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Research Article

Game Teaching Method in Preschool Education Based on Big Data Technology

Rui Bai

School of Education, YuLin University, Yulin, China

Correspondence should be addressed to Rui Bai; bairui@yulinu.edu.cn

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The traditional preaching way of imparting knowledge can only stifle children's imagination, creativity, and learning initiative a little bit, which is harmful to children's healthy and happy growth. This paper combines big data technology to evaluate the effect of game teaching method in preschool education, analyzes the teaching effect of game teaching method in preschool education, and combines big data technology to find problematic teaching points. Based on the collaborative filtering algorithm of preschool children, this paper estimates the current preschool children's score for the game by referring to the scores of neighbor preschool children on the predicted game and constructs an intelligent model. Finally, this paper combines experimental research to verify the model proposed in this paper. From the experimental research, it can be seen that the method proposed in this paper has a certain effect.

1. Introduction

The continuous development of information technology and network terminal technology has given mobile phones and other life tools great entertainment. The time required for games and the cost of money have been continuously reduced, and digital games have gradually entered various households. Whether it is young and middle-aged parents or the elderly taking care of children, they cannot avoid preschool children from coming into contact with games. The magic of this kind of game can make a crying child stop immediately, can make the child sit quietly in the corner and wait, and can be a variety of rewards for parents. However, this "game-style trick" can only bring more problems such as more eyesight and distracted attention, and seriously, it also causes communication barriers for preschoolers. While the digital age brings convenience to people's lives, there are also risks that cannot be underestimated [1]. As practitioners of preschool education, when seeing children with lively, smart, and witty nature being increasingly eroded by digital games, they deeply feel the crisis in preschool education and child development. It is the nature of children to like to play games, and games are also the best way for children to learn. Games cannot be discarded in the growth of preschool children. Based on such concerns, they began to think about how to construct a digital game curriculum suitable for the development of preschool children and implement it in real preschool education activities. Compared with traditional outdoor games for children, the design and implementation of digital games are easier to add elements that are conducive to the development of children's cognitive development and mathematical logic. It can be said that making good use of digital games is of great benefit to the development of preschool children [2]. Here, how to take the essence of digital games and remove the dross of digital games is extremely important [3].

This paper combines big data technology to evaluate the effect of game teaching method in preschool education and analyzes the teaching effect of game teaching method in preschool education. Moreover, this paper combines big data technology to discover problematic teaching points and, on this basis, further enhance the teaching effect of preschool education.

2. Related Work

Information multimedia technology is developing at a speed beyond people's imagination. The entire society is in a critical period of transition from an industrialized society to an informationized society. Informationization has become

a common trend in the world's economic and social development. At present, many developed countries have paid attention to the cultivation of the information quality of the next generation, and all countries in the world are accelerating the informatization process of basic education [4]. Educational informatization has a comprehensive impact on preschool education. It has changed the educational goals, educational structure, educational content, educational methods, and even teaching evaluation [5].

The United Kingdom no longer stacks computers but moves them into the class to make it a gaming area. Computer education is called information technology education in British kindergartens. Almost every kindergarten class is equipped with a computer and learning software that matches the model [6]. Computers can not only teach children English, mathematics, and science but also teach them to sing, draw, play chess, and walk through mazes. The more entertaining software can greatly arouse children's interest in learning computer and through the intervention of multimedia, such as sound, image, text, animation, and so on,, make children feel the endless joy of learning. The educational software associated with the teaching of various subjects can play a role in assisting education. Through the method of entertaining and teaching, children can learn easily and happily and increase their intelligence [7]. The method of computer education mainly adopts the game method, that is to say, computer education starts from the game. The game activity stimulates the children's learning interest and thirst for knowledge, and the children never get tired of it. Japanese families can receive a set of video tapes, books, and magazines every month to encourage parents to help their children play cartoon characters, text, and digital games, and open a hotline [8]. In the United States, computers are now popularized in all kindergartens. Under the guidance of full-time computer teachers, three- or four-year-old children "touch the future" in front of the keyboard and mouse. In addition to playing computer games, the community also provides gamification and information technology–teaching activities [9]. In Canada, kindergartens have opened "virtual schools" for teaching activities. Australia has a computer game group, New Zealand has a computer game center, and France and Sweden have also incorporated computers and networks into their preschool education plans. It should be said that the computer entering kindergarten is another development trend of today's kindergarten curriculum[10].

