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Article

An Investigation on Impact of Online Review Keywords on Consumers' Product Consideration of Clothing

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Abstract: Consumers need external information to support their product evaluation, especially with regard to experiencing the product during online shopping. Review keywords provide aggregated information of online reviews for consumers. However, whether and how review keywords affect consumers' product consideration is still unelucidated. Considering clothing as the research target, we built a model to depict the impacts of website-generated quality- and fit-related review keywords on consumers' consideration of clothing by bridging cue diagnosticity frameworks and product uncertainty theory. The hypotheses were verified by analyzing the objective data collected from e-commerce platforms and experiments. Results indicate that quality-related review keywords have a more salient positive impact on clothing consideration compared with fit-related keywords. Meanwhile, further complementary analysis based on self-generated review keywords suggests that presenting consumers with social-related keywords and consumer buyback keywords can improve clothing consideration significantly. The research contributes to the literature of product consideration and online review keywords, and related findings can help the platforms and e-merchants to better leverage the advantages of online review keywords.

Keywords: product consideration; cue diagnosticity framework; quality-related keywords; fit-related keywords; self-generated keywords

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1. Introduction

Clothing, as a typical type of experience product, occupies a large proportion of e-commerce transactions [1]. Leading e-commerce platforms, such as Amazon, Taobao and JD, have set up an independent category section for clothing on their websites. Different from search products with standardized attributes, consumers usually encounter quality uncertainty [2] as well as fit uncertainty [3] when they evaluate clothing products on e-commerce websites, especially when they are at a consideration stage with various potential choices [4,5].

As the intermediate stage of the consumers' online shopping process, product consideration plays a vital role in affecting subsequent shopping decisions [4]. In practice, online reviews at this stage are the most widely accessible information for consumers, and prior research has suggested that consumers use reviews more intensively in the consideration stage rather than in other stages [5]. Online reviews have important reference value for consumers to evaluate products [6]. However, the number of reviews is often in the tens of thousands for slightly popular clothing products on e-commerce websites, which is prone to information overload for consumers [7,8]. In this regard, websites generate and provide review keywords with the expectation to support consumers' decisions.

Review keywords are the core words extracted from all product reviews on the website and that are displayed to consumers in the top section of the review. When the number of reviews is large, review keywords help consumers understand the overall message of the reviews. For example, on the Taobao website, the products in the clothing category usually have approximately five keywords. As a majority of reviews for clothing focus on describing the quality (e.g., good fabrics, wear-resisting) and fit (i.e., accurate size, slim fit) information due to clothing products' experiential nature, the keywords extracted based on the frequency of term occurrence from these reviews mainly include quality- and fit-related keywords (We also conducted qualitative and quantitative analyses of more than 5000 website review keywords for more than 1000 clothing products on the Taobao website and found that all of these keywords belong to the two themes of quality and fit. For specific analysis results, please refer to Study 1) (Figure 1). Previous studies have analyzed the impact of text content from the perspective of a single review [9,10], while others did not choose to analyze the role of keywords in overall reviews.

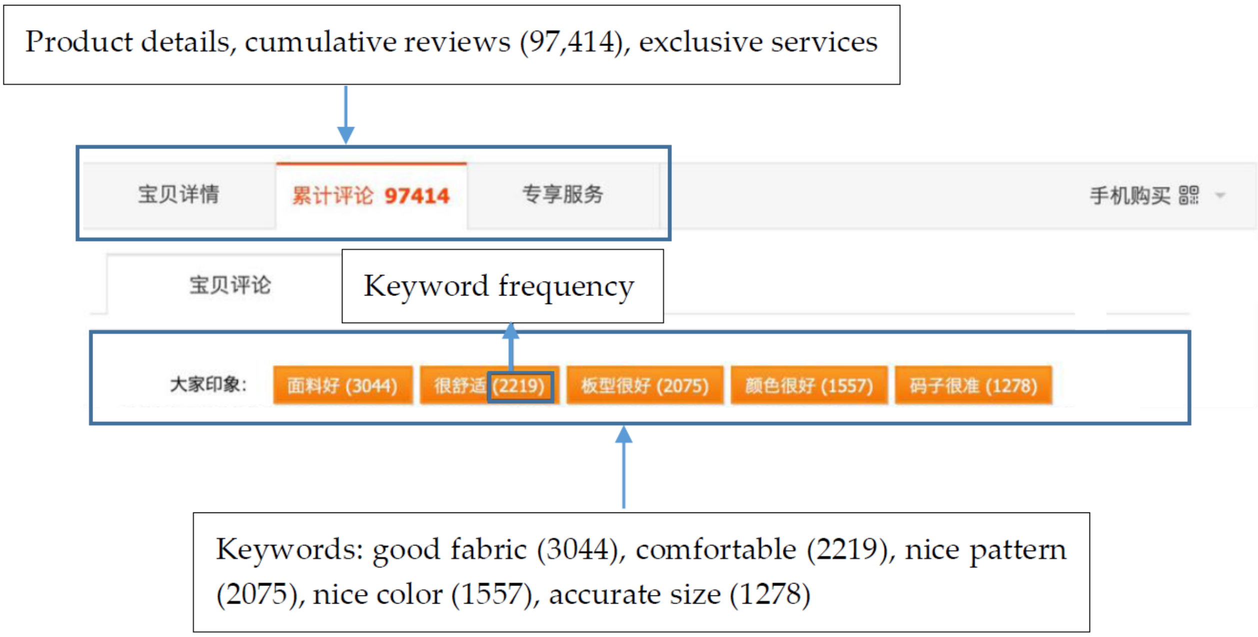

Figure 1. Review keywords on Taobao (source: https://www.taobao.com/) (accessed on 9 November 2020).

In practice, e-commerce websites also question whether and how the review keywords they provided matter during the consumers' decision process and whether extracting review keywords based on term frequency provides consumers with enough information to evaluate the clothing products. On the one hand, website-generated review keywords of different types (e.g., quality-related, fit-related) release different cues for consumers to evaluate the clothing products, which may further affect consumers' product consideration. However, the specific impacts and mechanisms underlying review keywords and clothing consideration are still unclear. On the other hand, e-commerce websites usually generate review keywords based on the frequency of term occurrence and mainly reflect the quality and fit aspects of clothing products. Whether some other types of review keywords may also bring benefits for consumers remains unknown. Therefore, the research questions of this study include:

RQ1: Whether and how the website-generated review keywords affect consumers' product consideration of clothing.

RQ2: Whether some other types of review keywords that can affect consumers' consideration of clothing, except for website-generated keywords, exist.

