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Consumer-Perceived Risks and Sustainable Development of China's Online Gaming Market: Analysis Based on Social Media Comments

Ling Lin [1], Tao Shu [2,*], Han Yang [3], Jun Wang [4], Jixian Zhou [1] and Yuxuan Wang [5]

[1] School of Computing and Artificial Intelligence, Southwestern University of Finance and Economics, Chengdu 611130, China; linling@smail.swufe.edu.cn (L.L.); zjx06288@163.com (J.Z.)
[2] School of Software Engineering, Chengdu University of Information Technology, Chengdu 610225, China
[3] School of Computer Science, Chengdu University of Information Technology, Chengdu 610225, China; yanghan199296@gmail.com
[4] School of Management Science and Engineering, Southwestern University of Finance and Economics, Chengdu 611130, China; wangjun1987@swufe.edu.cn
[5] School of Computer Science, University of Nottingham, Nottingham NG7 2RD, UK; alyyw56@exmail.nottingham.ac.uk
* Correspondence: shutao@cuit.edu.cn; Tel.: +86-138-8229-2020

Abstract: Online gaming constitutes an indispensable facet of China's digital economy, catalyzing consumer discussions on social media platforms. This study employs a comprehensive natural language processing framework, encompassing topic mining, multi-label classification, and sentiment analysis, to evaluate consumers' psychological perceptions of the risks associated with online games through social media comments. This study identifies 11 distinct perceived risk topics, including "Excessive Temptation", "Entry Regulation", and "Culture Implantation". Numerous comments encompass multiple topics, each infused with diverse emotional inclinations, thus unveiling disparate consumer perspectives. These findings underscore the critical significance of addressing potential perceived risks and mitigating negative consumer emotions for enterprises operating within online gaming. Such measures are pivotal to maintaining a brand image, business reputation, and enduring growth. Furthermore, this study extends valuable insights to regulatory bodies, contributing to enhancing administrative efficiency, safeguarding consumer rights, and fostering a robust and sustainable trajectory within China's online gaming market.

Keywords: online gaming market; perceived risk; emotion analysis; social media comments; natural language processing

Citation: Lin, L.; Shu, T.; Yang, H.; Wang, J.; Zhou, J.; Wang, Y. Consumer-Perceived Risks and Sustainable Development of China's Online Gaming Market: Analysis Based on Social Media Comments. *Sustainability* **2023**, *15*, 12798. https://doi.org/10.3390/su151712798

Academic Editors: Muhammad Mohiuddin, Slimane Ed-Dafali, Bilal Khalid and Saeb Farhan Al Ganideh

Received: 20 July 2023
Revised: 19 August 2023
Accepted: 22 August 2023
Published: 24 August 2023

1. Introduction

In recent years, the online gaming industry has experienced remarkable growth due to technological advancements, particularly in virtual commodities. In China, this has led to the emergence of a burgeoning new industry. As reported in the 2022 China Game Industry Report, the actual sales revenue of China's online gaming sector reached CNY 259.7 billion. Various online gaming enterprises have a trajectory of innovative development. These entities have actively expanded into overseas markets, resulting in an elevated impetus and reciprocal effects between the gaming industry and technological innovation. Gaming serves as a significant means of fulfilling the spiritual and cultural requirements of the populace. The advancement of online gaming is intricately linked to enhancing a nation's cultural soft power and the amplification of the influence of Chinese culture, thereby contributing to sustained progression of the digital economy.

However, numerous studies have highlighted the adverse effects of this development, including impacts on public health such as mental disorders [1] and addiction [2]. Moreover, research has indicated that chronic engagement in online gaming can be associated with poor social skills, learning difficulties, aggression, neglect of family responsibilities, job dereliction, and gambling [3,4]. However, despite these findings, only some studies have specifically examined the potential psychological risks consumers perceive in online gaming [5,6]. Furthermore, limited research investigates consumers' perceived risk toward online games and how this understanding can inform preventive measures in government regulatory policies [7,8] and business marketing strategies [9,10]. Such insights are crucial for fostering a healthy, green, and sustainable online gaming market in China [11,12].

Additionally, the existing literature that measures perceived risk toward online gaming products often employs research methods such as designing scales related to the human psychological structure and collecting quantitative data through questionnaires or interviews to represent psychological perceptions [5,6]. However, an increasing number of scholars argue that although traditional psychological measurement methods effectively maintain ecological validity and objectivity, they need more replicability, making it difficult to achieve consistent results and accurate analysis [13]. Some studies further suggest that traditional methods have limitations in terms of sample size, timeliness, duration, spatial range, and richness, making it challenging to comprehensively capture the psychological perceptions of most people [14,15]. Fortunately, the widespread adoption and evolution of information technology, coupled with the rise of social media, have transformed how to convey psychological perception information. This includes aspects such as the attitudes, emotions, and opinions of consumers, providing a new avenue for expression. At the same time, the advancement of psychology has been accompanied by studying human natural language. Chinese text social media comments contain genuine consumer feelings and hold significant research and mining value [16], offering a fresh perspective and rich data sources for measuring consumers' psychological perceptions.

Yet, analyzing comment text on social media in its digital form relies on computer-assisted analytical techniques. Natural language processing (NLP) methods, which aim to analyze and comprehend human language automatically [17], enable researchers to easily explore people's psychological perceptions contained in textual datasets while avoiding laborious computational tasks [18]. Some studies in the field of psychology have already begun to incorporate social media comment data and NLP approaches. For instance, researchers [19,20] have collected data from Weibo, a social media platform, and employed NLP techniques to identify the public's psychological perceptions of emotions and opinions regarding the built environment and analyze the correlations between built environment elements and sentiment intensity at different scales. In another example, researchers have used NLP technology to study consumer preferences for the charging infrastructure based on comments posted on public social media platforms [21].

Furthermore, scholars have deconstructed the multifaceted dimensions of Chinese customers' perceived risk toward electric vehicles through empirical research, utilizing a wealth of online textual data from social media [22]. Furthermore, other researchers have employed NLP methods to mine, identify, and reveal consumers' attitudes toward big data-driven price discrimination in online consumption by analyzing social media comment data [23]. Therefore, researchers can overcome the limitations and challenges posed by traditional methods by leveraging data retrieved from social media and adopting NLP technology to measure and analyze consumers' perceived risks toward online gaming products.

The preceding research underscores the efficacy of emerging computer technologies within the context of the big data era. Strategic utilization of artificial intelligence models has the potential to facilitate the extraction of more profound rules from vast volumes of textual data. However, owing to the challenges in data acquisition, we have observed a paucity of studies thus far that harnessed substantial social media comment data for the explicit purpose of analyzing consumer perceptions of the risks of online gaming. In order to enable governments and businesses to understand better and address issues related to online gaming products, as well as to develop targeted, specific, and effective favorable industrial policies and corporate strategies for sustainable development of the online gaming market, this study collected social media comments and constructed a comprehensive framework utilizing a variety of practical NLP technologies to assess consumer perceptions of the risks associated with online gaming. This study aimed to identify and quantify multiple dimensions of perceived risk and emotional dispositions in consumer comments and to reveal potential ways to promote the digital economy and mitigate the perceived risks posed by online gaming products.

