Research on User Satisfaction of Mobile Game in Chinese Style Based on Sentiment Analysis

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Abstract: Game review is an important way for players to give feedback on game quality. The authors built up a satisfaction evaluation model which demonstrates certain scores of sentiment tendency of game players on particular elements by using the technology of TF_IDF extracting factors influencing user satisfaction. Then sentiment dictionary was applied to calculate sentiment extremum of the factors above. The results proved that this approach is effective for analysis on mobile games in Chinese style. This provides data support usefully for game developers to improve the research and development and satisfaction of players towards mobile game in Chinese styles.

1. Introduction

With the development of China's game industry, "Chinese style" (a style of Chinese aesthetic characteristics) has become an important design styles used in mobile game to conform to the aesthetic preferences of Chinese consumers [1-3]. By 2018, there are over 300 million users of games in Chinese style with more than 30 billion market revenue, accounting for 20% of the overall revenue of the gaming market [4]. However, the emergence of a large number of mobile games in Chinese style in the market has also caused new problems. According to the data from Tencent Research Institute, the total number of mobile games in Chinese style has reached more than 2,300 since 2013 in China, however, among of which are replete with homogenized themes and contents without much differentiation or competitiveness [5,6].

Player's feedback is an important source of in-depth understanding of the defects and deficiencies of such games [7]. Game reviews not only reflect player's experience, but more importantly, drive the research and development of online games in the right way [8]. It has been widely used in game R&D and decision-makings such as functional selection, satisfaction evaluation and design guidance [9].

At present, very few researches have been done on sentiment analysis in the field of game reviews, and there is even less on mobile games in Chinese style. Sentiment analysis is based on machine learning or sentiment dictionary methods, and there is no sufficient study on the use of game reviews comparing with Chinese comments. Mobile games in Chinese style contribute to cultural communication, and sentiment analysis based on game reviews enables a more comprehensive understanding on game feedback. To address the problem, this paper proposes a research method on players' satisfaction of mobile game in Chinese style based on sentiment analysis by extracting the influencing factors and building up a user satisfaction evaluation model on mobile games in Chinese style so as to find the advantages and disadvantages in game design and give feedback to improve mobile games in Chinese style.

2. Literature Review

2.1 User Satisfaction of Games

In computer games, the attribute of satisfaction is the most important component of game usability [9]. Factors as the graphical interface of the game, the background story, the input device, etc., can influence players' satisfaction [10].

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Sweetser and Wyeth developed a model called GameFlow, to evaluate user satisfaction of games. They developed rating standards based on eight factors - concentration, challenge, skills, control, clear goals, feedback, immersion and social interaction, and experts evaluated satisfaction of game players on the basis of the rating standards [11].

Huang et al. made adjustment through GamingAnywhere Cloud to four system parameters: video resolution, frame rate, encoding bitrate, etc. They compared the feedback of subjects under different parameters and quantified user satisfaction in mobile cloud games [12].

Besides, researchers also extracted the factors that influence satisfaction from game reviews. Wang et al. proposed a method to generate dimensions of game experience by online reviews of video games [13]. They used the LDA algorithm to extract seven dimensions of game experience from online reviews, and used regression analysis to examine the relationship between the game experience dimensions and the satisfaction of players. The results show that achievement, narrative, visuals, social interaction, and social influence were core components for users to evaluate a game, narrative and achievement were the components most associated with satisfaction towards the video games [13].

2.2 Features of Mobile Games in Chinese Style

Adding traditional Chinese culture in visual design, narration and interaction is the feature of mobile games in Chinese style. Ye and other researchers, taking the mobile games *The Beautiful Dream* and *The Swords* as examples, analyzed the specific performance and application of Chinese traditional culture in the game's visual design, plot and interaction. As for the character costumes and scene props, the visual design of mobile games in Chinese style features for Chinese patterns, Chinese colors, and Chinese traditional art such as Chinese painting, paper-cutting, shadow puppetry, etc. Chinese fairy tales and classical literatures are adapted as game scripts, which constitute the world view in the game and improve the experience of game players. Reading comprehension of ancient poems and calligraphy writing principles are integrated in game interactions [14].