This study adopts information overload [7], the cue diagnosticity framework [11] and product uncertainty theory [2,3] to explore the aforementioned phenomena. Consumers usually experience quality and fit uncertainty during online purchases of clothing, and require external information, such as online reviews, to support their evaluation of the clothing products. However, tens of thousands of online reviews lead to information overload for consumers [7]. Thus, we treat website-generated quality- and fit-related review keywords as aggregated cues that can help consumers to mitigate uncertainties, which further affect consumers' clothing consideration. In addition to website-generated review keywords, the explorative text analysis approaches are adopted to uncover some other types of review keywords that affect consumers' consideration of clothing.

The remainder of this paper is organized as follows. We first provide a review of the literature related to our current research. We then discuss the hypotheses. The subsequent section elaborates our research method and describes the research site for collecting empirical data. Thereafter, we present the statistical analyses and provide related discussions concerning the results. Finally, we conclude with a summary of our research contributions, limitations, and potential future directions.

2. Literature Review

To explore the impact of review keywords on product consideration, three streams of literature are relevant to our research: (1) online reviews, (2) the consideration set, and (3) the cue diagnosticity framework.

2.1. Online Reviews

An online review is a typical form of online word-of-mouth. Consumers post their views and opinions on the products they purchased on e-commerce websites after a transaction [10]. In recent years, research on the characteristics of online reviews has rapidly emerged [12–14]. According to prior research, online reviews contain at least the dimensions of review sentiment polarity and review content [15].

In terms of review sentiment polarity, consumers have different perceptions when encountering reviews with varying sentiment polarities. In general, negative reviews are often more influential than positive reviews in affecting consumers' decisions [16]. For experience products, consumers find neutral reviews more useful than positive reviews [17]. Some studies also reveal that excessive emotional intensity can reduce the reliability of online reviews [18]. In terms of review content, scholars have directed extensive research efforts into the focal realm. Machine learning has been widely embraced, and typical approaches include natural language processing (NLP)-based text analysis [15,18,19] and deep learning-based image analysis [20]. For example, many previous studies have extracted informative topics or features based on the review text using NLP, such as product features [21]; and valuable keywords [22]. Other linguistic and text characteristics, including readability [23], lexical complexity [18], consistency (the degree of consistency of the focal review with other reviews) [24], and writing style [25], have been broadly discussed. The accumulated research of online reviews has contributed valuable insights into various aspects, such as consumers' purchase intention [26], product sales [6], and personal decision making [27].

Although extensive research efforts have been devoted to online reviews, the impact of online review keywords has gained inadequate attention, especially considering the sources (e.g., website-generated keywords, self-generated keywords) and types of review keywords (e.g., quality-related keywords, fit-related keywords) for clothing products on e-commerce websites, thereby leaving us with a compelling research gap to fill.

2.2. Product Consideration

The consideration set model is used to describe the shopping decision process of consumers [28]. In this model, consumers usually go through three stages during product selection. In the first stage, consumers narrow down all possible products to the awareness set. The awareness set refers to the product set for which consumers are likely to conduct subsequent evaluations. In the second stage, consumers narrow down the scope of the awareness set to the consideration set, which refers to the commodities that consumers are willing to consider. In the final stage, consumers narrow down the consideration set to a small choice set (or a single choice) and select the products they will buy from the choice set [28]. Therefore, product consideration refers to the degree to which the product is considered by the consumers [29]. The greater the product consideration, the higher the probability that the product enters the consumers' choice set.

As the intermediate stage of consumers' online shopping decision process, product consideration has drawn research attention. From a technical view, some scholars have focused on identifying the consumer consideration set from aggregate purchase data in online retailing [30], or estimating consumers' consideration probabilities by a business intelligence (BI) approach [31]. Another stream of studies has tried to identify various factors that can aid consumers' online shopping decisions, such as product brands and online WOM [6,32]. For example, consumers are more likely to consider pioneering brands rather than follower brands [33]. Consumers' attitudes toward the product affects product consideration [34]. When a consumer prefers a product, the product is more likely to be considered by the consumer. Meanwhile, the strength of the attitude will further increase the impact of consumers' preference on product consideration [34]. In the choice set stage, consumers are less susceptible to word-of-mouth information and are more likely to be affected by product information, such as price fluctuations [35].

Although online reviews have a potential impact on consumers' shopping intentions, few studies focus on the consideration stage [29,34]. Compared with the choice set stage, online reviews have a greater impact on the consideration set stage [28]. Vermeulen and Seegers (2009) revealed that exposure to online reviews increase consumer awareness of hotels, whereas positive reviews, in addition, improve attitudes toward hotels [4]. Gavilan et al. (2018) investigated the impacts of good vs. bad ratings and review volume on hotel booking considerations, and found an asymmetric interaction between numerical ratings and the number of reviews [29]. Hu and Yang (2020) explored how hotel review- and price-related attributes affect consumers' formation of consideration sets and hotel bookings, and found that overall rating and review volume contribute to consideration formation [36]. However, most of these studies focus on the hotel industry and ignore the influence of review keywords on product consideration, thereby leaving us with an open avenue to explore further.

2.3. Cue Diagnosticity Framework

The cue diagnosticity framework indicates that most of the decisions are based on multiple attributes [37]. Explaining the extremity and negativity biases that are commonly found in impression formation research [38] is proposed originally and is widely adopted in marketing [11,39]. Another similar concept is information diagnosticity, which has been used in the information systems area. Information diagnosticity indicates individuals' improved understanding or knowledge about a product, and is usually conceptualized as the degree of information helpfulness [40,41]. For example, Jiang and Benbasat (2004) defined information diagnosticity as consumers' perception of a website's ability to convey relevant product information that can help them to evaluate the products sold online [42]. Yi et al. (2017) defined the perceived diagnosticity of a search experience as the extent to which a user believes that a website helps her/him to effectively access and evaluate relevant products in a search process [43].

The cue diagnosticity framework builds on cue utilization theory, which suggests that the extent to which a cue is adopted in evaluating product quality varies with its perceived diagnosticity [11]. Product quality evaluation is a categorization process in which consumers use the available cues to assign a product to a specific quality category [11]. Cues that suggest one categorization over alternative categorizations are considered diagnostic, whereas cues that suggest multiple categorizations are nondiagnostic [39]. Following this argument, some researchers further distinguished high-scope and low-scope cues [11]. Specifically, high-scope cues refer to those that evolve over time such that their valence cannot be changed instantaneously; whereas low-scope cues are transient, and their valence can be changed. For example, the overall rating for a merchant on an e-commerce website can be deemed as a high-scope cue to reflect the merchant's reputation, because the overall rating is an aggregation of consumers' rating and entails a relatively long term accumulation. In contrast, a single review rating only reflects a specific consumer's attitude and/or opinion towards the e-merchant at a specific time point, and therefore acts as a low-scope cue to indicate the merchant's reputation.