The expected contributions of this study are as follows:

(1) We employ computer technology to facilitate the retrieval of public comment data from social media platforms, thereby capturing a wealth of semantic information from a vast array of comments, overcoming the limitations imposed by previous research.
(2) We introduce a natural language processing framework based on deep learning models, enabling the exploration of consumer-perceived risks within comments and conducting associated sentiment analysis. This framework offers a novel toolset to address this research problem.
(3) We analyze the perceived risk topics extracted from the acquired comment dataset, thus furnishing fresh perspectives for enterprises engaged in the marketing and promotion of online games and for governmental bodies overseeing online game regulation.

The structure of this study is as follows. Section 2 reviews the pertinent literature. Section 3 delves into the research materials and outlines the three NLP tasks that form the basis for our implementation and modeling details. In Section 4, we set up the experimental process and model parameters. Section 5 shows the analysis of our findings. Section 6 engages in discussion and explores the implications. Lastly, Section 7 concludes with the limitations and future research guidance.

2. Literature Review

2.1. Consumer-Perceived Risk Theory

Initially used in psychology research, the concept of perceived risk was introduced to consumer behavior studies in the 1860s, suggesting consumer purchases carry uncertainty, the essence of perceived risk [24]. This includes uncertainty and severity of potential consequences [25]. Scholars refined this concept, highlighting that incomplete information in the buying process leads to consumer uncertainty [26]. Perceived risk involves assessing consumers' judgments of potential harm from consumption events [27] and represents anticipated adverse outcomes when buying specific products or services [28]. The perceived risk significantly influences consumers' decisions to delay, modify, or cancel purchases [29], often overshadowing perceived gains [30]. In online gaming, perceived risks interact with consumption values and continuance intentions to affect purchases [6], and concerns over potential risks drive non-sustainable consumption [31]. Therefore, perceived risk is critical to online game market development.

2.2. Perceived Risk Measurement Research

Some scholars found in empirical studies that although consumers' perceived risks of different commodities have multiple dimensions, the most representative six dimensions, including financial, performance, social, psychological, physical, and time risks, can explain 88% of consumers' overall perceived risks [32–34].

As evident from the theory of bounded rational decision making, consumers need help accessing comprehensive information, making it challenging to achieve complete rationality when analyzing risks. Instead, consumers rely on psychological cognition, emotions, and feelings to identify risks. Numerous scholars have adhered to the traditional psychometric paradigm to measure perceived risks. Typically, each question in a questionnaire is on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

Featherman and Pavlou [28] noted that consumers may perceive different risks due to diverse product attributes and features. However, prior research has yet to measure consumers' psychological perceived risk regarding online games. Therefore, each study assessed the perceived risk dimensions of online games using traditional questionnaire survey methods, resulting in slightly different descriptions and definitions, as outlined in Table 1.

Table 1. Review of perceived risk measurement research.

Commodity Type	Dimension	Description
Generic commodities	1. Performance risk	The purchased commodity does not perform as expected [32–34].
	2. Physical risk	The personal injury caused by purchasing the commodity [32–34].
	3. Financial risk	The purchased commodities will result in a loss of money or other resources [32–34].
	4. Time risk	The time loss caused by purchasing or retaining commodities [32–34].
	5. Psychological risk	The commodity leads to an inconsistent self-image [32–34].
	6. Social risk	The commodities are not accepted by relatives and friends [32–34].
Online games	1. Performance risk	Performance risk is that consumers cannot correctly judge the quality of online games, and they do not meet expectations due to information asymmetry [35].
	2. Physical risk	There can be physical damage issues in online games, such as visual fatigue or eyesight loss, insomnia, dizziness, and neck pain [5]. Physical risks may occur if online games do not provide clear instructions for operation [35].
	3. Financial risk	Consumers worry that their account details in online games, such as credit cards, virtual currency, treasure, and equipment, will be misappropriated or stolen by others [35].
	4. Time risk	Consumers may lose time playing online games, leading to delays in their study, work, rest, and sports [5,6]. Due to the lack of information, consumers worry that time may be wasted understanding the features of online games [35].
	5. Psychological risk	Consumers who play online games will produce psychological pressure and will not have guilt or unease [5]. Online games belong to virtual goods, and there is uncertainty, resulting in psychological risks for consumers [6,35].
	6. Social risk	Consumers are concerned about the social risks of negative reviews from relatives or friends [35]. Consumers addicted to the illusory game world are led to bruising of the self-concept [5,6].
	7. Privacy risk	Consumers are concerned about loss of personal information when consuming or using online games [6].

2.3. Social Media Comments in Measuring Psychological Perception

The proliferation of social media has resulted in a wealth of user-generated comments, offering new avenues for psychometric research. These comments, reflecting diverse individual characteristics and psychological cognitions, have prompted researchers to adopt a bottom-up exploratory analysis approach [15]. In addition, social media comment data can supplement traditional measurement methods, especially where they are challenging to implement [16,36].

In the existing literature, Han et al. [8] highlighted the role of social media comments in disseminating information, expressing opinions, and sharing feelings, aiding emergency response and management efforts. Yu et al. [37] analyzed tourism reviews from social media to understand tourists' memories and intentions. Similarly, Yang et al. [38] used social media to analyze public opinion data and air pollution. Finally, Yin et al. [39] explored Chinese attitudes toward volunteerism amid COVID-19 through social media comments to boost volunteer participation. Studies [40] have shown the impact of online games on public health through social media comments. Jeon et al. [41] studied people's reactions to social media posts related to online games. The studies above demonstrate the diverse range of NLP methods employed when analyzing social media comments, including all six primary NLP methods: text preprocessing, text representation, classification, topic modeling, emotion analysis, and deep learning.

However, due to the massive and difficult-to-obtain amount of social media comments, much of the research involving social media and online games has predominantly focused on discussing the relationship between social media and gaming [42–44], with minimal studies delving into analysis of the perceptions related to online games through comment analysis. As a result, social media comments and NLP methods provide researchers with unparalleled opportunities to access a vast array of textual data and advanced technology for exploring individuals' psychological states of perception.

3. Materials and Methods

3.1. Data Sources and Preprocessing

This study used Python programming to collect 1,076,694 social media comments related to online games from 15 September 2017 to 17 April 2022 from six social media platforms. By employing data preprocessing techniques such as webpage cleaning, word segmentation, and stop word removal, we obtained valid data that met the input requirements of the NLP model. In addition, this significantly reduced the computational space needed for subsequent experiments. This laid the groundwork for enhancing the accuracy of feature mining, recognition, and sentiment analysis related to perceived risks. As depicted in Table 2, the preprocessed dataset contained 913,986 acceptable comments, with an average word count of 36.32.

