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Influence of Sports Value on Adolescent Participation and Preference of Sci-Tech Experience Activities

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Abstract
Through the combination of sports and education, sci-tech sports enable adolescents to master professional knowledge of sci-tech sports, while building a strong physique. Sports value has a great influence over adolescent participation and preference of sci-tech sports experience activities. However, few domestic scholars have surveyed adolescent preference of sci-tech sports experience activities, or their sports value. Therefore, this paper decides to study how sports value influences adolescent participation and preference of sci-tech sports experience activities. Firstly, the adolescent sci-tech experience was defined under the influence of sports value. Next, the authors judged the emotional state of text reviews on adolescent sci-tech experience, provided the method to compute the emotional score of each text, and explained how to analyze adolescent preference of sci-tech experience activities under the influence of sports value. On this basis, the themed portraits of adolescent sci-tech experience were extracted from different angles, and the effects of time and changing sports value on adolescent preference were evaluated. The proposed algorithm and model were proved effective through experiments.
Keywords: sports value; adolescent sci-tech experience; experience preference

1. Introduction

Sci-tech sports integrate multiple functions, such as sports fitness, intellectual development, and sci-tech knowledge popularization (J. Chen, 2021; Dasari et al., 2018; Dujuan, 2021; Dwipriyoko & Sari, 2021; Isogai et al., 2018; Liu & Wu, 2021; Naichun, 2016; Proshin & Solodyannikov, 2018; Shao-Hui & Xiaohong, 2017; F. Wang, 2020; H. Wang et al., 2021; Wu, 2021). Through the combination of sports and education, sci-tech sports enable adolescents to master professional knowledge of sci-tech sports, while building a strong physique (Kashino, 2020; J. Li, 2015; W. Li, 2014; Niu et al., 2017; Qin & Guan, 2014; Santirojanakul, 2018; Seet, 2016; W. Wang, 2017). The unique charm of sci-tech and tools arouses much interests among adolescents, and makes sci-tech sports a pleasant experience, exerting many positive effects on adolescents. As they experience the sci-tech contents, adolescents perceive the services from the sci-tech experience provider. The emotional experience produced during the perception is the core manifestation of adolescent sci-tech experience (Burhans & Dantu, 2017; Lin & Shaer, 2016; Southgate et al., 2017; H. Wang, 2020; Witt et al., 2011).

Zheng Moshan mentioned in *Sports Value of College Students* that sports value reflects the strong significance of current PE teaching to college students. The sports value of adolescents refers to an internal standard of adolescents to recognize the values of sports, and to judge the importance of sports. By participating in sci-tech sports activities, adolescents not only grasp professional knowledge in sci-tech sports, but also strengthen their bodies. These are the unique values of sci-tech sports participation. The sports value greatly affects the adolescent participation and preference of sci-tech sports experience activities. Every adolescent chooses the programs to be experience based on his/her sports value. However, Chinese scholars have rarely surveyed adolescent participation of sci-tech sports. The research into the effects of sports value on adolescent participation and preference of sci-tech sports experience activities could enhance their innovation ability of sci-tech sports, improve their psychical and mental qualities, and cultivate into potential talents of sci-tech sports.

Currently, there are many sci-tech sports experience programs for adolescents, including familiar conventional sports like aviation sports, aviation model, nautical model, vehicle model, architectural model, motor sports (karting), motorcycle sports, radio communication, radio direction finding, and orienteering, as well as emerging sports like e-sports, robot competition, wind tunnel flight, virtual reality sports, ford performance vehicles, and drone programming. Relevant studies have achieved much results. Xu et al. (2017) gained valuable insights by comparing the barefoot walking and neutral shoe walking of healthy youths. Obesity becomes a common problem among adolescents. It could be attributed to the falling frequency of physical activities, and the increase of excessive sitting. Through technology means, Altamimi et al. (2015) worked consistently to motivate children to take more physical activities, and introduced a framework

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called MySteps. The framework has been developed and applied to manage the screen time and sports performance of adolescents. Statistics show that the framework improves children and adolescents' awareness of their physical activity level and screen time. Mikami et al. (2018) described a system being developed to provide users with first-person visual experience. The goal is to enable athletes to experience the competition from their own perspective beforehand, so that they can better prepare for sports competition. Y. X. Chen et al. (2017) combined actual physical training with appropriate computer hardware and software to respond to different user commands, allowing users to complete the physical training in a simulated world. Besides, the sports dance teaching was analyzed, drawing on the knowledge of virtualization technology. Chu et al. (2019) applied artificial intelligence (AI) to weightlifting training. Hsia et al. (2019) took the time of flight as an auxiliary means, acquired the images of basketball players with a non-contact Kinect device, and detected shooting postures.

There are many independent research programs on adolescent sci-tech experience. But few have studied the factors affecting adolescent preference of sci-tech experience activities, or sports value. To fill the gap, this paper studies how sports value influences adolescent participation and preference of sci-tech sports experience activities. All figures and tables in this paper are original. The main contents fall into the following categories: Section 2 defines the adolescent sci-tech experience under the influence of sports value. Section 3 judges the emotional state of text reviews on adolescent sci-tech experience, and provides the method to compute the emotional score of each text. Section 4 explains how to analyze adolescent preference of sci-tech experience activities under the influence of sports value, extracts the themed portraits of adolescent sci-tech experience from three different angles, namely, the preferred sci-tech item, experience effect of the preferred item, and emotional features, and evaluates the effects of time and changing sports value on adolescent preference. Finally, the proposed algorithm and model were proved effective through experiments.