In this research, the website-generated quality-related and fit-related online review keywords act as potential cues in affecting consumers' clothing consideration. The detailed elaboration will be given in the following section.

3. Research Hypotheses

When purchasing clothing products on e-commerce websites, consumers usually encounter the problem of product uncertainty; that is, they cannot evaluate the quality of clothing accurately and whether the specific clothing products are suitable for them [1–3,44]. Therefore, consumers need external cues to assist in diagnosing product quality and fit. Online reviews have been repeatedly deemed as efficient cues for consumers to evaluate products, especially experience products. In reality, there are too many reviews for consumers to read, which leads to an information overload issue [7]. Therefore, review keywords emerge as an overall aggregation of review information. Based on the cue diagnosticity framework [11], online review keywords serve as efficient cues on e-commerce websites. In general, review keywords are extracted from all reviews based on the frequency of term occurrence and reflect consumers' opinions, feelings, and evaluations toward the products [45]. Different from single reviews, review keywords are displayed at an aggregated level, through which consumers can obtain the overall information of the reviews. Meanwhile, according to the distinction between high-scope and low-scope cues [11], the valence of review keywords is formed over a long period of time, and changing them instantly is difficult. By contrast, the single reviews are transient, and their valence can be changed easily. Therefore, review keywords are more credible and diagnostic than single reviews.

Websites provide quality-related review keywords for consumers to support their clothing evaluations during online shopping. Product quality uncertainty arises when consumers are unsure about whether the products are adequately described on the website and perform consistently well in the future [2]. Product quality uncertainty has been proven to be a powerful antecedent for consumers' purchase intention, and mitigating consumers' product quality uncertainty has been a central task for e-commerce platforms [46,47]. Quality-related review keywords, as typical high-scope cues, provide reliable overall product quality information for consumers. When consumers obtain cues about product quality attributes, they will diagnose the product quality to reduce uncertainty [2], and the sum of the diagnostic results for each attribute determines the consumers' attitude toward the overall product quality [48,49]. For example, if a consumer considered purchasing a T-shirt online, the quality of the T-shirt needs to be evaluated before purchase. When the consumer sees the quality-related keywords, such as "cotton fabric" or "thickness", s/he can quickly determine the quality of the T-shirt, thereby reducing the quality uncertainty of this product. In this study, we postulate that quality-related review keywords play a vital role in reducing consumers' perceived quality uncertainty, which further affects their clothing consideration. In sum, we have the following hypothesis:

H1: *Quality-related review keywords have a significant positive impact on consumers' clothing consideration during online shopping.*

In addition to quality uncertainty of clothing during online shopping, consumers are also unsure about whether the attributes of specific clothing products match their preferences or needs; that is, whether the clothing suits them. This phenomenon is originally defined as product fit uncertainty and has been deemed as a salient issue in online transactions [3,50], especially for products with unfamiliar experiential attributes (e.g., clothing) [1]. On e-commerce websites, fit-related review keywords act as useful cues for consumers to evaluate whether the specific clothing products are suitable for them. On the one hand, fit-related review keywords are extracted from all reviews, representing other consumers' impressions and their evaluation of the products. Therefore, the focal consumers can obtain overall clothing fit information by using such keywords. On the other hand, the fit-related review keywords are extracted on the basis of their frequency of occurrence in all reviews, and the valence is not easy to change. Thus, fit-related review keywords are high-scope cues and are more credible. Consumers are more likely to evaluate the fit of clothing products based on fit-related review keywords. For example, when a consumer wants to purchase a T-shirt online, in addition to the quality, s/he may also need to evaluate whether the T-shirt is suitable for her/his style. When s/he sees the fit-related keywords, such as "looking young" or "slim fit", s/he can directly obtain the overall fit information of the T-shirt, thereby reducing the fit uncertainty to a certain degree. In sum, we have drawn the following hypothesis:

H2: *Fit-related review keywords have a significant positive impact on consumers' clothing consideration during online shopping.*

Although quality-related and fit-related review keywords show positive impacts on consumers' clothing consideration, the degree of these two types of review keywords in reducing product quality and fit uncertainty varies. In general, quality-related keywords are universal and standardized to all consumers (e.g., clothing material). In contrast, for fit-related keywords, although they also release certain information for consumers (e.g., accurate size, slim fit), being universally applicable to every consumer is difficult for such information. The reason is that different consumers have unique requirements for the clothing products (e.g., body shape for clothing), and the fit-related keywords generated by the websites cannot completely eliminate product fit uncertainty for consumers. For example, a consumer wants to buy a T-shirt on an e-commerce website. Thus, s/he can easily evaluate the quality of the T-shirt based on the review keywords, such as "good fabrics" and "wear-resisting". However, when s/he sees the keywords, such as "accurate size" or "slim fit", s/he can only obtain preliminary information about the fit information of the T-shirt. If s/he wants to know more details about whether the T-shirt is suitable for her/him, then s/he may still need to search more information about the T-shirt size in the product detail page. Therefore, we propose that the impact of quality-related and fit-related review keywords on clothing consideration are different because two types of review keywords reduce product uncertainty to a different degree. In sum, we have the following hypothesis:

H3: *The positive impact of quality-related review keywords on consumers' clothing consideration is stronger than that of fit-related review keywords during online shopping.*

4. Research Methodology

4.1. Research Site and Data

The data for this research were collected from Taobao (http://www.taobao.com/) (accessed on 9 November 2020), which is owned by the Alibaba Group. The Alibaba Group's fiscal year 2022 annual report shows (Alibaba Group's fiscal year 2022 annual report (https://data.alibabagroup.com/ecms-files/886023430/190b9a46-b141-4e23-92d8-2828ca23e1b6.pdf) (accessed on 10 January 2023)) that Taobao is one of the largest e-commerce websites in China, with hundreds of millions of products available. In this study, medium-priced clothing is selected as the research object for two main reasons: First, clothing is a common product, and the majority of consumers have experience in buying clothes online. Second, clothing is a typical type of experience product. Compared with search products, evaluating the quality and fit of clothing before purchase is difficult for consumers, and online reviews have a more salient effect on consumers' evaluation of these products [51].

In Taobao.com, if a consumer considers a product and includes it as an alternative, the product will be added to their favorites list. The number of consumers who have added the product to their favorites list can be regarded as the product consideration (Figure 2), and consumers make subsequent selections and evaluations for the products in their favorite list. On November 9, 2020, we entered the keyword "clothes" in the Taobao search bar and crawl 1887 product data using the third-party software Houyi Crawler (http://www.houyicaiji.com/) (accessed on 9 November 2020). For each product, we collected data, including product links, sales, price, review keywords, image quantity, the type and number of reviews, and the number of consumers who have added the product to their favorites list. The more product reviews, the more prominent the information of the review keywords. Thus, we deleted products with less than 100 reviews and finally obtained data on a total of 1265 products.