Table 2. The summary of comment collection from social media platforms.

Social Media Platform	Number of Comments	Percentage (%)
Weibo	116,020	12.69
Zhihu	80,705	8.83
Toutiao	142,458	15.59
Xigua Video	116,619	12.76
Tiktok	365,486	39.99
Kuaishou	92,698	10.14
Total	913,986	100.00

3.2. Methods

Natural language processing, a subfield of machine learning, is utilized to identify semantic information from large, irregular, or unstructured databases and extract meaningful knowledge in the shortest time possible [45]. In recent years, using NLP to semantically understand social media comments has become popular in management research [46].

3.2.1. LDA Model

Topic mining is a machine learning technique for learning, identifying, and extracting semantic topics from unstructured comments, which divides collections of documents into natural groups to understand them separately [47]. Latent Dirichlet Allocation (LDA) is the most widespread and popular fitting topic-mining method [48]. LDA is a three-level Bayesian probability model [49]. In the LDA model, the relationship between topics and terms is estimated by assumptions. Topics consist of multiple words, and documents constitute poly-topics. Figure 1 shows the model structure of LDA, where nodes represent random variables and directed edges represent the conditional probability dependence between random variables. Given the substantial magnitude of the comment dataset, resorting to manual labeling methods would significantly allocate human and material resources. Consequently, we applied the LDA model, facilitating an automated topic clustering process within the comment dataset. This strategic choice enables the extraction of consumer focal points from the comments, thereby circumventing the resource-intensive nature of manual labeling.

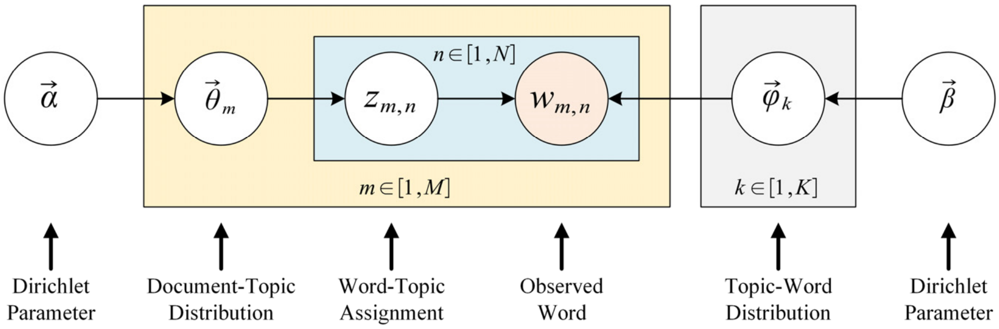

Figure 1. The LDA topic model.

3.2.2. Bi-LSTM Classification Model

Tsoumakas et al. [50] developed a multi-label method to identify text data better and intuitively reflect multiple semantic details of polysemous objects. Multi-label text classification is often used in practical applications [51]. For example, the comment text "Online games not only delay learning time but also cause myopia" includes the commodity attribute label "online games", time risk label "delay learning", and physical risk label "myopia", which indicates that the comment belongs to three categories. In this study, we employed the Bi-LSTM model, an improved version of the LSTM model, for the multi-label classification of Chinese text in social media comments. Through empirical observation, we discerned that the diversity of consumer expressions imparted a richness of semantic information within the comment dataset. Consequently, our selection of the Bi-LSTM model, surpassing the performance of the standard LSTM, was grounded in its enhanced capacity to capture contextual nuances within textual content [52,53] effectively. The model helped identify consumers' perceived risks toward online games in multiple dimensions. The classified labels originated from the perceived risks acquired in the first task. The Bi-LSTM model's structure is depicted in Figure 2.

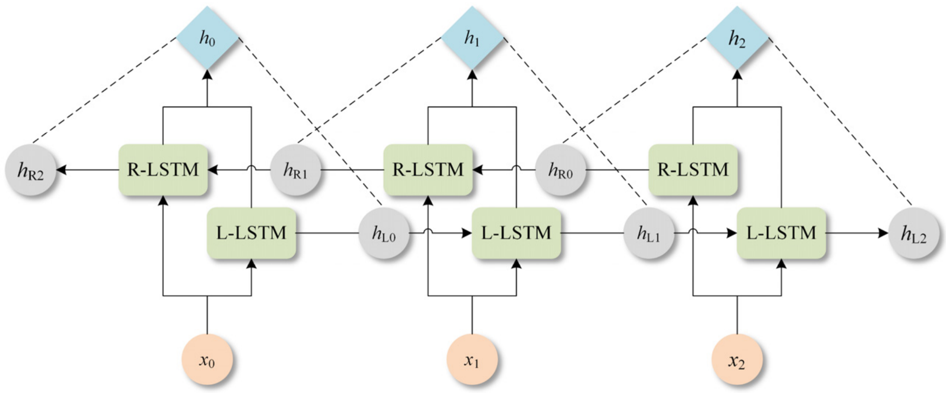

Figure 2. The Bi-LSTM multi-label classification model.

3.2.3. Snow-NLP Model

In order to comprehensively capture consumers' risk perception information for online games, a particular emotion analysis task was designed based on the results of multi-label classification to analyze consumers' emotions regarding different perceived risk dimensions of online games. Emotion analysis is an essential aspect of psychological perception measurement which assesses emotional states toward subjects, services, products, organizations, and attributes [54]. Automated sentiment analysis of social media data can help to understand genuine emotions for informed decision making [55]. The Snow-NLP model is a Bayesian classifier in the Scikit-learn Python machine learning library which is widely used to analyze Chinese text emotion. Our rationale for selecting Snow-NLP emanated from its specialized focus on Chinese text processing, rendering it more efficacious than specific general-purpose NLP libraries. Moreover, Snow-NLP offers sentiment analysis capabilities, facilitating the discernment of emotional inclinations within the text, such as positive, negative, or neutral sentiments. Furthermore, its status as a lightweight library obviates the need for excessive time investment in model training.

4. Experimental Process

The framework of this study consisted of three NLP tasks: topic mining, multi-label classification, and emotion analysis. The first task involved mining topics using the LDA model. The second task combined the topic mining results with a bidirectional long short-term memory (Bi-LSTM) model for semantic identification. Finally, the third task used the Snow-NLP model to analyze emotions based on the classified data. By analyzing the results of these three tasks, we could examine perceived risk-related topics concerning online games in social media comments and assess the emotional intensity of different topics. Figure 3 illustrates the specific experimental process of this study.

Figure 3. The experimental process.