2. Definition

Table 1

Mean value of each dimension of adolescent sports value

	SV_1	SV_2	SV_3	SV_4	SV_5	SV_6
N	295	296	294	291	296	294
M	3.5421	3.9657	4.0521	4.2512	4.2014	4.0851
SD	6.8521	7.5284	7.6284	7.1240	7.6548	7.8412

This paper breaks down adolescent sports value into six dimensions: economic value SV_1, aesthetic value SV_2, social value SV_3, health value SV_4, entertainment value SV_5, and moral value SV_6. Table 1 lists the mean value of each dimension. It can be observed that adolescents tend to improve SV_4 of sports value, that is, sports value is mainly manifested by sports and mental/physical health.

Let DX be an evaluation subject of adolescent sci-tech experience; SX be an attribute of the subject; CY be the owner of an emotional state; ZT be the emotional state of an adolescent towards attribute SX of subject DX. Then, ZT can be divided into three levels: negative (-1), positive (1), and neutral (0). Further, the time of occurrence for an emotional state is denoted as ψ, and the parameter of adolescent sports value as υ. Then, the adolescent sci-tech experience FT under the influence of sports value can be defined as a 5-tuple:

$$FT = (DX, SX, CY, ZT, \psi, \upsilon) \tag{1}$$

Subject DX and its attribute SX are the evaluation targets of adolescent sci-tech experience. Taking the experience of man-machine battle (MMB) for example, the unsatisfactory experience of adolescent SH for the intelligent setting of training model TM can be described as:

$$FT = (MMB, TM, SH, passive, 2020.04.16, Y) \tag{2}$$

Let SY be the set of all evaluation subjects of sci-tech experience and all their attributes. Then, the perception of adolescent SH for the overall sci-tech experience can be described as:

$$FT_p = (SY, SY, SH, passive, 2020.04.16, Y) \tag{3}$$

3. Analysis on Overall Adolescent Sci-Tech Experience

Drawing on the previous definition of adolescent sci-tech experience, the overall adolescent sci-tech experience can be defined as the subjective emotional feeling of adolescents for the entire sci-tech experience. Let DX_{SY} be the set of all evaluation subjects of sci-tech experience; SX_{SY} be the set of all attributes of all subjects; CY_p be the owner of an emotional state; ZT_p be the overall emotion for all attributes of all subjects; ψ_p be the time of occurrence for an emotional state. Then, the overall adolescent sci-tech experience can be expressed as:

$$FT_p = \left(DX_{SY}, SX_{SY}, CY_p, ZT_p, \psi_p, \upsilon_p\right) \tag{4}$$

As an unsupervised rule-based emotional analysis tool, the emotional dictionary-based emotional analysis method was selected to identify and evaluate the overall adolescent sci-tech experience. Firstly, an emotional dictionary was created for the field of each kind of experience item. Next, the review texts on the overall adolescent sci-tech experience were subjected to word segmentation, grammatical analysis, and semantic analysis. In addition, the words were matched with the emotional words in the dictionaries. Finally, the emotional state of each text was determined, in the light of grammar and semantics. Figure 1 shows the flow of emotional state judgement.

The emotional dictionaries for sci-tech experience items were constructed in four steps: extracting the set of candidate emotional words, constructing basic emotional dictionary, judging the emotional tendency of each emotional word, and processing similar words. Among them, the judgement of emotional tendency was completed using *Word2vec*, a package for the acquisition of word vectors:

Firstly, the vectors of the words are extracted from each review text on overall adolescent sci-tech experience by *Word2vec*. After that, a comparative analysis is performed against the dictionary of candidate emotional words. If a word q is found in the dictionary, the next word will be analyzed. Otherwise, the M most similar words (ZT_1, ZT_2, ..., ZT_{SY}) to word q will be found in the dictionary. Then, ZT_1, ZT_2, ..., ZT_{SY} will be searched for in the basic emotional dictionary to obtain their emotional intensity scores. Next, the unmatched words are filtered out, producing a set of M_C similar words and their emotional intensity scores: $GA(q)=\{(ZT_{C1}:UF_{C1}), (ZT_{C2}:UF_{C2}),...,(ZT_{DND}:UF_{DND})\}$. There are n and m positive and negative emotional words in the set, respectively. Let $S(q, ZT_{Ci})$ be the similarity between word q and a similar word ZT_{Ci} from the dictionary. Then, the emotional score of word q can be calculated by:

$$SS(q) = \sum_{i=1}^{n} UF_{Ci} * S(q, ZT_{Ci}) - \sum_{j=1}^{m} UF_{Cj} * S(q, ZT_{Cj}) \quad (5)$$

where, $S(q, ZT_{Ci})$ can be calculated based on the similarity of word vectors. For word vectors $q_1=(a_{11},a_{11},...,a_{1n})$ and $q_2=(a_{11},a_{11},...,a_{1m})$, their cosine similarity can be calculated by:

$$S(q_1, q_2) = \frac{\sum_{l=1}^{m} a_{1l}a_{2l}}{\sqrt{\sum_{l=1}^{m} a_{1l}^2} * \sqrt{\sum_{l=1}^{m} a_{2l}^2}} \quad (6)$$

The emotional score of word q can be characterized by the emotional tendency of the words in the review texts on overall adolescent sci-tech experience, as well as the corresponding emotional intensities. Here, the number M of most similar words is set to 10. If $SS(q)>0$, word q is a positive emotional word; if $SS(q)<0$, word q is a negative emotional word.