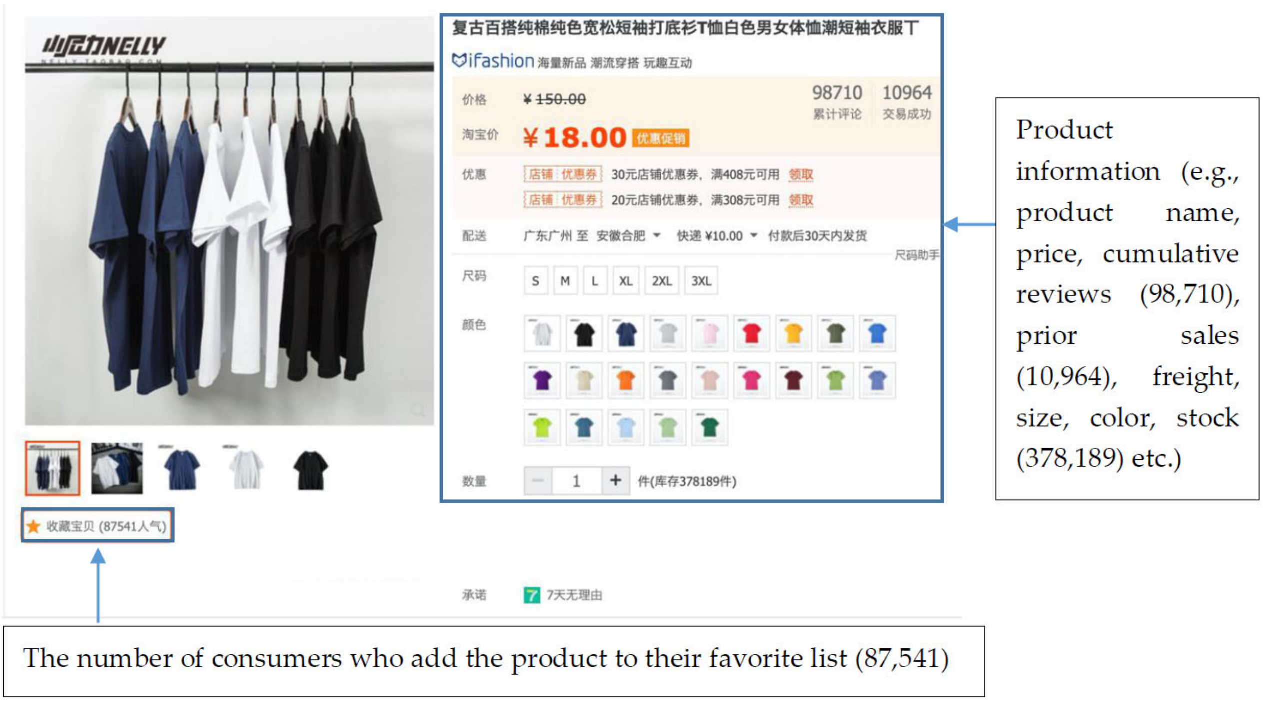

Figure 2. Product consideration (source: https://www.taobao.com/) (accessed on 9 November 2020).

4.2. Study 1

In Study 1, we aim to explore the impact of website-generated review keywords on product consideration by regression analysis.

We used the Python program to summarize and deduplicate the review keywords of 1265 product samples and merge them according to the semantics, and finally obtained 81 unique labels. In this research, manual coding was adopted to classify the 81 keywords [52]. Following the item sorting procedure established in prior studies [1,52], four research assistants were invited to manually encode and classify the same sample data. Specifically, the four assistants participated in the sorting, and one of the authors acted as the instructor to guide the sorting process. First, the instructor introduced the purpose of the sorting and explains the detailed process to all the assistants; second, the four assistants were asked to classify the keywords into different categories by considering whether the specific keywords reflect quality or fit-related aspects of products. After each manual encoding, Kappa scoreswere calculated to measure the internal consistency of the classification of the four assistants [53]. The average Kappa reaches 0.79, which is higher than the threshold value of 0.65 [52], indicating that the four research assistants have a high degree of consistency in the classification of the sample data. Third, the instructor pooled the keywords together and invited the assistants to discuss any inconsistencies among the keywords. Finally, we obtained two topics of product quality (45 keywords) and fit (36 keywords). In the sample data, each review keyword generated by the Taobao algorithm owns its corresponding weight. The absolute value of the weight indicates the frequency of the review keywords in product reviews. For each review, if the label under the manual classification dictionary appears in the review, the weight of this label was assigned to its corresponding category topic.

- Regression analysis

In the regression model, we used the positive review rate, the number of images, and the sales and the price of the products as the control variables to reduce the possible interference of review polarity, review content and quantity, and product attributes on the results. For fit-related and quality-related review keywords, we used the keyword percentage (There may be multiple fit-related/quality-related keywords in a review, so the keyword percentage can be greater than 1) (keyword frequency/the total number of reviews) to normalize the variables. Table 1 provides the variable notations used in the model and their explanations. Tables 2 and 3 show the descriptive statistics and correlation matrix of the variables. Regression analysis results are presented in Table 4. The established regression model of online product consideration is as follows (we use the log-transformation on several variables to manage the skewed data issue):

$$\begin{aligned} &\mathrm{LOG}(Consideration)_n \\ &\quad = \alpha + \beta_1 (Fit - related)_n + \beta_2 (Quality - related)_n + \beta_3 (Positive)_n + \beta_4 (Images)_n \\ &\quad + \beta_5 \mathrm{LOG}(sales)_n + \beta_6 (Price)_n + \varepsilon_n \end{aligned} \tag{1}$$

Table 1. Variables and description.

Variable	Description
$(Consideration)_n$	The consideration of product n, reflected by the number of consumers who have added the product to their favorite lists
$(Fit - related)_n$	For product n, the percentage ratio of fit-related keywords frequency to the total number of reviews
$(Quality - related)_n$	For product n, the percentage ratio of quality-related keywords frequency to the total number of reviews
$(Positive)_n$	For product n, the percentage ratio of the number of positive reviews to the total number of reviews
$(Images)_n$	The number of review images of product n
$(Sales)_n$	The sales of product n
$(Price)_n$	The price of product n

Table 2. Descriptive statistical analysis of variables.