Qi concluded that the features of mobile games in Chinese style were reflected in the use of ancient Chinese architecture and painting in the game scene, the application of traditional Chinese literature in character design and costume design, and the embodiment of traditional customs in plot levels. From the perspective of the player's experience, the researcher pointed out that mobile games in Chinese style makes players feel close to the real virtual experience, making the symbolic cultural elements easily to understand and eliminating the space-time boundary [6].

2.3 Sentiment Analysis

Sentiment analysis is a way to classify opinions of players from the emotional dimension by judging whether players has a positive or negative attitude towards the product through their opinions in the form of text [15-19]. At present, the commonly used methods of sentiment analysis can be divided into two categories. One is based on machine learning, extracting the text characteristics of comments and excavating valuable features [20]. This method uses the corpus to train and test classifier, and then trains the corpus in a specific field to complete the analysis of sentiment tendency [21]. Pang et al. first proposed the use of machine learning to solve the problem of sentiment analysis in 2002 by applying classifiers such as Naive Bayes, maximum entropy classification and support vector machines (SVM) to conduct analysis on movie reviews which were used as corpus [16]. The advantage of machine learning method is that it is simple and easy to conduct analysis. However, the disadvantage is that the performance of the classifier heavily depends on the quality of the labeling corpus. Obtaining high-quality labeling corpus requires a lot of labor costs, and the distribution of evaluative sentiment words in a large language database makes it harder to categorize these words [22].

The other method is based on sentiment dictionary. According to sentimental tendency of the words in sentiment dictionary, sentiment score is calculated by score accumulation or quantitative comparison between commendatory words and derogatory words in the comments [20]. Commonly used English basic sentiment dictionaries include: WordNet, General Inquirer, etc., Chinese basic sentiment dictionaries include: HowNet sentiment dictionary, DUTIR emotional vocabulary ontology database and NTUSD (a Chinese sentiment polarity dictionary of the Natural Language Processing Laboratory of National Taiwan University), etc.[20]. The method based on sentiment dictionary has the advantages of obtaining sentiment words comprehensively and accurately. Sentiment analysis based on a comprehensive and accurate sentiment dictionary can usually obtain a higher accuracy rate [20]. Therefore, this paper mainly uses the method based on sentiment dictionary to conduct sentiment analysis on reviews of mobile games in Chinese style.

3. Methods

The research process of this paper is divided into the following steps: 1) to obtain game reviews data; 2) to process text information, including data cleaning, Chinese word segmentation and stop words removal, etc.; 3) to extract keywords and influencing factors from TF_IDF values; 4) to build a user satisfaction evaluation model based on sentiment analysis to obtain the overall score of mobile game in Chinese style and the scores of various influencing factors. According to the score, satisfaction of players on mobile game in Chinese style is evaluated. The experiment design framework is shown in Figure 1.

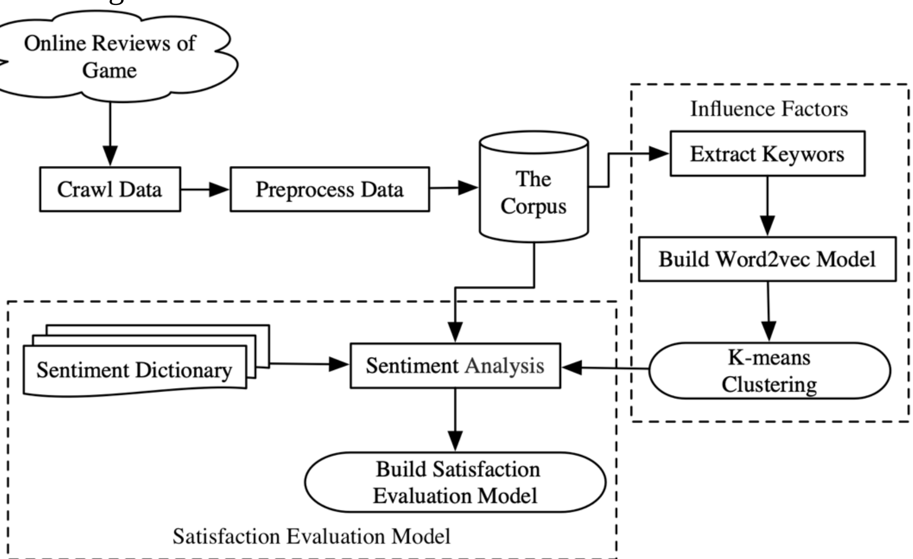

Figure 1 Experiment design framework.