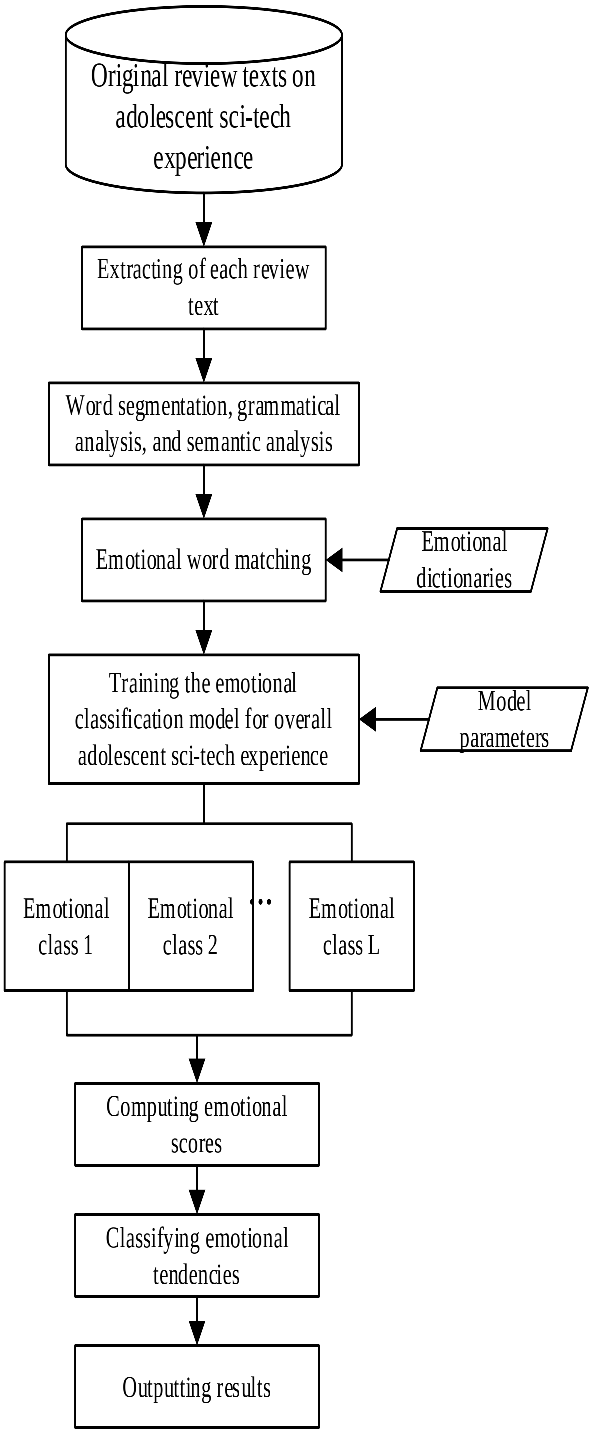


Figure 1. Flow of emotional state judgement

After building the emotional dictionaries for the field of each kind of experience item, it is possible to judge the overall adolescent sci-tech experience through preprocessing the text data, processing the emotional words, degree adverbs, and negative words, computing the emotional score of each text, and processing special statements. Figure 2 explains how to compute the emotional score of each text.

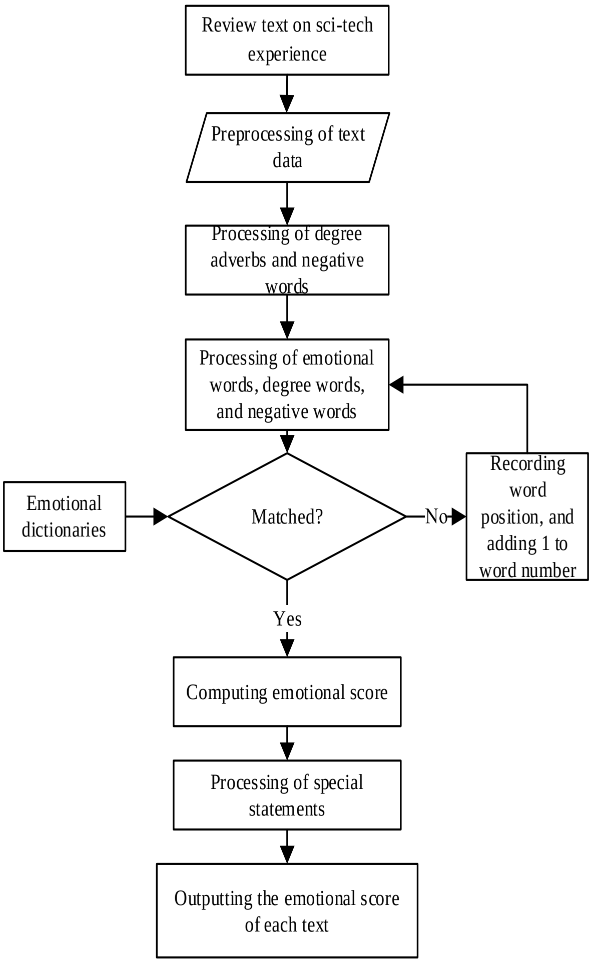


Figure 2. Flow of calculating the emotional score of each text

After segmenting each review text c into words, it is possible to obtain a statement of word segmentation results, which contains τ emotional words, n degree adverbs, and m negative words. Then, the results of word segmentation are compared with the dictionary of candidate emotional words. The position of each matched emotional word $ZT_i(0\leq i\leq\tau)$ is recorded. Similarly, comparative analyses are performed against the dictionary of degree adverbs and the dictionary of negative words to find all the matched degree adverbs $DA_{ij}(0\leq j\leq n_i)$ and all the matched negative words $NW_{il}(0\leq l\leq m_i)$. Let $\omega(DA_{ij})$ and $\omega(ZT_i)$ be the weights of DA_{ij} and ZT_i, respectively. After word segmentation, the emotional score of each review text c can be calculated by:

$$FS(c) = \sum_{i=0}^{\tau}\left\{(-1)^{m_i*}\prod_{j=0}^{n_i}\omega\left(DA_{ij}\right)*\omega\left(ZT_i\right)\right\} \tag{7}$$

$$\sum_i n_i = n \tag{8}$$

$$\sum_i m_i = m \tag{9}$$

Following the above method, it is possible to obtain the emotional score $FS(c)$ of every text. Let ξ_v and ξ_c be the upper and lower emotional thresholds, respectively. Then, the emotional tendency of each text can be classified by:

$$O(c) = \begin{cases} active & FS(c) > \xi_v \\ indifferent & \xi_c \leq FS(c) \leq \xi_v \\ passive & FS(c) < \xi_c \end{cases} \tag{10}$$