Variable	N	Min.	Max.	Mean	St. Deviation
Consideration	1265	230	480,000	32,529.49	41,686.80
Fit-related	1265	0.00	1.33	0.98	0.01
Quality-related	1265	0.15	1.39	0.81	0.15
Positive	1265	0.82	1.00	0.98	0.015
Images	1265	6	10,170	275.88	466.732
sales	1265	575	40,000	1742.46	1959.61
Price	1265	9.90	799.00	89.18	80.38

Table 3. Correlation matrix of variables.

	Log(Consideration)	Fit-related	Quality-Related	Positive	Images	Log(sales)	Price
Log(Consideration)	1						
Fit-related	0.414 **	1					
Quality-related	0.500 **	0.774 **	1				
Positive	0.371 **	0.096 **	0.298 **	1			
Images	0.326 **	0.544 **	0.589 **	0.091 **	1		
Log(sales)	0.317 **	0.383 **	0.436 **	0.045	0.417 **	1	
Price	0.264 **	−0.060 *	−0.008	0.189 **	−0.101 **	0.059 *	1

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

Table 4. Regression Analysis Results (N = 1265).

Variable	Coefficients		Collinearity Statistics		t-Statistic	Sig.
	B	Beta	Tolerance	VIF		
Constant	−10.992				−6.330	0.000 **
Fit-related	0.844	0.150	0.372	2.687	4.135	0.000 **
Quality-related	1.548	0.220	0.304	3.291	5.501	0.000 *
Positive	16.887	0.233	0.829	1.206	9.598	0.000 **
Images	0.000	0.059	0.599	1.670	2.062	0.039 **
Log(sales)	0.280	0.143	0.765	1.308	5.674	0.000 **
Price	0.003	0.245	0.949	1.054	10.813	0.000 **
R-squared			0.388			
Adjusted *R*-squared			0.385			
F-value			132.674 **			
Durbin–Watson stat			1.989			

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

- Results and discussion

The results of the model are acceptable ($R^2 = 0.388, p < 0.05$). The variance expansion factor and tolerance of each variable (tolerance value > 0.1) are within the appropriate range. VIF < 10 indicates that multicollinearity is not observed in the model, and the Durbin Watson test value is 1.989, indicating that the autocorrelation of the independent variables is not obvious. Fit-related and quality-related keywords show significant positive impacts on clothing consideration. Meanwhile, the impact of quality-related keywords on clothing consideration is greater than fit-related keywords ($Beta_{quality-related} = 0.220, Beta_{fit-related} = 0.150$), thereby supporting H1–H3.

The aforementioned regression analysis results are based on Taobao's objective data. However, the dataset may have an endogenous issue, that is, the consideration of a product is not only determined by the features of online reviews, but may also be affected by factors such as product brand and advertisements. In addition, products with high consideration may attract more reviews.

4.3. Study 2

To control the interference of other possible influencing factors on the results in Study 1, we further adopt experiment design to validate the impacts of online review keywords on clothing consideration.

We selected the eight most frequent review keywords under clothing products, among which four belong to the quality topic, and the rest belong to the fit topic. We designed four groups using the same product introduction and 10 reviews in each group. The only difference between the different groups is the content of review keywords, and the participants were randomly assigned to any one of the four groups. The experimental design is shown in Table 5 (for more detail see Figure A1 in Appendix A):

Table 5. Four groups of experimental design.

Groups	Product and Review Information	Review Keywords
G1	Product introduction and 10 reviews information	None
G2		4 fit-related review keywords
G3		4 quality-related review keywords
G4		2 quality-related review keywords and 2 fit-related review keywords

We added these four groups to the questionnaire and published them through the wjx website (https://www.wjx.cn/) (accessed on 25 December 2020), a well-known online survey platform in China. At the end of each group, the respondents were asked whether they would consider this clothing product for one of their male friends (scale 1–7).

Before the formal experiment, we conducted a survey on consumers' habits of reading online reviews and keywords:

If you are going to buy a piece of clothing on Taobao, do you read review keywords when you browse consumer reviews?

- Data collection and analysis

We used the sample research service on wjx website, and invited the participants from a major university in Beijing, which is a common practice in prior studies [43,54]. After removing incomplete responses, 236 valid questionnaires were finally obtained. The average response time of the respondents is 5.13 min (SD = 3.07), indicating that the majority of respondents answered the questionnaire carefully. The sample size and descriptive statistics of the respondents are shown in Tables 6 and 7.

Table 6. Number of samples in different experimental groups.

Groups	Number of Responses	Frequency (%)
G1	67	28.39
G2	54	22.88
G3	53	22.46
G4	62	26.27

Table 7. Descriptive statistics of the questionnaire.

Variable	Options	Number	Frequency (%)
Gender	Male	129	0.55
	Female	107	0.45
Education	High school or below	2	0.85
	College	9	3.81
	Bachelor	148	62.71
	Master's or above	77	32.63
Have you seen this product before?	Yes	11	4.66
	No	225	95.34
Is the price of this product right for you?	Suitable	219	92.80
	Inappropriate	17	7.20
Frequency of online shopping in last three months.	Never	3	1.27
	1~5	116	49.15
	6~10	82	34.75
	More than 10	35	14.83
Do you have the habit of browsing review keywords?	Never	10	4.24
	Sometimes	136	57.63
	Often	90	38.14

Prior research reveals that the awareness set affects the consideration set [4]. Therefore, we need to control the impact of the consumer's product awareness on product consideration. In other words, we need to select the products that consumers are not familiar with.

In this study, 95.34% of the respondents reveal that they did not know the product before, and more than 90% of them accept the product price. Except for the same product introduction, the review information in the experiment is the only source of product information for the respondents. Therefore, the consumer's awareness of the product is basically the same before seeing the online review. More than 90% of the respondents have recent online shopping experience, and approximately 95% of the respondents have the habit of reading review keywords, indicating that they are appropriate for answering the questionnaire. Moreover, 99% of the interviewees have a college degree or above, indicating that they have the sufficient knowledge and ability to understand the content of the reviews.

For the sample data, the Mann–Whitney rank sum test was used to compare whether the data among different groups vary significantly [55]. The results are shown in Table 8 and Figure 3.

Table 8. Difference test of product consideration under different groups.