3.1 Data Collection

The research data in this article were collected from the top ten “Chinese style” mobile games published by TapTap in July 2020 (as shown in Table 1). TapTap is a high-quality mobile game sharing community in China which can fully demonstrate mobile games in Chinese style in the application market. Ten selected games have high public familiarity, player activity and topicality and the researchers can obtain rich data sets from these ten games. The web crawler algorithm was used and crawled 66,538 reviews in total on mobile games in Chinese style.

Table 1 The information of mobile games in Chinese style.

Name	Game Type	Company
One Hundred Scenes of Jiangnan	Simulation Game	Coconut Island Game
Mortise & Tenon	Puzzle Game	Leiting Games
The Everlasting Regret	Puzzle Game	Tencent
Emperor Project 2	Simulation Game	4399
A Dream of Jianghu	MMORPG	Netease Games
The Swords	Action Game	X.D. Network Inc.

The Tale of Food	Simulation Game	Tencent
Hanjia Jianghu	Action Game	Hanjiasongshu
Gujin Jianghu	Roguelite DBG	Duyouwu3k
Eastward Legend: the Empyrean	MMORPG	Tencent

3.2 Data Pre-processing

The language of game reviews is flexible and the structure is loose. Before text analysis, it is necessary to preprocess the collected game reviews, including data cleaning, Chinese word segmentation, and stop words removal [23]. The sorted text data can be used as a corpus for analysis of game reviews.

1) Data cleaning. HTML tags, spaces and special characters were removed. The Emojis were also excluded from the reviews because they do not critically represent user's opinions and sentiments.

2) Chinese word segmentation. Game reviews were processed by using the precise mode of Python's Jieba package and then the words that were not in the original dictionary were sorted out preferentially by using a custom dictionary. According to word segmentation, game words such as "charge money", "mission clear" and "Chinese style" and theme words such as "Chinese traditional culture", "oriental aesthetics", "style of Chinese ink painting" were added in the custom dictionary.

3) Stop words removal. Add a custom stop word list in the word segmentation process. In addition to filtering out prepositions and conjunctions in game reviews, vocabularies related to time and quantity need to be removed according to contexts and vocabularies contingent on contexts as well, such as "from my personal perspective", "generally speaking", etc.

3.3 Extraction of Factors Affecting Satisfaction of Mobile Games in Chinese Style

1) TF_IDF is a statistical-based method used to evaluate the importance of words to the review. The larger the value of TF_IDF, the more important the word is to the review, and the more likely it is to be a keyword in the review [24]. Therefore, the factors that affect user satisfaction can be determined by extracting the keywords of the game reviews. The calculation formula of the TF_IDF algorithm is presented as follows:

$$\mathrm{TF}_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \tag{1}$$

$$IDF_i = \log \frac{N}{n_i + 1} \tag{2}$$

$$\mathrm{TF\_IDF}_{i,j} = \mathrm{TF}_{i,j} * IDF_i \tag{3}$$

Among them, $n_{i,j}$ represents the number of occurrences of the word in game reviews; $\sum_k n_{k,j}$ is the sum of the number of occurrences of all words in the reviews. N is the total number of reviews in the corpus; n_i is the word number of reviews.

After the game reviews have been preprocessed, the scikit-learn package was applied to calculate the TF_IDF value of the words in the review. After denoising the nouns in the results, a total of 40 keywords were obtained. Five keywords are listed in Table 2.

Table 2 Example of keywords.

Keywords	Card Game	Function	Mechanism	Mode	Storyline
TF_IDF	0.015	0.019	0.014	0.014	0.014

2) A trained Word2Vec model was used to vectorize each word in the text, and then extracted word vectors were clustered by using K-means algorithm to obtain the categories of the features, in which the Euclidean distance between word vectors was defined as the similarities between words.

Silhouette Coefficient can evaluate the clustering quality by examining the separation and compactness of clusters in the clustering results [25]. To find an optimal number of clusters K, the Silhouette Coefficient scores with different K value were calculated continuously. As shows in Figure 2, the Silhouette Coefficient reaches the highest value when K=6, that indicates that the cluster number of 6 is the optimal at this time.

