceived risks, leading to more cautious purchase decisions and a greater reliance on cross-platform UGC information. The length of online reviews is unrelated to the product price and thus is not sensitive to the influence of price factors.

7. Conclusions and Implications

In this section, we discuss the theoretical implications and practical implications of this study, and provide a general conclusion.

7.1. Theoretical Implications

Our study presents three primary contributions to the existing literature. First, compared with previous studies that focused on single-platform or same-type platforms (only e-commerce or third-party platform) UGC [28,53,58], the findings of this article highlight the significance of considering UGC from both e-commerce and third-party platforms by examining the impact of cross-platform UGC on consumer purchase intention and product sales. Furthermore, this study empirically investigates the mechanisms through which cross-platform UGC influences consumer purchase intention and product sales. It supplements and also extends existing studies [15,16] by uncovering potential underlying reasons for the differential impact of UGC from various platform types on product sales. Although previous studies have examined UGC from different platform sources, they have not explained the underlying mechanisms that contribute to the varying effects on product sales. Our research identifies these underlying mechanisms and also provides insights for future studies. Future research can further explore the relationship between motivations for UGC generation [7,102] and UGC sources, such as e-commerce platforms and third-party platforms. This analysis can then examine the impact of motivations for UGC generation on consumers' purchasing decisions.

Second, existing research generally suggests that third-party UGC is more trustworthy [15,17,103]. However, our study, conducted in the context of cross-platform UGC, revealed contrasting findings. We argue that UGC on e-commerce platforms has a greater impact on product sales and deserves more attention. Similar conclusions have been drawn in previous studies, attributing this effect to the earlier accessibility or ease of information retrieval on e-commerce platforms [16,19,20]. Nonetheless, our research unveils deeper underlying mechanisms, highlighting the crucial role of purchase intention in mediating the influence of cross-platform UGC on sales. Consequently, this discrepancy in the magnitude of impact sheds new light on comprehending the role of cross-platform UGC in marketing and addresses a theoretical gap in the current literature. To achieve this, we propose an innovative model that integrates cross-platform UGC perspectives with the ELM, providing a novel understanding for future research in the field. Future research can utilize consumers' information processing strategies towards cross-platform UGC to identify user segments and potential needs [104], enabling more accurate predictions of consumer purchasing behavior and product sales.

Third, previous research has generally acknowledged that factors influencing the ELM primarily encompass motivation and ability. When motivation or ability is high, the central path is adopted, whereas when motivation or ability is low, the peripheral path is employed [47,48,62]. The findings of this study, however, reveal that when faced with cross-platform UGC, some consumers with strong motivation or ability also resort to the peripheral path, while others with weak motivation or ability solely choose the peripheral path. These conclusions, on one hand, support the simultaneous occurrence of central and peripheral routes, with one path exerting a stronger influence on attitudes and assuming a dominant role [65,105,106]. On the other hand, this study emphasizes the significant and transformative role of cross-platform UGC in altering consumer information processing patterns. Additionally, the results of this study shed light on the impact of cross-platform UGC on purchase intention and product sales [15], thereby advancing our understanding of the ELM theory. Most existing literature on the ELM suggests that the choice of consumer information processing path is primarily influenced by consumer motivation and ability, which are personal attributes. However, some studies have shown that consumers' deepened understanding and perception of UGC can also impact their actual purchase decisions [53,107]. Our study contributes to the ELM and UGC literature by uncovering a new understanding of the transfer of information processing routes, which is influenced by cross-platform UGC. Future research can further explore the relationship between consumer motivation, ability, and UGC, gradually unveiling the black box of the ELM's influence process [53,62].

7.2. Practical Implications

The findings of this study offer several valuable managerial implications. First, our research concludes that online reviews on e-commerce platforms have a stronger impact on product sales than the number of product evaluations on third-party platforms. Furthermore, the inconsistency of online reviews on the e-commerce platform negatively affects product sales. These findings carry important implications for marketers, emphasizing the significance of attending to online reviews on e-commerce platforms, particularly the sentiment inconsistencies conveyed within these reviews [108], which negatively impact consumers' purchase intention. Importantly, based on the underlying mechanisms revealed by our study regarding the differential impact of cross-platform UGC, the lower purchase intention of consumers not only affects the promotional effectiveness of UGC on e-commerce platforms but also influences the promotional effectiveness of UGC on third-party platforms. This requires the marketer to monitor and manage product reviews effectively, communicate with consumers in a timely manner, and address extremely negative reviews that may lead to inconsistencies in consumer feedback. On the other hand, our study concludes that there is a positive correlation between the average character count of online reviews and product sales. However, the strength of this positive impact of review character count on product sales does not significantly vary based on the price of the product. Therefore, marketers do not need to adopt a differentiated strategy based on product price when incentivizing consumers to generate longer online reviews to enhance sales.