Variable	Group	Sample	Mean	Standard Deviation	Mann-Whitney Test	
					Z-Value	*p*-Value
Product consideration	G1	67	3.046	1.278		
	G2	54	3.686	1.273		
	G3	53	4.381	1.396		
	G4	62	4.944	1.379		
	G2 − G1				−2.483	0.013
	G3 − G1				−4.359	0.000
	G4 − G1				−6.332	0.000
	G3 − G2				−2.109	0.035
	G4 − G2				−4.331	0.000
	G4 − G3				−2.050	0.040

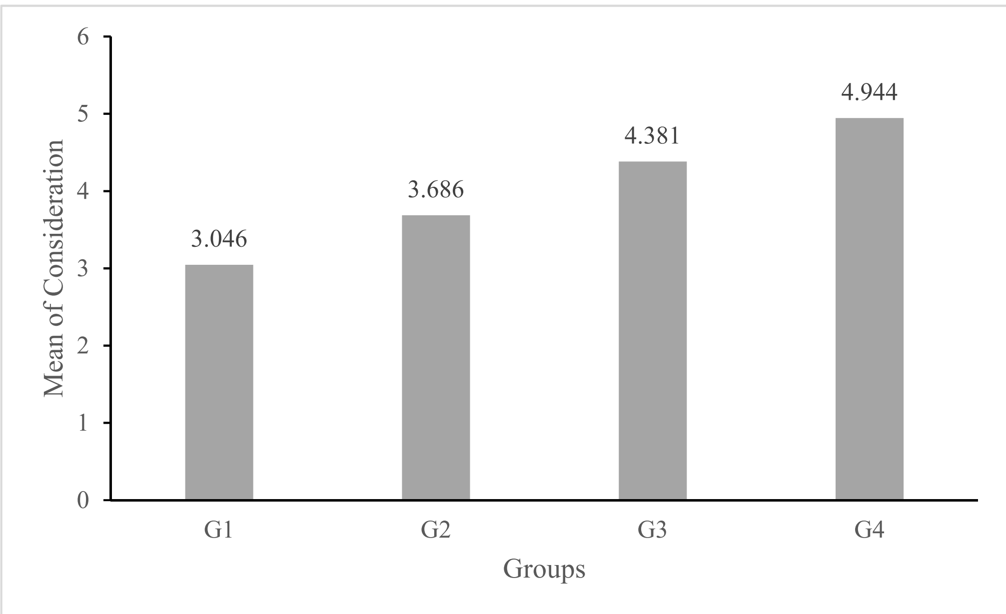

Figure 3. Mean value of product consideration among different groups.

- Findings and discussion

Different types of review keywords have various impacts on product consideration. From the Mann–Whitney rank sum test results in Table 8, when the keywords are added to the reviews, product consideration has improved significantly ($M_{G2\sim G4} > M_{G1} = 3.046$, $p < 0.05$). In addition, compared with the fit-related review keywords, the impact of the quality-related review keywords on the product consideration is more prominent ($M_{G3} = 4.381$, $M_{G2} = 3.686$), and the difference is significant ($z = -2.109$, $p < 0.05$). Therefore, we obtain the same results through the experiment and regression analysis. Finally, the review keywords of mixed topics have a greater impact on product consideration than the review keywords of a single topic. After combining the quality- and fit-related review keywords, its effect is significantly improved compared with the original single-topic groups ($M_{G4} = 4.944$, $M_{G3} = 4.381$, $M_{G2} = 3.686$, $P_{G4-G3} < 0.05$, $P_{G4-G2} < 0.05$).

The impact of review keywords in mixed topics becomes more salient in the experiment, therefore, the diversity of the topic for the review keywords may affect product consideration. However, the website-generated review keywords usually focus on the clothing quality and fit and cannot represent the online review content well. Other types of review keywords may play an important role in affecting product consideration.

4.4. Study 3

The content diversity of review keywords displayed on e-commerce websites is limited. In Study 3, we further explore the variety of keywords in the review content and investigate whether other types of keywords have a significant impact on product consideration.

- Review keywords analysis

We have found that review keywords have a significant impact on clothing consideration. Therefore, in commodity reviews with high and low product consideration, the difference in the proportion of influential keywords in the review, which affects the product consideration, will be significant. Based on this, we conducted an explorative analysis on the text content of product reviews.

To find the most discriminative expressions for product consideration, we selected six products with roughly the same number of reviews but significantly different product consideration values from 1265 product samples and divided them into two groups (i.e., a high consideration group and a low consideration group). The average product consideration of the high level group is 10 times higher than that of the low-level group. We used the product links in the original data set to crawl all reviews of these six products on the same day. Excluding the review data that contain missing values and are obviously suspected of advertising, the number of words in the review is controlled between 10 and 100 words, and finally a total of 14,955 valid reviews were obtained (Table 9).

Table 9. Product consideration and review data of six products.

ID	Product Consideration	Number of Reviews
P1	16,877 (high)	2501
P2	16,197 (high)	2477
P3	17,673 (high)	2463
P4	1512 (low)	2495
P5	1431 (low)	2467
P6	1570 (low)	2552

We marked 7441 reviews under products with a high level of consideration as 1 in turn and 7514 reviews under products with a low level consideration as 0 in turn. We used the Python jieba word segmentation package (https://github.com/fxsjy/jieba) (accessed on 15 February 2021) to preprocess Chinese reviews. The jieba package has strong word segmentation performance and is widely used in Chinese word segmentation [19].

We then used the Python scikit-learn 0.21.3 package (http://scikitlearn.org/) (accessed on 15 February 2021), which integrates many mainstream machine learning algorithms, and ran the polynomial naive Bayes classifier on the review words that appear at least 10 times. The classifier uses Bayesian rules and the hypothesis of independence between words to estimate the probability of each word that appears for products with a high level of consideration and products with a low level of consideration. The probability of each word appearing in products with a high or low level of consideration is then estimated using the following formula [56]:

$$p_{high} = prob(word \,|\, consideration = high)$$

$$p_{low} = prob(word|consideration = low)$$

$$p_1 = p_{high}/p_{low} \tag{2}$$

The higher the $p1$, the greater the probability of the word appearing with the product with high level consideration and the smaller the probability of appearing with products with a low level of consideration. Based on this, we calculated the $p1$ value of each word, and then select the 30 words with the highest $p1$ value to generate a word cloud (Figure 4):

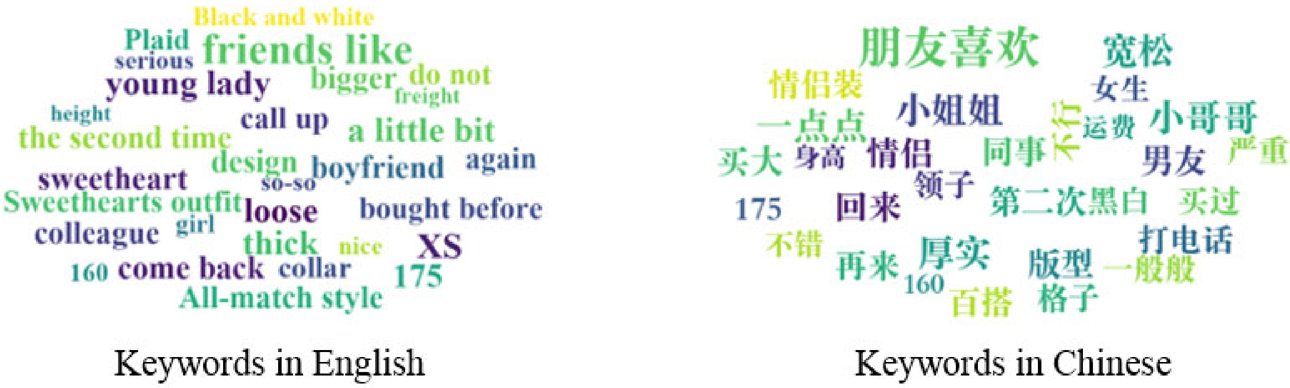

Figure 4. The most different words under different product consideration (6 products).