As a probabilistic discriminant model, the *N-Gram* model can sufficiently consider the feature words and the words near the feature words. This paper extracts the *N-Gram* features of the review texts on the overall adolescent sci-tech experience. The *N-Gram* model receives the word series of the original text, and outputs the joint probability of all the words. The occurrence probability of the statement $E=(q_1,q_2,\ldots,q_m)$ of a review text can be calculated by:

$$CH(E) = CH(q_1,q_2,\ldots,q_m) = CH(q_1)CH(q_2|q_1)\ldots CH(q_m|q_{m-1}\cdots q_2q_1) \tag{11}$$

Introducing the Markov hypothesis, formula (11) can be converted into:

$$CH(E) = \prod_i^m CH(q_i|q_{i-1}\cdots q_1) \approx \prod_i^m (q_i|q_{i-1}\cdots q_{i-M+1}) \tag{12}$$

If M=1, the model is transformed into a *Bi-gram* model. Then,

$$CH(E) = CH(q_1,q_2,\ldots,q_m) = CH(q_1)CH(q_2|q_1)\ldots CH(q_m|q_{m-1}) \tag{13}$$

If M=2, the model is transformed into a *Tri-gram* model. Then,

$$CH(E) = CH(q_1,q_2,\ldots,q_m) = CH(q_1)CH(q_2|q_1)\ldots CH(q_m|q_{m-1}q_{m-2}) \tag{14}$$

Let $NU(q_1q_2\ldots q_m)$ and $NU(q_1q_2\ \ldots\ q_{m-1})$ be the times of occurrence of all statements with word series $q_1q_2\ldots q_m$ and $q_1q_2\ldots q_{m-1}$, respectively. Then, the conditional probability of each item can be solved by maximum likelihood estimation:

$$CH(q_m|q_{m-1}\cdots q_2q_1) = \frac{NU(q_1q_2\cdots q_m)}{NU(q_1q_2\cdots q_{m-1})} \tag{15}$$

After extracting the features of the review texts, this paper trains the extracted features with naïve Bayes polynomial and logistic regression model, aiming to evaluate the overall adolescent sci-tech experience.

In the naïve Bayes polynomial, all features of the text data are independent of each other, facing the emotions to be classified. Let m be the dimensionality of the text data; a_l be the value of a sample on feature l; $CH(\theta_i)$ be the prior probability. Then, the posterior probability for a given sample $a=(a_1, a_2, \ldots, a_m)^T$ to belong to emotional class θ_i can be calculated by:

$$CH(\theta_i|a) = \frac{CH(a,\theta_i)}{CH(a)} \propto CH(a,\theta_i) = CH(a|\theta_i)CH(\theta_i) = CH(\theta_i)\prod_{l=1}^{m} CH(a_l|\theta_i) \tag{16}$$

Formula (16) shows that $CH(a,\theta_i)$ characterizes the joint distribution of the emotional classes in overall adolescent sci-tech experience, and the features of the review texts. Thus, it is necessary to estimate the class-conditional probability density. The prior probability $CH(\theta_i)$ can be obtained by maximum likelihood estimation:

$$CH(\theta_i) = \frac{|Q_i|}{|Q|} \quad (17)$$

Let $|Q_i|$ be the number of samples $|Q|$, which belong to emotional class θ_i, in review text training set Q. Then, $CH(\theta_i)$ can still be obtained by maximum likelihood estimation:

$$CH(a_l|\theta_i) = \frac{|Q_{i,a_l}|}{|Q_i|} \quad (18)$$

where, the numerator is the number of samples, whose feature l is valued a_l, in the sample set Q_i belonging to emotional class θ_i.

As for the logistics regression model, the eigenvector a_l of the input text data is mapped to a probability function based on the *sigmoid* function. Then, the emotions of the overall adolescent sci-tech experience are classified. The hypothesis function that the regression model predicts a positive class can be expressed as:

$$f_\xi(A) = \frac{1}{1+r^{-\xi^T A}} \quad (19)$$

where, parameter ξ can be obtained through model training. Let b=1 and b=0 be the positive samples, and negative samples, respectively. To optimize the emotional classification, and measure the effect of model training, a loss function is introduced to our model:

$$Loss(f_\xi(A), b) = -\left[blog\left(f_\xi(A)\right) + (1-b)log\left(1-f_\xi(A)\right)\right] \quad (20)$$

Since the final emotions of overall adolescent sci-tech experience are divided into positive, neutral, and negative classes, the modeling method and loss function need to be adjusted to expand binomial regression to polynomial regression. Here, only the samples in the positive class are treated as positive samples, and the other samples as negative samples. The probability for a sample to be positive and negative is denoted as CH_2 and CH_3, respectively. Finally, the most probable emotional class is introduced to the *softmax* function to generate the final output. Let l be the number of emotional classes; ω_i and δ_i be the weight vector and bias vector of class i, respectively. Then, the probability for a review text to fall into emotional class j can be calculated by:

$$CH(b=j|A) = \frac{\omega_j a + \delta_j}{\sum_{i=1}^{l} r^{\omega_i a + \delta_i}} \quad (21)$$

In the end, the output of logistics regression model is compared with that of naïve Bayes polynomial. The most probable emotional class is outputted as the final result.