Literature [11] elaborated on the influence of multimedia computer-assisted teaching MCAI in children's teaching and mentioned the combination of multimedia computer-assisted teaching and the use of game courseware to carry out mathematics education. Practice has proved that children learn best in a game environment, and what they learn can be quickly applied to more abstract and formal situations. The action thinking in the game can solve their more disciplinary problems in the future. The formation of abilities, such as mind image and recording, lays a solid foundation. Therefore, it is feasible to carry out research on gamification theme teaching in kindergartens, and it has significant effects. The main research content of the literature [12] is how to build a kindergarten modern education environment, strengthen teacher information technology training, pay attention to teaching research and practice under the information technology environment, and establish a comprehensive evaluation system for kindergarten information technology education. The process evaluation, stage evaluation, and comprehensive evaluation here have given me a lot of enlightenment and provided a reference for the monthly stage evaluation standard selection and formulation. Literature [13] studies the informatization of environmental education and integrates the element of information technology into environmental education, making environmental education with the characteristics of informatization. The two are interactive and two-way integration. This integration is not a simple application of courseware for demonstration auxiliary teaching, but the integration of modern information technology methods and courses, and it is no longer just a demonstration of media or tools. More abstract environmental knowledge and problems are more visualized, promote children's environmental protection emotions, and trigger the use of information technology to present a holographic learning environment for environmental education, so that children can be in the information world and deeply feel the application of information technology [14].

3. Game Teaching Method in Preschool Education Based on Big Data Recommendation Algorithm

The recommendation algorithm is one of the cores of the recommendation system because it is directly related to the accuracy of the recommendation system and the satisfaction of preschoolers. A tag is a kind of keywords used to describe information without hierarchical structure. It can be used to describe the semantics of the game and the interests of preschoolers, and to connect the two. As shown in Figure 1, there are three main ways to source tags in the recommendation system. (1) Preschoolers use labels to describe their personal interests. (2) The administrator uses tags to describe the game features when creating the game. (3) Preschool children use several tags to describe the game. Figure 1 also shows the relationship between preschoolers, tags, and games. When the tags used by the preschool children match the tags added by the game, to a certain extent, the preschool children and the game have a set of potential consumption relationships. The tags used by preschoolers here include tags for preschoolers to describe personal interests and tags for preschoolers to describe games.

Therefore, the process of tag-based recommendation algorithm is as follows:

(1) The algorithm calculates the common labels of each preschooler, and the number of times the preschoolers have used these labels.

(2) The algorithm calculates the number of times each game has been hit by each tag. The more times a game is described by a tag, the more relevant the game is to that tag.

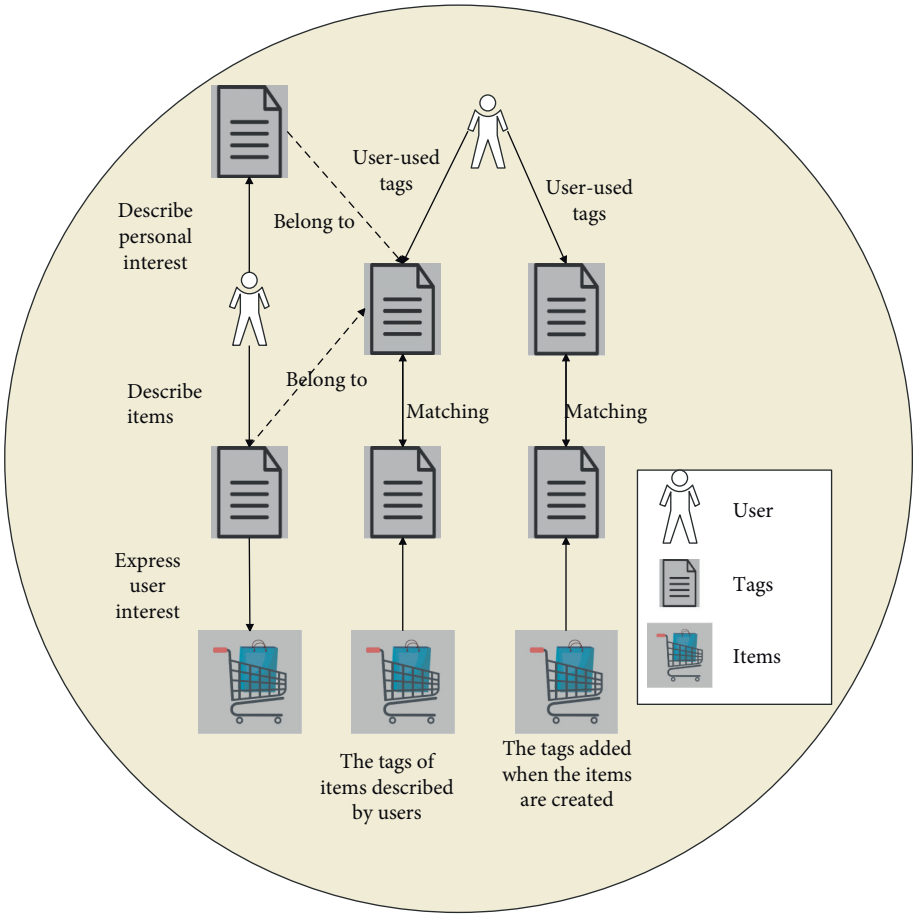

Figure 1: The relationship between preschoolers, tags, and games.