To test the robustness of the word cloud results, we selected different numbers of products to repeat the above process, and the word cloud results are detailed as follows (Figures 5 and 6):

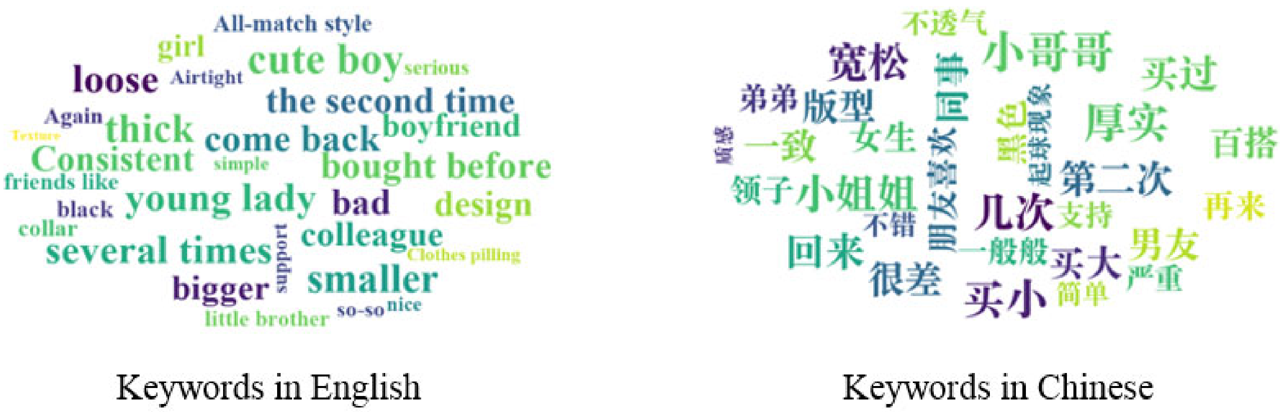

Figure 5. The most different words under different product consideration (10 products).

Figure 6. The most different words under different product consideration (16 products).

Through the qualitative analysis of review keyword clouds (after removing product quality and fit-related review keywords), we found that, compared with reviews of products with low-level consideration, reviews of products with high-level consideration are more likely to mention the following two types of wording:

- Social keywords: “boyfriends”, “colleagues”, “friends like”, “sweethearts”, etc.;
- Consumer buyback keywords: “bought before”, “come back”, “the second time”, etc.

Thus, the keywords in reviews about social-related information and consumer buyback information may have significant impacts on product consideration. Moreover, our analysis of review content revealed that quality-related and fit-related keywords account for approximately 70% of all the keywords involved in Study 3, but self-generated keywords (social keywords and consumer buyback keywords) account for less than 10%.

- Review keyword test

To further test the impact of social-related keywords and consumer buyback keywords, we conducted a new experiment based on Study 2. Specifically, we designed four groups using the same product and review information, but the review keywords were different (Table 10). We used the sample service of wjx, and invited the participants from a major university in Beijing, similar to what we did in Study 2. Finally, 243 valid samples were obtained. The Mann–Whitney rank sum test was performed on the sample data, and the results are shown in Table 11.

Table 10. Number of samples in different groups.

Groups	Sample	Frequency (%)	Review Keywords
G4	62		Good fabric (quality-related), thick (quality-related), comfortable (fit-related), look slimmer (fit-related)
G5	67	27.57	Replace the keyword “good fabric” with “friends and family like” in G4
G6	59	24.28	Replace the keyword “comfortable” with “friends and family like” in G4
G7	55	22.63	Replace the keyword “good fabric” with “buy again” in G4
G8	62	25.51	Replace the keyword “comfortable” with “buy again” in G4

Table 11. Test results of differences in product consideration under different groups.

Variable	Group	Sample	Mean	Standard Deviation	Mann-Whitney Test	
					Z-Value	p-Value
Product consideration	G4	62	4.944	1.379		
	G5	67	5.667	0.970		
	G6	59	5.508	1.105		
	G7	55	5.482	1.144		
	G8	62	5.539	1.029		
	G5 − G4				−2.878	0.004 **
	G6 − G4				−2.296	0.022 *
	G7 − G4				−2.054	0.040 *
	G7 − G5				−0.834	0.404
	G8 − G4				−2.417	0.016 *
	G8 − G6				−0.065	0.949

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

- Results and discussion

Studies 1 and 2 demonstrate that website-generated review keywords, including quality-related and fit-related keywords, show positive impacts on consumers' clothing consideration. Furthermore, quality-related keywords play a more salient role in affecting clothing consideration compared with fit-related keywords. However, website-generated keywords are extracted based on the frequency of term occurrence and mainly reflect quality- and fit-related aspects due to the clothing products' experiential nature. As a complementary and explorative study, Study 3 further demonstrates that aside from website-generated review keywords, other types of review keywords also have significant effects on clothing consideration. When the social-related keywords (e.g., friends and family likes) or consumer buyback keywords replace the original topic keywords, the clothing consideration is significantly improved. Meanwhile, quality-related keywords (e.g., good fabric) and fit-related keywords (e.g., comfortable) are less effective than self-generated review keywords. The keywords of different topics have various impacts on clothing consideration, and the experiment groups with several types of keywords perform better.