4. Portrait Extraction and Preference Analysis

4.1 Portrait extraction

The previous analysis mainly focuses on the emotional information hidden in the reviews on overall adolescent sci-tech experience. In fact, further mining of these reviews can reveal the adolescent preference of sci-tech experience, i.e., their interest in the experience.

This paper defines the adolescent preference of sci-tech experience as the dynamic attention of adolescents towards specific experience themes, depending on their personal interests and needs. The adolescent preference of sci-tech experience was measured by confusion. Figure 3 shows how confusion changes with the changing number of themes. It can be seen that the optimal number of themes is 7, and each theme should contain 10 keywords.

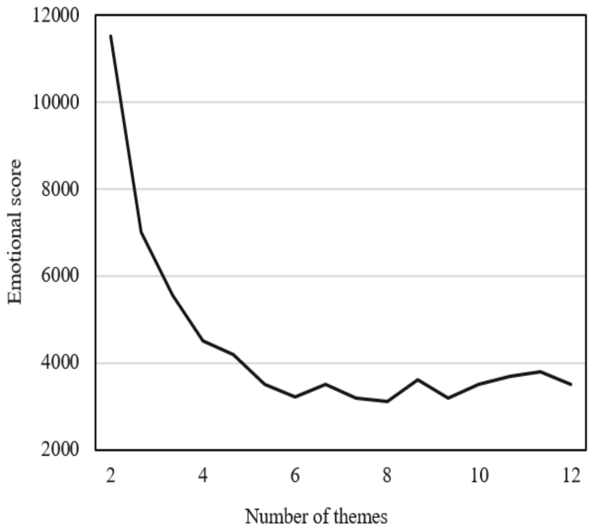


Figure 3. Confusion curve at different number of themes

Concerning the adolescent preference of sci-tech experience, the factors related to the themes of the experience items are already determined, and the emotional factors of the adolescents can be derived from the extracted emotional features. On this basis, it is necessary to extract the themed portraits of adolescent sci-tech experience from three angles, namely, the preferred sci-tech item, experience effect of the preferred item, and emotional features, and examine the influence of time and adolescent sports value over the three angles.

Under different time points and sports values, the distribution of preferred themes varies with the angles. Let φ_m be the current time point, and φ_τ be a time point close to the current time point. Then, the preferred theme distribution of the adolescents with sports value at φ_τ has a greater impact on the themed portrait than that of the adolescents with no sports value at φ_m.

To demonstrate the influence of time and adolescent sports value, this paper represents the preferred theme distribution of the adolescents at φ_τ as an L_d-dimensional eigenvector $PRD\varphi_\tau=(\tau_{d1\text{-}PN},\tau_{d2\text{-}PN},\ldots,\tau_{dLd\text{-}PN})$, where $\tau_{d1\text{-}PN}$ is the number of characteristic point pairs on theme τ_{d1}, the experience effect distribution of the adolescents at φ_τ as an L_d-dimensional eigenvector $PTD\varphi_\tau=(\tau_{d1\text{-}IP},\tau_{d2\text{-}IP},\ldots,\tau_{dLd\text{-}IP})$, where $\tau_{d1\text{-}IP}$ is the adolescent preference of theme τ_{d1}, the emotional feature distribution of the adolescents at φ_τ as an L_e-dimensional eigenvector $ED\varphi_\tau=(\tau_{r1\text{-}ET},\tau_{r2\text{-}ET},\ldots,\tau_{rLe\text{-}ET})$, where $\tau_{r1\text{-}ET}$ is the probability density distribution of emotional feature τ_{e1}.

Let φ_0 be the initial time point. Then, the preferred theme distribution, experience effect distribution, and emotional feature distribution of adolescents under the influence of time and sports value can be respectively expressed as:

$$PRD'_{\phi_\tau}=e^{-\mu_1\frac{|\phi m-\phi_\tau|}{|\phi m-\phi_0|}}*\mu_2\left(\tau_{d1-PN},\tau_{d2-PN},\ldots,\tau_{dL_d-PN}\right)\quad(22)$$

$$PTD'_{\phi_\tau}=e^{-\sigma_1\frac{|\phi m-\phi_\tau|}{|\phi m-\phi_0|}}*\sigma_2\left(\tau_{d1-IP},\tau_{d2-IP},\ldots,\tau_{dL_d-IP}\right)\quad(23)$$

$$ED'_{\phi_\tau}=e^{-\varepsilon_1\frac{|\phi m-\phi_\tau|}{|\phi m-\phi_0|}}*\varepsilon_2\left(\tau_{r1-ET},\tau_{r2-ET},\ldots,\tau_{rK_e-ET}\right)\quad(24)$$

Let μ_1, σ_1 and ε_1 be time attenuation factors; μ_2, σ_2 and ε_2 be the sports value parameters of adolescents. The time attenuation factors control the influence of previous time points on the current time point, while the sports value parameters control the influence of sports value over the three angles.