4.1. Topic Mining

The first task combined quantitative and qualitative analysis. Initially, the quantitative analysis aimed to retrieve topics about online games from the self-built corpus in this study. Then, we employed the LDA model to mine feature words and topics from the entire corpus, generating a topic model. Subsequently, an essential reasoning task for researchers is to analyze the feature words mined by the LDA model to determine the topics [56,57]. Finally, the qualitative analysis was divided into four steps as follows:

- We invited three experts to participate in determining the topics: two doctoral students majoring in business administration and one doctoral student majoring in psychology;

- Each expert independently analyzed the feature words corresponding to each topic and labeled the topics according to their prior knowledge;
- The three experts discussed the separately marked topics and decided on the number and name of the topics through voting;
- We invited two professors of related disciplines to review the topics and ultimately determine the results.

Moreover, hierarchical cluster analysis was adopted to construct a tree diagram for topic grouping to eliminate correlations and maintain the independence of the determined topics. Hierarchical cluster analysis converts a set of potentially correlated observations into a set of linearly uncorrelated components [38]. Based on the clustering results, the connection between various dimensions of consumer-perceived risk and different topics was constructed.

4.2. Semantic Identification

The experimental process for the second task was divided into three steps as follows:

- We manually annotated 10% of the corpus data, referencing the topics and feature words determined in the first task to form a dataset with marked topics;
- The labeled datasets would be randomly divided into training, validation, and test data subsets at an 8:1:1 ratio for training and testing the multi-label classification model Bi-LSTM;
- We set the topic mining results from the first task as classification labels for the classification model, ensuring that the classifiable comment data belonged to one or more topics. The classified dataset obtained is one of the critical outcomes of this study and serves as the foundation for subsequent experiments.

4.3. Emotion Analysis

In the experimental process of the third task, the classified dataset obtained in the second task served as the basis for emotion analysis. Next, the classified datasets were input into the Snow-NLP model, and emotion analysis was conducted separately for each topic.

5. Results and Analysis

5.1. Task 1

Following the experimental procedures outlined in the first task, we completed feature word extraction and topic identification related to the perceived risks of online gaming within the preprocessed database, as presented in Table 3. The fourth column displays the LDA model's feature word extraction results. The 10 most important words for each topic correspond to those with the highest probability within that topic and a lower probability in other topics. The third column lists 11 identified topics, which include "Excessive Temptation" (T1), "Entry Regulation" (T2), "Culture Implantation" (T3), "Addiction" (T4), "Physical Damage" (T5), "Mental Injury" (T6), "Recharge Cost" (T7), "Time Expenditure" (T8), "Social Relationships" (T9), "Adolescent Education" (T10), and "National Future Venture" (T11). The researchers determined these topics based on the LDA model's output. Then, the first column illustrates the clustering of consumers' perceived risk dimensions, which include "Performance Risk" (PR1), "Physical Risk" (PR2), "Financial Risk" (PR3), "Time Risk" (PR4), and "Social Risk" (PR5).

As evident from the results above, several topics aligned with common topics found in existing studies. However, a significant portion of the dataset distinctly clustered under different topics, highlighting specific risk topics that have been overlooked or understudied but which surfaced in social media comments. This suggests that consumers indeed harbor these concerns. The advantage of topic mining becomes evident in its capacity to uncover new topics. For instance, three such topics reflected in the last column include "Excessive Temptation" (T1), "Entry Regulation" (T2), and "Culture Implantation" (T3). Accordingly, these topics should be incorporable into the research purview. Table 3 shows that no risk topics were under the time risk dimension or the financial risk dimension. No recurrent feature words related to time risk concepts were found in the comments, apart from "Time Expenditure" (T8).

Table 3. Determined topics and dimension clustering.

Perceived Risk Dimensions Clustering	Topic Code	Topic Name	Top 10 Feature Words Belonging to Each Topic	Appeared in the Literature
Performance Risk (PR1)	T1	Excessive Temptation	Inducement, Seduction, Dopamine, Being on the List, Cool, Irresistible, Temptation, Attraction, Deception, Tittytainment	No
	T2	Entry Regulation	Facial Recognition, Real Name Authentication, Classification, Mobile Phone, Ban, Age Restriction, Registration, IP Address, Authority Control, Monitoring	No
	T3	Culture Implantation	Culture Invasion, Foreign Cultures, America, Europe, Japan, Korea, Thor, God of War, Roman Empire, Vikings	No
Physical Risk (PR2)	T4	Addiction	Addiction, Obsession, Ecstasy, Obsession, Falling into Obsession, Self-Control, Psychotropic Drugs, Obsession, Inability to Extricate Oneself, Internet Addiction	Yes
	T5	Physical Damage	Poor Vision, Myopia, Headache, Physical Strength, Nausea, Obesity, Insufficient Sleep, Back Pain, Exercise Less, Physical Weakness	Yes
	T6	Mental Injury	Depression, Emotional Stress, Negative Emotions, Nervous Breakdown, Identity Crisis, Avoid Reality, Obsessed, Solitary, Loneliness, Mental Disorders	Yes
Financial Risk (PR3)	T7	Recharge Cost	Recharge, Payment, Lottery, Local Tyrant, Devaluation, Pocket Money, Quota, Poverty, Wealth, Refund	Yes
Time Risk (PR4)	T8	Time Expenditure	Hours, No Sleep, Every Day, All Night, Punch in, Practice, Delay, All Day, Early Morning, Lack of Sleep	Yes
Social Risk (PR5)	T9	Social Relationships	Social Interaction, Parents and Children, Husband and Wife, Interests, Interpersonal Communication, Contacts, Social Phobia, Divorce, Isolation, Friends, Teachers and Students	Yes
	T10	Adolescent Education	Academic Record, Teenagers, Students, Cut Class, Stop Schooling, Ignore Study, Disciplining Child, Rebellious, Lack of Learning Interest, Bad Classroom Discipline	Yes
	T11	National Future Venture	Detrimental to the Future, Detrimental to Next Generation, Weaken the Country, Strengthen the Country, Patriotism, Future Trouble, No Successor, Lose the Ability to Innovate, Harm the Country and the People, National Strategy	Yes

Consequently, the "Time Risk" (PR4) dimension only encapsulates one risk topic. A similar situation arises with "Financial Risk" (PR3), which only includes "Recharge Cost" (T7). This pattern demonstrates that the perceived risks of online gaming, which have garnered consumer consensus, exhibited singular characteristics in the comments. This observation aligns with the inherent characteristics of the commodity in question.

In summary, Task 1 extracted and identified a range of perceived risk topics related to online gaming, as expressed in the consumer comments. A total of 11 topics and their supporting word lists are displayed in Table 3. However, the extent of consumer concern for each topic varied, and the interrelationships among topics differed and needed further deconstruction in the subsequent task.