The social-related keywords reflect the opinions of the people around the consumers. When consumers are faced with the choice of experience products, such as clothing, they not only pay attention to the basic quality and fit attributes but they also consider the social attributes. In other words, will this product bring consumers added value in social situations? Some scholars summarize this value as the symbolic value of a product [44]. In addition, consumer buyback keywords reflect that the specific product has been purchased multiple times, indicating that the product is popular among consumers. In response to this result, we further conducted a small-scale interview with 20 questionnaire respondents. A total of 17 respondents mentioned that they care about other people's opinions when buying clothes. For example, one of the respondents recalled that "*if this dress is praised by others, I think it is right to buy it.*" A total of 14 interviewees expressed that the greater the number of consumers who have purchased the product, the better the quality of this product. They are more likely to trust the reviews posted by the consumers who have purchased the product multiple times, thereby enhancing their positive attitude toward the product. For example, one of the respondents said that "*as some consumers have bought the same product multiple times, I believe the quality of the product will not be bad.*"

5. Theoretical Contributions and Practical Implications

This study makes several contributions to the extant literature. First, different from prior studies that focus on review-level analysis [6,17,23], our study focuses on the online review keywords from different sources, such as e-commerce website-generated and self-generated keywords. As a specific e-commerce website embedded mechanism, review keywords have received scarce research attention. To the best of our knowledge, this study is the first one to consider the impacts of website-generated and self-generated review keywords. Second, with a significant departure from existing literature investigating the impacts of online reviews on various outcomes, such as product adoption [24], product returns [14], and purchase decisions [26], this study uncovers the impacts of online review keywords on consumers' clothing considerations. On the one hand, through analyzing review keywords from different sources (i.e., website-generated and self-generated), this study demonstrates that website-generated review keywords based on the frequency of term occurrence cannot fully capture consumers' concerns during online shopping. The self-generated review keywords based on analyzing popular products can be an efficient supplement for website-generated review keywords. On the other hand, this study uncovers the impacts of review keywords with different topics. Specifically, website-generated quality-related review keywords show a more salient impact on consumers' product consideration compared with fit-related keywords. Meanwhile, self-generated social-related review keywords and consumer buyback keywords can further enhance product consideration. In sum, analyzing online review keywords by considering the sources and topics provides us with a full landscape to uncover the various impacts of online review keywords on consumers' product consideration.

The results of this research can also help e-commerce websites and e-merchants to improve the management of online reviews. First, this research reveals that social-related keywords and consumer buyback keywords, though accounting for a lesser amount compared with product quality and fit-related review keywords, have significant impacts on clothing consideration, even greater than the quality and fit topics. Therefore, the websites can actively guide consumers to publish reviews based on their friends' or family members' opinions on the clothing products and encourage consumers to buy the products again by efficient promotional strategies. Second, in the context of the rapid increase in the number of online reviews, the review keywords on the e-commerce websites have an important reference value. However, the review keywords generation algorithm on e-commerce websites still needs improvement with regard to reflecting the representativeness of the review content. The approach designed in this study provides some preliminary insights into generating more representative review keywords. The e-commerce websites can refer to the approach used in this paper to analyze the topics that consumers really care about when facing the review content under different product types.

6. Conclusions

This research confirms the role of online review keywords in the intermediate stage of consumers' shopping decisions (i.e., clothing consideration). By applying product uncertainty as a potential underlying mechanism, we built a link between various review keywords and consumers' clothing considerations. For website-generated review keywords, although both quality- and fit-related keywords matter for consumers' clothing consideration by reducing product uncertainty, quality-related keywords show a more salient impact compared with fit-related keywords. In addition to website generated keywords, the self-generated keywords (e.g., social-related keywords, consumer buyback keywords) obtained through text analysis can further improve the impact of review keywords on clothing consideration significantly.

This study has some limitations, which shed additional light on some potential future directions. First, we only considered clothing as the research target in this study. Clothing is a typical type of experience product, and review keywords will act as efficient cues for consumers to evaluate such products. However, whether review keywords also play a similar role for other types of products (e.g., search products) remains unclear, which requires future research attention. Second, the measure of clothing consideration is based on the number of consumers who have added the product to their favorites list. In fact, some other measures, such as adding products to their online shopping cart can also measure product consideration to some extent. However, due to data access restrictions, we cannot obtain these internal data, leaving an open avenue for future research. Third, in Study 2 and

Study 3, the experiment participants were invited from a major university. Although this is a common practice in some studies, it is expected that future research can invite participants with more diversified backgrounds to guarantee the representativeness of research samples. Fourth, in the analysis of review content in Study 3, the difference of keywords is analyzed on the basis of the hypothesis of word independence, whereas the semantic relationship between the words is ignored. Future research on product consideration can combine various topic analysis techniques to further optimize the model.

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Data Availability Statement: Not applicable.

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Conflicts of Interest: The authors declare that they have no conflicts of interest.

Appendix A

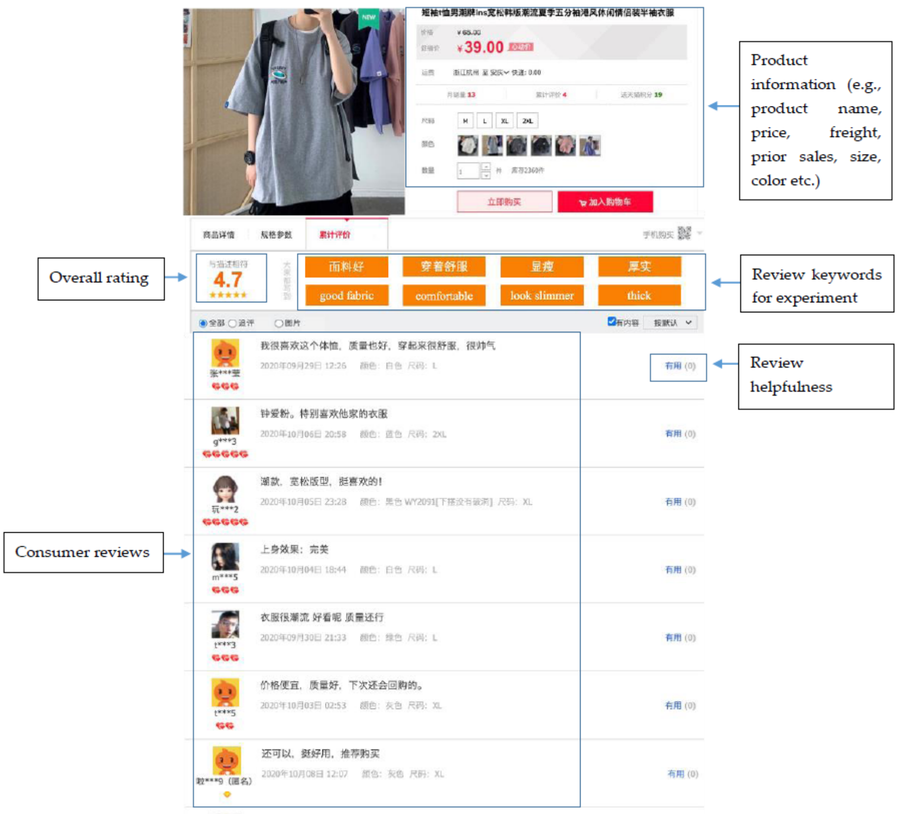

Figure A1. An example of experiment design (adapted from Taobao website, source: https://www.taobao.com/) (accessed on 10 December 2020).

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