At the current time point, the themed portraits under different sports values should be plotted through full consideration of the preferred theme distributions from the previous time points to the current time point under each level of sports value. Suppose adolescent v_i gives $M_{V(vi)}$ reviews $V(v_i)$ on the items he/she has experienced. Then, the portrait of adolescent v_i can be plotted from the three angles, respectively:

$$PRDP(v_i)=\frac{\sum_{\tau\in V(v_i)}PRD'_{\phi_\tau}}{M_{V(v_i)}}\quad(25)$$

$$PTDP(v_i)=\frac{\sum_{\tau\in V(v_i)}PTD'_{\phi_\tau}}{M_{V(v_i)}}\quad(26)$$

$$EDP(v_i)=\frac{\sum_{\tau\in V(v_i)}ED'_{\phi_\tau}}{M_{V(v_i)}}\quad(27)$$

Suppose an adolescent gives $M_{V(EPj)}$ reviews $V(EP_j)$ on item EP_j. Then, the portrait of the item EP_j can be plotted from the three angles, respectively:

$$PRDP(EP_i)=\frac{\sum_{\tau\in V(EP_i)}PRD'_{\phi_\tau}}{M_{V(EP_i)}}\quad(28)$$

$$PTDP(EP_i)=\frac{\sum_{\tau\in V(EP_i)}PTD'_{\phi_\tau}}{M_{V(EP_i)}}\quad(29)$$

$$EDP(EP_i)=\frac{\sum_{\tau\in V(EP_i)}ED'_{\phi_\tau}}{M_{V(EP_i)}}\quad(30)$$

4.2 Preference analysis

Based on the preferred items, this subsection further examines how adolescent preference changes with the elapse of time and the dynamic changes of sports value, and predicts their preferred items of sci-tech experience. Figure 4 shows the flow of the preference analysis.

The adolescent reviews on a specific theme of sci-tech experience reflect their preferences. Therefore, the dynamic attention of adolescents towards a theme can be captured by analyzing the time series of the theme under different sports values. On this basis, it is possible to predict the attention of adolescents towards new items in future.

Let OR_v be the time series of the preference of adolescent v for a specific theme; YO_{BH} be the serial number of adolescents; TH_{BH} be the serial number of themes; $PL_\lambda=(PL_1, PL_2, \ldots, PL_i, \ldots, PL_\lambda)$ be the adolescent reviews on the specific theme in multiple equal-length time cycles, where PL_i is the adolescent reviews in cycle i and λ is the current time cycle; υ be the parameter of adolescent sports value. Then, adolescent theme preference can be expressed as a structured time series:

$$OR_v=\left(YO_{BH},TH_{BH},PL_\lambda=\upsilon(PL_1,PL_2,\ldots,PL_i,\ldots,PL_\lambda)\right)\quad(31)$$

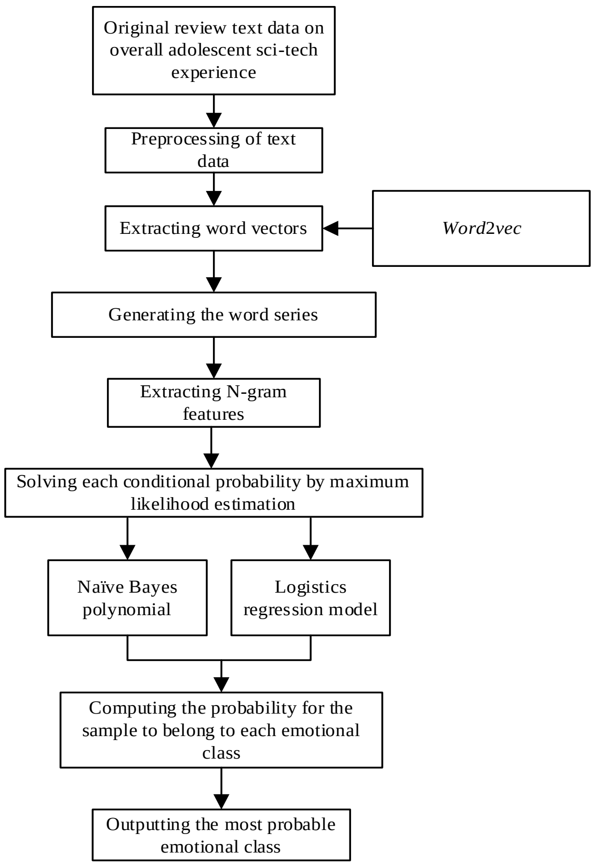


Figure 4. Flow of preference analysis

Concerning the time series of adolescent theme preference, many null values can be found in the time series for the attributes like novelty, intelligence, pattern setting, and dynamic response. To disclose the law of the time series, this paper decides to classify them first. Let $CD(PL_\lambda)$ be the total length of the time series of adolescent theme preference; $SP(PL_{i(where\ PLi-1,\ldots,PLk=0)})$ be the position of the subscript of the first non-zero element. Then, the effective length of the time series of adolescent theme preference PL_λ can be defined as the length from the first non-zero element to the last element in the time series:

$$LCD(PL_\lambda) = CD(PL_\lambda) - SP\left(PL_{i(where\ \mathrm{PL}_{i-1,\ldots,}PL_1=0)}\right) + 1 \quad (32)$$

The length of effective elements in PL_λ can be defined as the number of nonzero elements in the time series:

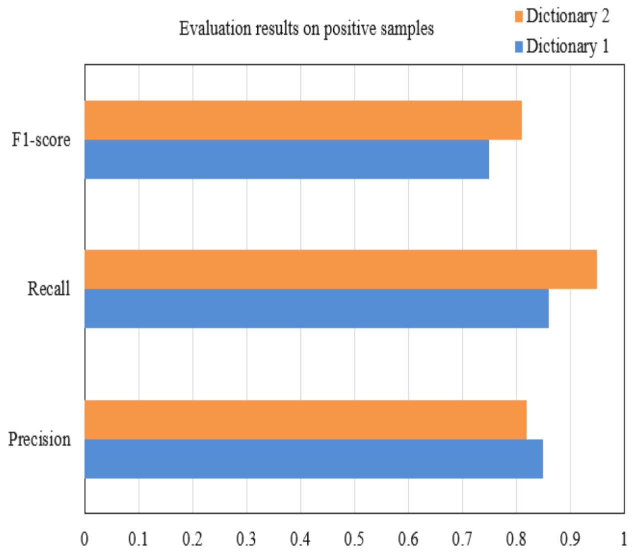
$$ELCD(PL_\lambda) = NZE(PL_i \neq 0) \quad (33)$$