5.2. Task 2

We obtained semantic identification results upon executing the multi-label classification in the second task. Around 61.58% of the social media comments showed concern for at least one topic, resulting in 744,899 valid comments. On the other hand, approximately 19% of the comments did not pertain to topics, indicating that some consumers may express their feelings about online games through text comments on social media, such as "I do not like online games". Table 4 shows the top 30 classification results. Based on this principle, this study identified 1,229,956 consumer-perceived risks from 744,899 valid comments. This suggests that consumers can express more than one perceived risk in a single comment, with an average of 1.65 perceived risks expressed per comment for this experiment. This strongly suggests that numerous Chinese consumers express their perceived risks regarding online games and their understanding of the relationships between different topics through social media comments.

Table 4. Semantic identified results of multi-label classification mode.

	Proportion (%)	**Description**
1	19%	Only emotion expression, not involving topics.
2	9.79%	T7
3	8.29%	T1
4	7.21%	T10
5	4.36%	T8
6	3.62%	T10 + T8
7	2.34%	T7 + T1
8	2.18%	T1 + T8
9	2.15%	T2
10	2.02%	T1 + T10
11	1.92%	T11
12	1.58%	T3
13	1.51%	T4
14	1.47%	T10 + T7
15	1.32%	T9
16	1.25%	T6
17	1.22%	T10 + T11
18	1.15%	T10 + T4
19	1.04%	T10 + T2
20	0.91%	T7 + T8
21	0.80%	T1 + T7 + T10
22	0.69%	T7 + T4
23	0.65%	T1 + T11
24	0.62%	T10 + T6
25	0.59%	T11 + T2
26	0.55%	T8 + T4
27	0.53%	T1 + T8 + T10
28	0.47%	T7 + T8 + T10
29	0.46%	T1 + T7+ T8
30	0.46%	T4 + T6
-	-	Those accounting for <0.4% were omitted.

Additionally, as per the results in Table 4, "Recharge Cost" (T7) constituted 9.79% of the results, ranking first among labels with a single topic and representing the most prominent and sensitive topic in consumer-perceived risk. Among the paired topics, "Adolescent Education" and "Time Expenditure" (T10 + T8) took the top spot, accounting for 3.62% of the results. Furthermore, combinational semantic expressions involving more than two topics, such as "Excessive Temptation", "Recharge Cost", and "Adolescent Education" (T1 + T7 + T10, 0.80%), held a considerable proportion. The multi-label classification model's output results demonstrate that most consumers paid attention to or recognize one or two combinations of risk topics related to online gaming products. At the same time, a minority expressed three or more perceived risks in their comments.

Moreover, based on the frequency statistics of permutation and combination topics, it became apparent that "Adolescent Education" (T10) co-occurred most frequently with other topics (over 20%). This indicates that youth education is a crucial factor closely associated with other topics, revealing that many consumers were primarily concerned with online gaming products' potential impact on adolescent education issues.

Upon further analysis of the multi-label classification experiments, all labels and their combinations formed a 2N space, where N is the number of topics. Consequently, Table 4 represents the number of comments classified under a corresponding individual label. This means that if a comment involved multiple topics, then it would be counted multiple times. Therefore, the total statistical result of risk classification exceeded the original comment database. Ultimately, the degree of consumer concern for each risk topic is quantified and visualized in Figure 4.

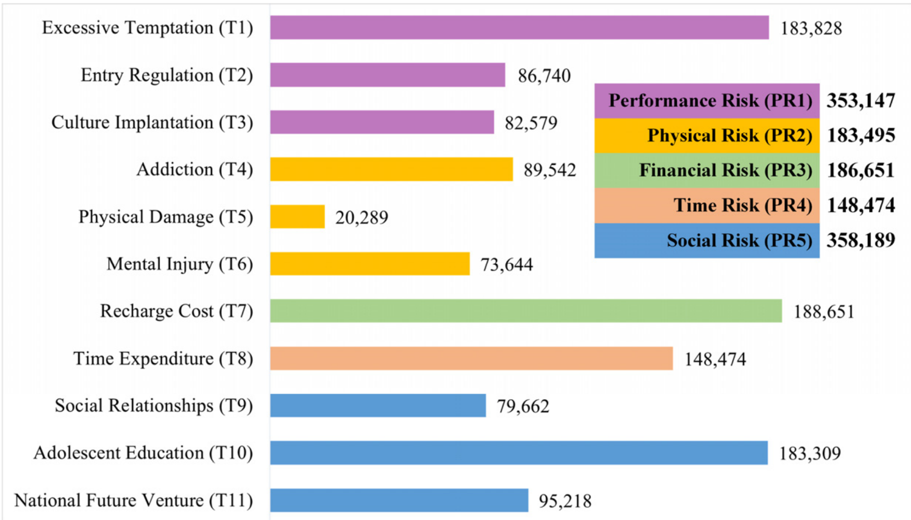

Figure 4. Consumer concern degree of each topic.

Figure 4 illustrates that different colors represent various dimensions of consumers' perceived risks concerning online games. In terms of frequency of occurrence, they are ranked as follows: "Social Risk" (PR5, 358,189), "Performance Risk" (PR1, 353,147), "Financial Risk" (PR3, 186,651), "Physical Risk" (PR2, 183,495), and "Time Risk" (PR4, 148,474). This ranking reflects consumers' perceptions of online gaming risks across different dimensions, with "Social Risk" (PR5) being most frequently mentioned in the consumer comments. Notably, the "Performance Risk" dimension (PR1), which has received little attention in previous research, was often mentioned in the social media comments, ranking second among all five dimensions.

At the level of risk topics, the number of comments related to "Excessive Temptation" (T1) in the performance risk dimension reached 183,828, ranking first among the 11 risk topics. Following this, the leading risk topic in other dimensions was "Adolescent Education" (T10) in the social risk dimension with 183,309 comments. The physical risk dimension included 89,542 comments about "Addiction" (T4). The financial risk dimension did not have fine-grained topics in the output results of Task 1, and thus the risk topics in the corresponding Task 2 results were equivalent to those in the risk dimension (PR3 = T7). The same situation existed with time risk (PR4 = T8). It is worth mentioning that a study in 2022 [4] pointed out that the business model of online games that excessively entices users to top up may be potentially harmful to users, especially teenagers. The high frequency of "Excessive Temptation" in our research also confirms that this phenomenon is widespread in the operation of online games in China. Moreover, the same high frequency of the theme of "Adolescent Education" and "Excessive Temptation" co-occurred with a high frequency, indicating that the harm of online games to teenagers was achieved through the destruction of the education process. This would be considered unacceptable by Chinese society, whether they be ordinary people, the community, or the government itself.