Second, our research findings indicate that reducing product prices can mitigate the adverse impact of inconsistent online reviews on product sales for e-commerce platforms. Therefore, for products with high levels of inconsistency in online reviews, increasing sales can be achieved through promotional price reductions. However, our study also revealed that lowering product prices diminishes the positive influence of third-party platform UGC on product sales. Consequently, for products with high levels of inconsistency in online reviews, marketers need to carefully consider the impact of price factors on sales when employing price reduction promotions and find a balance point of price. Furthermore, in the practice of product promotion, higher-priced items often receive smaller price reductions, while lower-priced products tend to have larger price reductions. This study provides a new potential theoretical explanation: excessive price reductions on high-priced products may diminish the promotional impact of third-party UGC and adversely affect sales.

Third, marketers should consider incentivizing consumers to generate more third-party UGC specifically for high-priced products. Our research findings indicate that increasing the quantity of third-party UGC for high-priced products yields better sales improvement compared to low-priced products. Therefore, marketers should encourage consumers of high-priced products to contribute more UGC on third-party platforms. Additionally, establishing an upscale product fan community on these platforms and motivating opinion leaders, or influencers, to spread UGC can be beneficial [13].

7.3. General Conclusions

This study investigates how cross-platform UGC influences the sales of experiential products on e-commerce platforms. The main conclusion can be summarized as follows:

- UGC originating from the e-commerce platform has a stronger impact on product sales than the UGC from the third-party platform. Moreover, the cross-platform UGC has a stronger impact on sales than the UGC from any single platform.
- UGC on e-commerce platforms can impact sales directly and through purchase intention, whereas third-party UGC only influences sales through purchase intention. Additionally, product price can strengthen the positive relationship between the number of third-party UGC and sales.

8. Limitations and Future Research Directions

This paper has some research limitations that warrant discussion. Firstly, as an initial exploration of the underlying mechanisms behind the varying effects of cross-platform UGC on product sales, which is a novel problem within the intersection of e-commerce and UGC, this study did not uncover the hidden emotions in the third-party platform's evaluation of video content. Secondly, the empirical analysis in this study was conducted solely on liquid foundation products, which were chosen as representatives of experiential products in the cosmetic industry. Although the selection of liquid foundation is justified in Section 4.2, focusing on this category constrains the study's scope. These limitations, primarily arising from the heterogeneity of cross-platform UGC features and the challenges associated with video data processing techniques, need to be addressed and further explored in future research. With the continuous advancement of technology, especially the AI and automation technologies, future studies can further advance the study in several ways.

- Unravel the mechanisms at the emotional level. Advances in auto-emotion-detection AI technologies may aid in uncovering and analyzing hidden emotions within UGC videos. Future research can employ these technologies, along with neuromarketing techniques (Neuromarketing technologies refer to the application of neuroscientific methods and techniques in marketing research and practice. These technologies aim to understand and measure consumers' cognitive and emotional responses, subconscious processes, and neural activities when they engage with marketing stimuli. For more about neuromarketing, see, for example, [21,22,109,110].), to gain a deeper understanding of consumers' emotional responses to the emotions expressed in both textual and video UGC. This approach enables a more comprehensive examination of the emotional dynamics present in cross-platform UGC.
- Broaden the range of products as well as the content type under investigation. By including multiple product types (not limited to the liquid foundation) and content types (i.e., UGC and MGC), future studies may consider how UGC and MGC from multiple platforms affect product sales differently. Many other experiential products can also be examined to generalize our findings.

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Abbreviations

The following abbreviations are used in this manuscript:

UGC	User-generated content
ELM	Elaboration likelihood model
NLP	Natural language processing
VIF	Variance inflation factor
eWOM	Electronic word-of-mouth
MGC	Marketer-generated content

Appendix A

Table A1. Text sentiment polarity analysis steps.

No.	Steps	Explanations	Tools or Methods
1	Building corpus	Building an adaptive corpus for online reviews of cosmetics in the e-commerce industry	Sentiment kernel file sentiment.marshal.3 of SnowNLP library
2	Word segmentation	The most basic step in text processing and analysis, which means dividing complete sentences into meaningful words	Segmentation tool jieba library; Marking rules: ICTCLAS tagging method of Chinese Academy of Sciences
3	Stop word filtering	Removing words unrelated to sentiment words, such as "one", "prepare", "several degrees", etc. that appear in sample reviews	Self-built stop word table based on Baidu stop word table
4	Text feature weight calculation	Feature weight coefficients can not only represent the importance of features, but also represent the correlation, expression ability, and other aspects of features	TF-IDF algorithm
5	Text feature vectorization	Converting natural language text words into digital variables that machines can execute	Vector Space Model (VSM)
6	Text classification	Distinguishing text words into positive sentiment words and negative sentiment words	Naive Bayes Classifier (NBC) model; SnowNLP sentiment lexicon

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