According to the effective length of PL_λ, the time series can be divided into two types: the time series effectively affected by sports value, and the time series ineffectively affected by sports value. For simplicity, the two types of time series are referred to as SVEA time series, and SVIA time series. Let λ_K and λ_M be the effective length thresholds of SVEA and SVIA time series, respectively. Then, two judgement formulas can be given by:

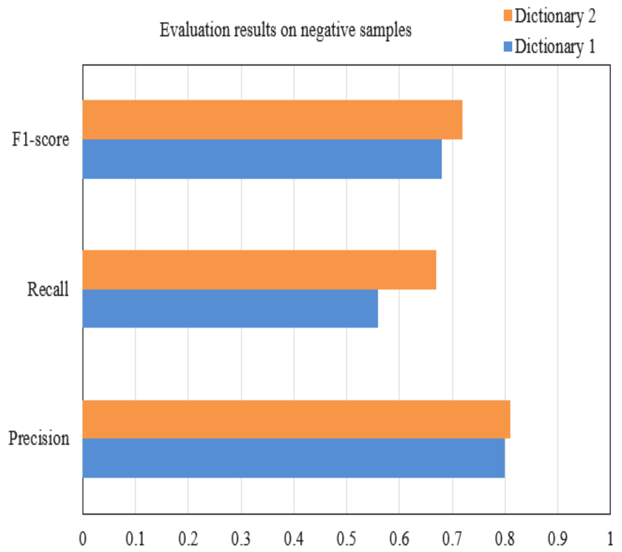
$$BJ(PL_\lambda) = \begin{cases} Vaild\ \ TSI, VAildCD(PL_\lambda) \geq \lambda_K\ \ and\ \ VaildEleLen(PL_\lambda) \geq \lambda_M \\ Sparse\ TSI, \quad else \end{cases} \quad (34)$$

5. Experiments and Results Analysis

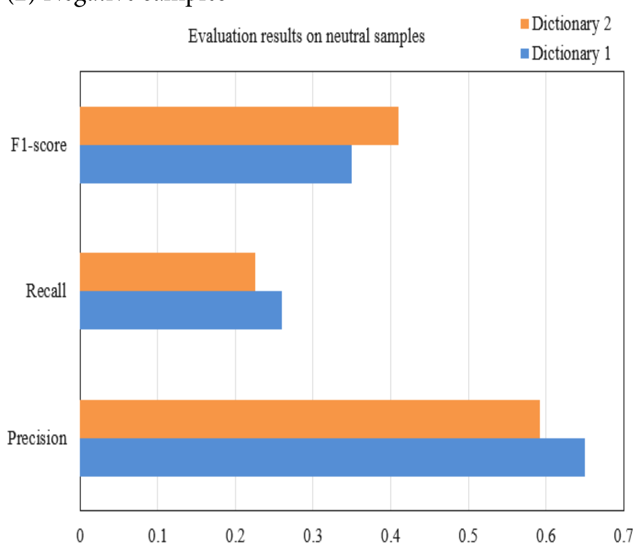
Two emotional dictionaries were prepared from Taiwandict and BosonNLP, respectively. The dictionary based on Taiwandict is denoted as Dictionary 1, and that based on BosonNLP as Dictionary 2. On this basis, the emotions of adolescent sci-tech experience were analyzed under the influence of sports value. The experimental results were measured by precision, recall, and F1-score. The evaluation results on positive, neutral, and negative samples are reported in Figure 5.



(1) Positive samples



(2) Negative samples



(3) Neutral samples

Figure 5. Evaluation results on different types of samples against different dictionaries

Table 2

Emotional features extracted from adolescent sci-tech experience items

Adolescent number	0	1	2	3	4	5
Happy	78.25	0.09	0.34	65.24	2.15	0.02
Boring	0.12	79.65	76.28	0.53	0.62	0.01
Fearful	6.07	8.41	1.84	0.12	0.14	0.08
Anxious	5.04	11.45	0.82	0.75	38.75	0.07
Calm	0.50	0.51	0.24	0.03	0.14	0.01
Interesting	0.15	0.12	2.85	0.04	0.76	0.02
Exclamatory	9.65	0.16	18.57	36.42	57.41	99.75
Maximum	78.28	79.65	76.28	65.24	58.43	99.14
Emotional class corresponding to the maximum	Happy	Boring	Boring	Happy	Exclamatory	Exclamatory
Second largest value	9.65	11.34	18.27	36.42	38.75	0.08
Emotional class corresponding to the second largest value	Exclamatory	Anxious	Exclamatory	Exclamatory	Anxious	Fearful

As shown in Figure 5, the emotional analysis on adolescent sci-tech experience based on Dictionary 2 was generally more precise than that based on Dictionary 1. This is because Dictionary 2 contains more Internet slangs, informal abbreviations, and non-standard texts. Table 2 shows some of the emotional features extracted from adolescent sci-tech experience items.

Figure 6 compares the distribution of adolescent preference time series for different sci-tech experience items. Comparing the time series under sports value and those without sports value, it can be learned that, in most adolescent preference time series, there were more SVEA time series than SVIA time series. The SVEA time series concentrated in themes like physical quality improvement, and mental quality improvement. This further verifies the adolescent preference for these themes of sci-tech experience.