In conclusion, this task accomplished semantic recognition of social media comments through the multi-label classification model revealing consumers' genuine psychological perceptions, further deconstructing the relationships between different risks, and quantifying the degree of concern for each risk topic. However, the consumer comments encompassed perceived risk expressions for online games and the perception and expression of emotions. Therefore, the subsequent task had to analyze the emotional intensity corresponding to each risk topic and conduct a multidimensional and fine-grained analysis of consumers' perceived risks toward online gaming commodities.

5.3. Task 3

The sentimental classification experiment results are illustrated in Figure 5. The dimensions of "Performance Risk" (PR1), "Physical Risk" (PR2), and "Social Risk" (PR5) encompassed the emotional classification of three respective risk topics. Tasks 1 and 2 revealed that the consumers primarily focused their comments on financial and time risks. As a result, the dimensions of "financial risk" (PR3) and "time risk" (PR4) did not yield explicit risk themes, which resulted in Task 3's sentiment analysis being limited to the dimension level.

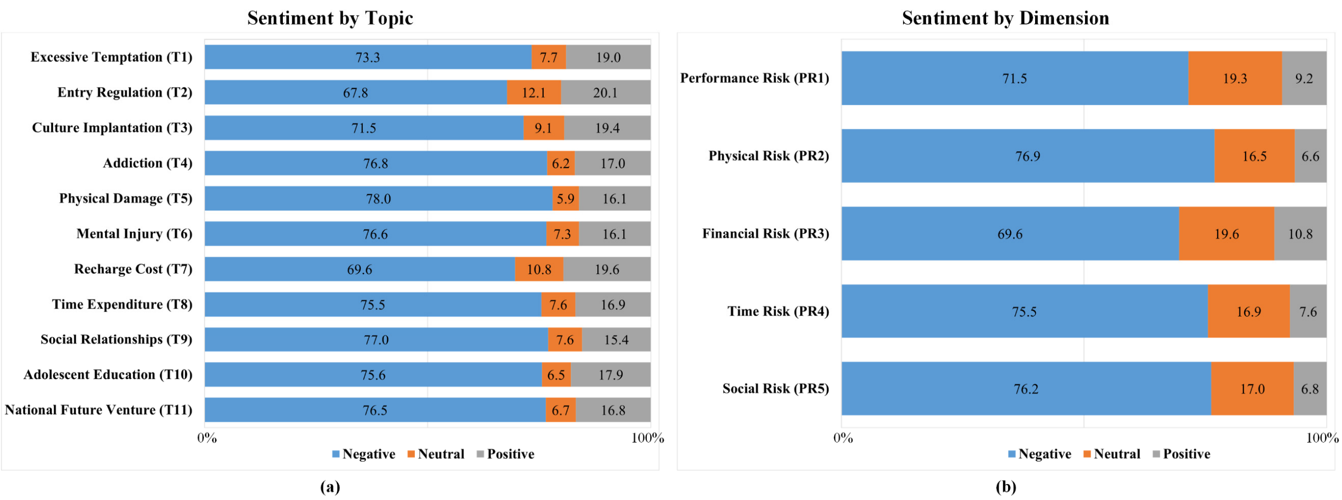

Figure 5. Emotion graph of consumers' perceived risk toward online games. (**a**) shows the consumer sentiment polarity and percentage corresponding to each topic; and (**b**) shows the consumer sentiment polarity and percentage corresponding to each perceived risk dimension.

From a perceived risk perspective, the experimental results indicated that comments on "Physical Risk" (PR2), "Social Risk" (PR5), "Time Risk" (PR4), "Performance Risk" (PR1), and "Financial Risk" (PR3) all displayed high levels of negative emotion, being at 77%, 76%, 75%, 72%, and 70%, respectively. This suggests that the consumers exhibited similar emotional responses to online gaming products across different risk dimensions. Overall, the consumers harbored strong negative feelings toward online games, as evidenced by a weighted average of 72%.

At the granular level of risk topics, “Physical Damage” (T5) caused by online gaming products garnered an overwhelming amount of negative sentiment in the social media comments, reaching 78%. This was closely followed by “Addiction” (T4), “Mental Injury” (T6), and “Social Relationships” (T9), each with a negative emotion making up 77% of the sentiment. Notably, the “Excessive Temptation” (T1) topic was not covered in previous studies, yet it incited negative emotions at a rate of 73%, exceeding the average for all risk topics.

The primary objective of this emotion analysis task was to gauge consumers’ support or opposition to each risk topic. The results from the preceding three tasks objectively illustrate consumers’ psychological perceptions, offering valuable insights for management practices. These will be discussed further in the subsequent section.

6. Discussion and Implication

6.1. Discussion

The findings from the three tasks structured in our study collectively evaluated consumers’ psychological perception of risks associated with online gaming commodities. Task 2′s semantic recognition outcomes revealed that the most to least prominent perceived risk dimensions were “Social Risk” (PR5), “Performance Risk” (PR1), “Financial Risk” (PR3), “Physical Risk” (PR2), and “Time Risk” (PR4). Task 3′s emotion analysis disclosed that consumers’ negative sentiments toward online games accounted for more than 70% of the sentiments, significantly outweighing the neutral and positive emotions. This suggests that most consumers have strong negative feelings when discussing online gaming risks on social media. Utilizing the findings from these two tasks, coupled with the perceived risk features list from Task 1, we delve into a more detailed discussion as follows:

- The dimensions of “Social Risk” (PR5) and “Performance Risk” (PR1) garnered a higher volume of comments than other perceived risk dimensions. First and foremost, the experimental results from Task 2 reveal that the comments concerning “Adolescent Education” (T10) risk reached a total of 183,309, ranking it as the most discussed among the 11 risk topics within the “Social Risk” (PR5) dimension. Following an emotion analysis of “Adolescent Education” (T10) in Task 3, it was found that 76% of the sentiment expressed was negative, surpassing both the positive and neutral reactions. Key terms related to “Adolescent Education” (T10) in Task 1, such as “Teenagers”, “Students”, “Stop Schooling”, “Ignore Study”, “Disciplining Child”, “Rebellious”, and “Lack of Learning Interest”, were used to assess the perceived risk of online games impacting students and minors. The high level of attention and strong negative sentiment indicates a consensus among consumers about the detrimental effect of online games on education. Next, within the “Performance Risk” (PR1) dimension, the number of risk-related comments on “Entry Regulation” (T2) and “Culture Implantation” (T3) was substantial, reaching 86,740 and 82,579, respectively, and negative sentiments accounted for 68% and 71% of the sentiments, respectively. The discussion around “Entry Regulation” (T2) was fueled by specific terms such as “Facial Recognition”, “Real Name Authentication”, “Mobile Phone”, “Age Restriction”, “Registration”, “IP Address”, and “Authority Control”. Similarly, the topic of “Culture Implantation” (T3) was stimulated by terms like “Culture Invasion”, “Foreign Cultures”, and “Vikings”. These discussions indicated a heated debate among consumers about the risks associated with online gaming access mechanisms and cultural integration, with a notable presence of negative emotions. The discourse on “Entry Regulation” (T2) mainly involved specific debates on regulatory measures such as the real name system, face ID, and authentication. Furthermore, the prevalence of negative sentiments in these comments indicates a call by consumers for relevant departments to regulate online games.