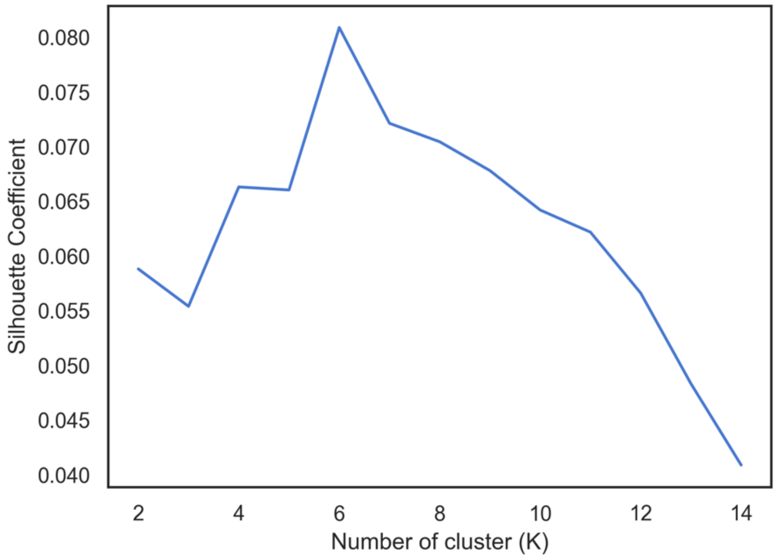

Figure 2 The result of Silhouette Coefficient.

Finally, in order to visualize the result of categories, a t-SNE was implemented to display the word vectors of high-dimensional space in low-dimensional space. The vectors were reduced from 300 to 2 dimensions, and then put into the plane coordinate system to draw the clustering diagram as shown in Figure 3. On this basis, clusters were hierarchized that resulted in 6 dimensions that can be used to divide the opinion factors of mobile game in Chinese style: Achievement, Narrative, Gameplay interaction, Game type, Experience ang Design. The result of hierarchical clustering is shown in Figure 4.

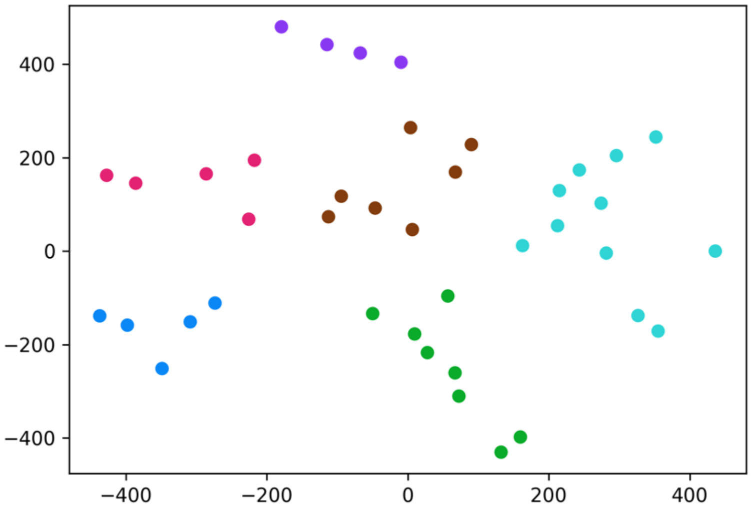

Figure 3 The clustering diagram of the optimal K value (K=6).