After parameter determination and fitness test, our model was adopted to fit the adolescent preference time series for different themes, and predict their preferred themes in fixed periods in future. Figure 7 shows the predicted adolescent preference time series for different themes. To evaluate the prediction effect, this paper divides all the adolescent preference time series into a training set and a test set, and evaluates the prediction effect by mean square error (MSE). The MSE of our prediction was 0.7025, indicating that our model can effectively fit and predict the time series of adolescent preference for the themes of sci-tech experience.

Figure 8 compares the errors of our model (model 4) with decision tree 1, support vector machine 2, k-th nearest neighbors (KNN) 3. Compared with the three contrastive models, our model achieved very small mean absolute error (MAE) and root-mean-square error (RMSE), respectively. Therefore, it is possible to rate the adolescent preference more accurately for future sci-tech experience items, after fully considering the preferred sci-tech item, experience effect of the preferred item, and emotional features, and predicting the sci-tech experience themes preferred by the adolescents.

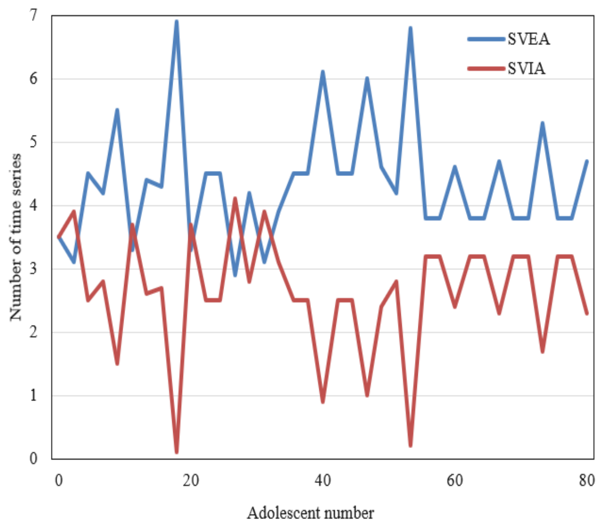


Figure 6. Distribution of adolescent preference time series for different items

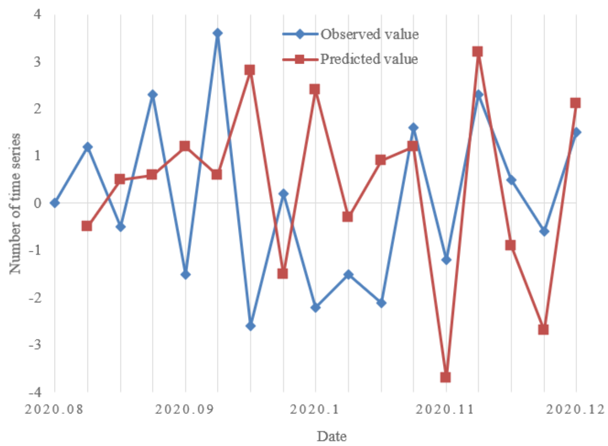


Figure 7. Predicted adolescent preference time series for different themes

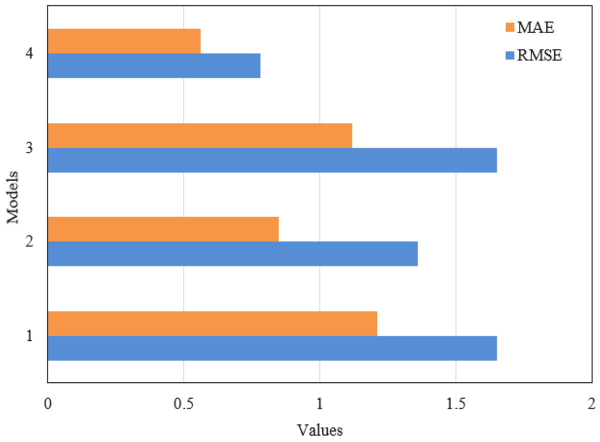


Figure 8. Preference analysis results of different models

6. Conclusions

This paper investigates the influence of sports value over adolescent participation and preference of sci-tech sports experience activities. The boom of sci-tech sports competitions in China magnifies the influence of sci-tech sports on adolescents. Based on our research, effective measures and suggestions can be developed to promote adolescent participation in sci-tech sports. These measures and suggestions help to enhance adolescent innovation ability of sci-tech sports, improve their psychical and mental qualities, and cultivate into potential talents of sci-tech sports. After defining adolescent sci-tech experience under the influence of sports value, the authors judged the emotional state of text reviews on adolescent sci-tech experience, specified the method to compute the emotional score of each text, and explained how to analyze adolescent preference of sci-tech experience activities under the influence of sports value. In addition, the themed portraits of adolescent sci-tech experience were extracted, followed by evaluating the effects of time and changing sports value on adolescent preference. Through experiments, the different classes of samples were evaluated against two different emotional dictionaries, revealing that Dictionary 2 is more accurate in emotional analysis of adolescent sci-tech experience. Moreover, the authors obtained the distribution of adolescent preference time series for different items, and predicted adolescent preference time series for different themes. These results show that our model can effectively fit and predict the time series of adolescent preference for the themes of adolescent sci-tech experience. Finally, the preference analysis results of our model were compared with those of three other models. The comparison confirms that it is possible to rate the adolescent preference more accurately for future sci-tech experience items, after fully considering the preferred sci-tech item, experience effect of the preferred item, and emotional features, and predicting the sci-tech experience themes preferred by the adolescents.

The future research will target more sports professionals in wider areas, probe deeper into the effects of adolescent participation in sci-tech sports, and reveal the psychological effects of adolescent sports value. This research suggests that sports value is correlated with adolescent participation and preference of sci-tech sports. The exact correlation will be investigated further in future.

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