- The dimension of "Physical Risk" (PR2) registered the highest level of negative emotion. Primarily, the results of the risk topic classification within this dimension revealed that the volume of comments on "Addiction" (T4, 89,542) and "Mental Injury" (T6, 73,644) significantly surpassed that of "Physical Damage" (T5, 20,289). Emotion analysis of these three topics indicated that the negative emotion was 77%, 78%, and 77% of the sentiments, respectively, showing slight variation. Delving into the key terms associated with these topics, we found words such as "Addiction", "Obsession", "Ecstasy", and "Psychotropic Drugs" for T4, "Depression", "Negative Emotions", "Nervous Breakdown", "Identity Crisis", "Solitary", "Loneliness", and "Mental Disorders" for T6, and "Poor Vision", "Myopia", "Headache", "Physical Strength", "Nausea", "Obesity", "Back Pain", "Exercise Less", and "Physical Weakness" for T5. These terms suggest that the discourse around the physical harm caused by online games is extensive, particularly concerning addiction symptoms akin to drug dependency. The impact of online games on mental health also attracted significant commentary, with discussions on uncontrollable behaviors, difficulty in disentanglement, and obstinacy, as well as descriptions of symptoms similar to depression, demoralization, and both physical and mental exhaustion. Moreover, comments on the risk topics of "Addiction" (T4), "Mental Injury" (T6), and "Physical Damage" (T5) related to online games demonstrated strong resistance and aversion, signaling a call to relevant medical institutions and government departments for intervention. Furthermore, this suggests that consumers are hoping for attention and assistance from these entities.
- The dimensions of "Time Risk" (PR4) and "Financial Risk" (PR3) lacked granular risk topics, with discussions primarily driven by characteristic feature words. For example, words related to time and financial risks such as "Recharge", "Payment", "Lottery", "Local Tyrant", "Devaluation", "Refund", "Hours", "All Night", "Punch in", "Delay", and "All Day" exhibited singular semantic characteristics, which resulted in these two risk dimensions not being divided into more nuanced risk topics. Based on the classification results, the volume of comments on "Time Risk" (PR4) and "Financial Risk" (PR3) was 148,474 and 186,651, respectively. Further integration with the emotion analysis results showed that negative sentiments accounted for 75% and 70% of the sentiments, respectively. This suggests that consumers have reached a consensus regarding the risks and harm inflicted by online games regarding time and finance. Hence, there was a lack of specific descriptions or discussions in the comments. However, consumers frequently discussed the time and financial risks posed by online games, often with a high degree of negative sentiment. Although these concerns are commonplace, their lack of adequate resolution warrants the attention of relevant government departments.

The output from the multi-label classification model in Task 2 merits further discussion. We selected the top 10 pairs of risk subject tags and, drawing from social network analysis methods, formed a co-occurrence network, as displayed in Figure 6. The interrelationships between the perceived risk topics, as manifested through co-occurrences, are discussed below:

- "Adolescent Education" (T10) was the risk topic most frequently appearing in the paired co-occurrences, emerging seven times. As the central node of the network, it formed a symbiotic relationship with the other risk topics, possibly serving as a critical factor influencing consumers' perceived risk. Within the same dimension, the co-occurrence of "Adolescent Education" (T10) and "National Future Venture" (T11) suggests that consumers perceive the educational risks posed by online games as potentially affecting the country's future development, sparking concurrent discussions on these two topics on social media.
- "Adolescent Education" (T10) co-occurred 45,072 and 41,490 times with "Addiction" (T4) and "Mental Injury" (T6) within the "Physical Risk" (PR2) dimension, respectively. The results indicate a widespread belief that potential educational risks are associated with the addiction and mental health issues caused by online games.

- "Adolescent Education" (T10) also co-occurred with the newly identified "Entry Regulation" (T2), suggesting consumer concern about the entry permissions established by online game developers and related operators. The comments contained numerous calls and suggestions for companies to implement access restrictions, such as facial recognition and login authentication.
- The co-occurrence network diagram reveals a local network formed by four risk topics: "Adolescent Education" (T10), "Time Expenditure" (T8), "Excessive Temptation" (T1), and "Recharge Cost" (T7). This indicates that the joint effects of time wasting, misleading influence, and financial expenditure caused by online games significantly impact educational risk. Specifically, online games occupy substantial learning time, leading to educational risks and further inducing other societal problems.

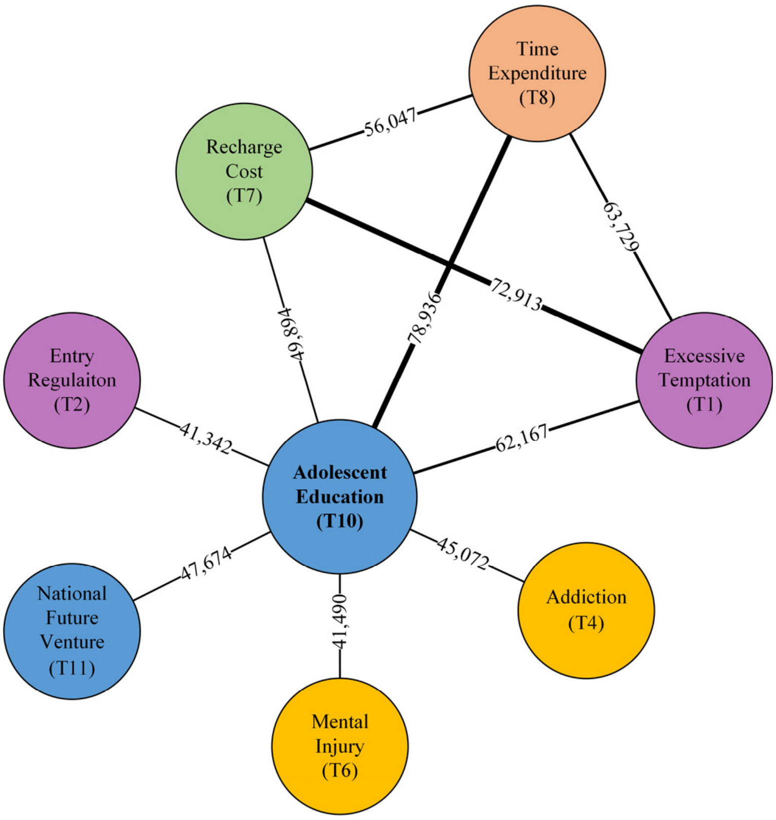

Figure 6. Co-occurrence network graph of risk topics.