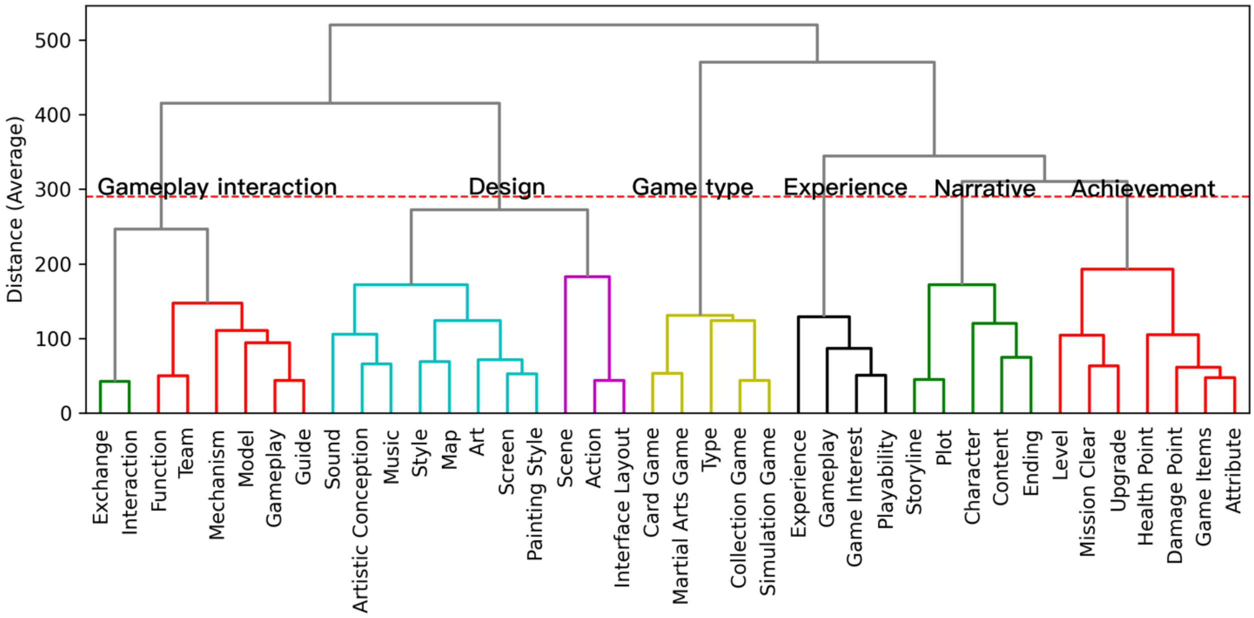

Figure 4 Hierarchical clustering dendrogram.

3.4 Sentiment Score Calculation Based on Sentiment Dictionary

According to the score of the words in sentiment dictionary, sentiment score is calculated by the score accumulation of commendatory words and derogatory words [20]. The positive, negative and magnitude of the score respectively indicate sentiment polarity and the strength of the review [26]. In order to evaluate the impact of certain factor on players' satisfaction, it is necessary to calculate a sentiment score for each influencing factor. In sentiment analysis, a positive score indicates that the factor has a positive impact on user satisfaction and vice versa.

1) Sentence segment. Usually, players will mention multiple factors about the game when they make comments. For example, "The picture is still good. The style of Chinese ink painting is very ancient. The sound effects are very appropriate, especially the sound of the pass. The storyline of each sword is very well connected". In this comment, "picture", "sound", "storyline" and other factors have been included. Therefore, it is necessary to segment each comment into an independent short sentence first, and then classify these short sentences with the influencing factors as the classification criterion. As a result of classification, each short sentence only evaluates one influencing factor. Therefore, the score of influencing factors of satisfaction can be worked out by calculating the score of the corresponding short sentence.

2) Construction of sentiment dictionary. Sentiment words refer to vocabularies that can express users' sentiment tendency as the basis of the calculation of sentiment polarity score [27]. This paper grouped the positive and negative sentiment words into a positive and negative basic sentiment dictionary applying four dictionaries including HowNet dictionary, TSING, DUTIR and NTUSD after duplicate removal.

Degree adverbs can strengthen or weaken the text sentiment to a certain extent, and are generally placed before or after sentiment words. The sentiment weight of sentence is updated through traversal by locating the position of degree adverbs. Negative words, as a prefix used to modify sentiment words, can directly change the polarity of sentences [27]. In our research, the negative words immediately ahead of sentiment words were searched through traversal so as to confirm whether the polarity of sentences has been changed. The 219 adverbs of degree and 79 negative words were sorted out, as shown in Table 3.

Table 3 Examples of the degree adverbs dictionary and the negative word dictionary.

Type of Dictionary	Word	Weight	Count
Degree Adverbs	Extremely / Most / Very...	1.8	69

Degree Adverbs	Super/ Over / Too...	1.6	30
Degree Adverbs	Very/ Especially / Particularly...	1.5	42
Degree Adverbs	More / Comparatively...	1	37
Degree Adverbs	More or less / Slightly...	0.7	29
Degree Adverbs	Not very / A bit...	0.5	12
Negative Words	No / Not / Without...	-1	79

3) To calculate the sentiment score. This article used a weighted sum method to calculate the sentiment score of each short sentence. Each short sentence is represented as S_j, and the formula for calculating sentiment score $E(S_j)$ is as follows:

$$E(S_j) = (-1)^{Neg} \prod_{i=1}^{n} Deg_i \sum_{j=1}^{m} EO(W_j) \tag{4}$$

Among them, Neg is the number of negative words in the sentence; n is the number of i^{th} degree adverbs; Deg_i is the weight corresponding to the i^{th} degree adverb; m is the number of sentiment words in the sentence; $EO(W_j)$ represents the sentiment score of each word in the sentence.

According to the results above, Sen_j, the sentiment score of the j^{th} influencing factor, is:

$$Sen_j = \frac{\sum_{j=1}^{n} E(S_j)}{n} \tag{5}$$

Among them, $\sum_{j=1}^{n} E(S_j)$ is the sentiment score of all short sentences S_j under the influence of j^{th} factor.

3.5 Model Calculation

The above results were combined and analyzed, and the weights of influencing factors were calculated based on the TF_IDF value obtained in preprocessing.

(1) $w_{i,j}$ is the weight of the j^{th} factor evaluation index under the i^{th} dimension, as follows:

$$w_{ij} = \frac{(TF\_IDF)_{ij}}{\sum_{j=1}^{m}(TF\_IDF)_{ij}} \tag{6}$$

Among them, $\sum_{j=1}^{m}(TF\_IDF)_{ij}$ is the sum of the TF_IDF values of all influencing factors in the i^{th} dimension; and $(TF\_IDF)_{ij}$ is the TF_IDF value of the j^{th} factor in the i^{th} dimension.

(2) w_i is the weight of the i^{th} first-level influencing factor, as shown below:

$$w_i = \frac{\overline{\sum_{j=1}^{m}(TF\_IDF)_{ij}}}{\sum_{i=1}^{n}\overline{\sum_{j=1}^{m}(TF\_IDF)_{ij}}} \tag{7}$$

Among them, $\sum_{i=1}^{n}\overline{\sum_{j=1}^{m}(TF\_IDF)_{ij}}$ is the sum of TF_IDF values of all influencing factors; $\overline{\sum_{j=1}^{m}(TF_{IDF})_{ij}}$ is the TF_IDF value of the j^{th} dimension.

(3)In the end, the satisfaction score of mobile games in Chinese style is calculated, and the calculation formula is shown in the figure below:

$$\mathrm{Score} = \sum_{i=1}^{n}(w_i \sum_{j=1}^{m} w_{ij} Sen_j) \tag{8}$$

4. Results

According to the model constructed in Section 3, the sentiment scores and weights of various factors influencing satisfaction on mobile game in Chinese style were obtained (the data in this paper is account to 3 decimal places). The experimental results are shown in Table 4:

Table 4 The sentiment score and weight of each dimension and influencing factor.

Dimension	Dimension's Weight	Influencing Factor	Influencing Factor's Weight	Influencing Factor's TF_IDF	Sentiment Score
Achievement	0.203	Health Point	0.137	0.016	-0.788
		Attribute	0.154	0.018	1.103
		Upgrade	0.128	0.015	1.623
		Damage Point	0.154	0.018	-0.274
		Level	0.154	0.018	1.205
		Game Items	0.162	0.019	1.868
		Mission Clear	0.111	0.013	0.961
Narrative	0.192	Character	0.228	0.018	1.378
		Content	0.152	0.012	1.936
		Plot	0.215	0.017	0.304
		Ending	0.228	0.018	0.158
		Storyline	0.177	0.014	2.638
Gameplay Interaction	0.207	Mode	0.103	0.014	1.167
		Mechanism	0.103	0.014	1.380
		Function	0.140	0.019	2.289
		Team	0.118	0.016	1.233
		Gameplay	0.132	0.018	1.761
		Guide	0.125	0.017	1.282
		Interaction	0.140	0.019	2.402
		Exchange	0.140	0.019	3.591
Game Type	0.014	Simulation Game	0.198	0.017	1.397
		Martial Arts Game	0.221	0.019	3.391
		Collection Game	0.198	0.017	2.618
		Type	0.209	0.018	2.759
		Card Game	0.174	0.015	2.822
Experience	0.188	Gameplay	0.242	0.015	1.095
		Experience	0.161	0.010	2.593
		Game Interest	0.306	0.019	4.197
		Playability	0.290	0.018	1.664
Design	0.196	Action	0.102	0.018	1.908
		Music	0.090	0.016	3.079
		Artistic Conception	0.096	0.017	3.938
		Sound	0.090	0.016	-0.016
		Art	0.090	0.016	2.539
		Screen	0.096	0.017	2.259
		Painting Style	0.056	0.010	3.268
		Style	0.096	0.017	4.878
		Map	0.090	0.016	0.622
		Scene	0.090	0.016	1.798
		Interface Layout	0.102	0.018	2.336
User Satisfaction Score					**1.783**