6.2. Implication

First of all, our research results support the justice of the Chinese government's control policy on the game industry: The negative sentiment of the public is high (73.94%). A total of 86,740 comments from the public called for the competent authorities to implement "Entry Regulation" (T2) in online games. The education of young people was highly relevant in 183,309 comments.

Secondly, government supervision policies and measures are effective. This research carries significant practical implications from a market research perspective. In 2022, the actual sales revenue of China's online game market reached CNY 259.7 billion, a year-on-year decrease of 11% or CNY 30.6 billion [58]. In addition, the report that "Chinese regulatory authorities have frozen the filing and approval of online game editions" has triggered a major earthquake in the gaming industry, leading to a decline in the stock prices of several gaming companies [59]. Concurrently, over 14,000 Chinese online gaming SMEs and start-ups ceased operations [60]. These events are linked to the Chinese government's tightened control over the online gaming industry in response to public appeals.

Consequently, although still immense, China's online gaming industry has experienced its lowest annual growth rate in the last 20 years. This research highlights the Chinese government's awareness of the highly negative sentiments expressed by the general public regarding online gaming risks, particularly those involving adolescents. Consequently, for the nation's sustainable development, it is necessary and prudent to reinforce online gaming regulations in line with public concerns.

The research conclusions of this paper have significant strategic reference value for small- and medium-sized enterprises or start-ups. Of course, the Chinese government and society will welcome the continued growth of the digital economy. However, as mentioned in this article, a business model that merely indulges in enticing users to charge through various escalating ways, similar to gambling [4], faces a considerable challenge. Despite the vast population, China's online gaming industry maintains a bright future. However, relevant enterprises, particularly start-up online gaming companies, must adapt their development strategies to meet the demands of the new industrial landscape. Therefore, the perceived risk topics identified in this research can serve as a valuable reference for the online gaming market's sustainable development.

7. Conclusions and Limitations

7.1. Conclusions

This study employed NLP technology to mine, identify, and expose consumers' perceived risks associated with online gaming. The research results unveiled 11 topics related to perceived risk dimensions. Notably, the topics of "Excessive Temptation" (T1), "Entry Regulation" (T2), and "Culture Implantation" (T3), although previously under-researched, were objectively present in consumer's social media comments. Moreover, the multi-label classification model quantified the consumer concern levels for each topic, revealing that "Excessive Temptation" (T1) garnered a substantial number of comments and "Adolescent Education" (T4) was a crucial factor, often co-occurring with other topics. Lastly, emotional intensity analysis for each topic uncovered varying consumer attitudes, with the "Physical Risk" (PR2) and "Social Risk" (PR5) dimensions eliciting high negative emotions. Notably, "Physical Damage" (T5, 78%) and "Social Relationships" (T9, 77%) expressed strong negative sentiments. Based on these results, this paper offers several theoretical contributions.

First, it introduced an innovative approach to examining the perceived risks of online gaming products in China's market. Analyzing social media comments via NLP techniques offers insights that can guide governmental and corporate actions toward sustainable development of the online gaming industry and digital economy.

Second, this study amassed a new corpus of comments from multiple social media platforms to objectively and accurately gauge consumers' perceived risks regarding online games. This novel dataset can serve as a valuable foundation for future research into consumers' perceived risks of online gaming.

Third, this study employed a data-driven approach to establish a natural language recognition process for consumers' psychological perceptions of online games. The LDA model and hierarchical clustering method applied in this study can unearth new topics from unstructured text data, enabling precise representation and discovery of research topics. In addition, the multi-label classification model quantified the consumers' level of concern for each topic and unraveled the interrelation between topics. Meanwhile, the sentiment analysis task assigned emotional intensity to each topic, further deconstructing consumers' genuine feelings about online games. Collectively, the outcomes of these experiments provide a comprehensive understanding of the varying dimensions and granularities of the research task.

Due to commercial reasons, research on the perceived risk of online games needs to be improved. Vendors of online games are always trying to convince consumers that their products are fun and safe. Regarding game genres, China's censorship system cannot be said to be lax. Our study is consistent with previous studies in terms of the perceived risk dimension. The advantage of our research is that it relies on large-scale social media data, reflecting a more comprehensive range of users' accurate psychological perceptions without experimental pressure and with higher objectivity to detect the specificity of the perceived risk of the target commodity in real time. Unlike the questionnaire research available to us, the questionnaire design in the process of questionnaire research highly relies on prior knowledge, subjective judgment, and the skills of the researchers. However, our research took basic theory and prior knowledge as a guide and matched them with accurate data based on this guide, thus achieving better objectivity. It was also better adapted to the characteristics of the product itself.

Based on a systematic analysis of social media comments, our study indicates that the existing business model has caused some actual harm and a high negative consumer risk perception for the online game industry. Given the healthy development of the whole society, it is inevitable for the Chinese government to take specific restrictive measures. "The impact on the online game industry is already reflected in financial reports". The three themes of "Excessive Temptation", "Recharge", and "Adolescent Education" showed significantly high frequencies of occurrence, revealing that the key factor affecting the sustainable development of the online game industry is the negative effect of the current business model to induce consumers to recharge. The future online game industry, especially start-ups, must be highly reflected in the corporate strategy of concern to ensure the sustainability of their development.

7.2. Limitation

While the findings of this research have made noteworthy contributions, there remain certain limitations and opportunities for enhancement. For example, this study did not incorporate a timeline into the research process to understand the evolving psychological perceptions of consumers. In future studies, we plan to collect social media comments from different periods, enabling continuous tracking of perceived risk changes as the life cycles of online gaming commodities unfold. The results of this study will further encourage us to evaluate the appropriateness of strategic adjustments made by businesses or the efficacy of governmental regulatory measures.

This method is also suitable for more in-depth and detailed research on online games, and the results can also provide more specific decision-making suggestions for online game enterprises with different positioning. This is also one of our follow-up research goals.

Moreover, while this paper primarily focused on online games, its research framework applies to other merchandise types. With China setting ambitious new targets for its national development, businesses are required to align their practices with the imperatives of sustainable development and societal well-being. Consequently, the methodology used in this study to measure the consumers' perceived risk of online games necessitates further improvement and expansion.

Author Contributions: Conceptualization, T.S. and L.L.; methodology, T.S. and L.L.; software, J.Z.; validation, H.Y., J.W. and Y.W.; formal analysis, T.S.; investigation, T.S. and L.L.; resources, T.S.; data curation, H.Y.; writing—original draft preparation, T.S. and L.L.; writing—review and editing, T.S. and L.L.; visualization, T.S. and L.L.; supervision, J.Z.; project administration, T.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Automatic Software Generation and Intelligence Service Key Laboratory of Sichuan Province (No. CUIT-SAG202206).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors without undue reservation.

Conflicts of Interest: The authors declare no conflict of interest.

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