Table 4 shows the satisfaction score of the top ten mobile games in Chinese style on TapTap is 1.783, and the sentiment polarity is positive. Achievement, narrative, gameplay interaction, and experience have more weighted score and have a greater impact on satisfaction from the perspective of weight. Comparing with other dimensions, game type has less influence on satisfaction scores.

Dimension 1: Achievement. The higher weight of “attributes”, “damage point”, “level”, and “props” demonstrate that these factors have a greater impact while the lower weight of “mission clear” and “upgrade” have a smaller impact on the achievements. Among them, the sentiment score of “health point” and the damage point is -0.788 and -0.274 respectively. Both negative scores represented a negative attitude of players towards these two factors and resulted in a negative impact on the achievement.

Dimension 2: Narrative. The factors “character” and “ending” have a higher weight which represents a greater influence on the narrative than other factors. In this dimension, the sentiment scores of each factor are all positive. Compared with other factors, the lowest sentiment score of “ending” does not make more positive impact on narrative.

Dimension 3: Gameplay interaction. The weight of each factors is of little difference, and “mode” and “mechanism” are lower. In this dimension, the sentiment score of “exchange” gets the highest scores of 3.591, indicating that players have a more positive evaluation on the interaction experiences of mobile games in Chinese style.

Dimension 4: Game type. The factor “martial arts game” gets the highest sentiment score and the most positive sentiment polarity. Players prefer martial arts game and are inclined to give a higher evaluation on it.

Dimension 5: Experience. The maximal influencing factor on this dimension is “game interest” whose sentiment score is the highest among other factors. The game interest of mobile games in Chinese style enables players to have a better experience and more fun.

Dimension 6: Design. The negative sentiment score of “sound” indicates the dissatisfaction and negative evaluation of players on the game design.

To sum up, the results of more positive evaluation represent a higher satisfaction of players towards mobile games in Chinese style. The “achievement” dimension and “gameplay” dimension have a greater impact on satisfaction, have a greater impact on satisfaction. Among the influencing factors in Table 4, players only evaluate three factors negatively including the health point, damage point and sound; and players hold a positive attitude toward other factors.

5. Conclusion

In this paper, the researcher extracted 40 keywords that players pay close attention to as factors influencing satisfaction through the online review of mobile games in Chinese style and divided them into 6 dimensions with the application of the word2vec model and clustering algorithm. Besides, the sentiment scores and TF_IDF value of each influencing factors were calculated to produce the final score of user satisfaction. From this point of view, sentiment analysis is of assistance to identify which dimensions or factors impact more on mobile games in Chinese style. The results of this paper provide data support for game developers and promote the evaluation of game through the approach of text mining and analysis which can complement the traditional research methods.

However, there are some shortcomings in this research. Firstly, flexible language of game reviews and its heterogeneity will undoubtedly introduce noise when extracting influencing factors, which may interfere the research results. Consequently, a more complex natural language processing technique to denoise will probably be applied to solve this problem. Furthermore, the research method based on sentiment dictionary relies on its accuracy and comprehensiveness. Therefore, future research should be devoted to build a sentiment dictionary in game field to improve the accuracy and comprehensiveness of sentiment analysis.

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