(3) When recommending for a preschooler, the algorithm associates the preschoolers' common labels with the most relevant games described by these labels and recommends them to the preschoolers according to the correlation, as shown in formula (1) [15]:

$$P(u,i) = \sum_{t \in T(u)} n_{u.t} n_{t.i}. \tag{1}$$

Among them, $P(u, i)$ represents the degree of interest of the preschooler u in the game i and T(u) is the set of tags used by the preschooler u. $n_{u.t}$ is the number of times the preschooler u has used the label t, and $n_{t.i}$ is the number of times the label t is used to describe the game i.

In practical applications, certain tags will be used many times by preschoolers, and tags of certain popular games will also be used repeatedly by preschoolers when evaluating the game. The algorithm described in formula (1) will be overly inclined to popular tags and popular games for preschool children in terms of results. The main problem is that the algorithm cannot distinguish which labels are popular labels and which labels are personalized labels for preschoolers. Therefore, we borrow the idea of TF-IDF5. Considering how many different preschoolers use each tag and how many different preschoolers describe each game with tags, we use these two to punish popular tags and popular games. The improved algorithm (TFIDF Tag Based) is shown in formula (2) [16]:

$$P(u,i) = \sum_{t \in T(u)} \frac{n_{u.t}}{\log\left(1 + n_t^{(n)}\right)} \frac{n_{t.i}}{\log\left(1 + n_i^{(u)}\right)}. \tag{2}$$

Among them, $n_t^{(n)}$ indicates how many different preschoolers have used the label t, and $n_i^{(u)}$ indicates how many different preschoolers have used the label to describe the game i.

In response to this problem, the solution used in this paper is to extend the original label. The original tags include tags used by preschool children or tags that have been described in games, while the expanded tag set includes the original tags and the tag set with higher similarity to the original tags. Measuring the similarity between two tags can be simplified to calculate the proportion of the number of games that have been described by the two tags at the same time to the total number of games that have been described by the two tags. The Jaccard formula can be used to calculate the similarity between tags t1 and t2, as shown in formula (3) [17]:

$$\operatorname{sim}(t_1, t_2) = \frac{\left|I(t_1) \cap I(t_2)\right|}{\left|I(t_1) \cup I(t_2)\right|}. \tag{3}$$

Among them, $I(t)$ represents the set of games described by the label r. In addition, the cosine similarity formula can also be used to calculate the similarity between tags t_1 and t_2:

$$\operatorname{sim}(t_1, t_2) = \frac{\sum_{i \in I(t_1) \cap I(t_2)} n_{t_1,i}^{(u)} n_{t_2,i}^{(u)}}{\sqrt{\sum_{i \in I(t_1) \cap I(t_2)} n_{t_1,i}^2 n_{t_2,i}^2}}. \quad (4)$$

Among them, $n_{t,i}^{(u)}$ is the number of preschool children who have described game i with the label t.

The accuracy of the tag-based recommendation algorithm has a lot to do with the quality of the tag itself. The quality here refers to whether the label is descriptive, whether it is distinguishable, whether it follows the standard grammar, and so on. The quality of the labels in the recommendation system is mainly guaranteed through low-quality label cleaning and high-quality label recommendation.

The entire cleaning process is shown in Figure 2. The nonreferenced tags are primarily screened by identifying commonly used stop words and defining and expanding the stop dictionary. After that, we can let preschoolers mark useless labels through feedback from preschoolers. Tags with high-text content similarity can be identified and processed through regular expressions and string edit distance algorithms.

To describe the collaborative filtering algorithm, this paper introduces the following symbols: U represents the set of preschool children in the recommendation system; I represents the set of all recommended candidate games; R represents the set of score records in the system; a score record is a triple set of preschool children, games, and scores; and S represents the range of scores (e.g. $S = \{1,2,3,4,5\}$, $S =$ {interest, not interested). At the same time, we assume that any preschooler $u \in U$ can only have at most one score for each game $i \in$ I, and this score is recorded as $R_{u,i}$. U_i represents the subset of preschoolers who have evaluated game i, and $I_{u,v}$ represents the subset of games evaluated by preschooler u. I_u means preschooler u and preschooler v [18].

The intersection of the reviewed items is $I_{u,v} = I_u \cap I_v$, $U_{i,j}$ represents the set of preschoolers who have reviewed both game i and game j, that is, $U_{i,j} = U_i \cap U_j$.

The collaborative filtering algorithm based on preschool children estimates the current preschool children's score for the game by referring to the scores of neighbor preschool children on the predicted game. The neighbor preschoolers here refer to a collection of preschoolers with similar scoring patterns to the current preschoolers. The calculation of preschooler u's prediction score for game ü is shown in formula (5) [19]:

$$P(u, i) = \frac{\sum_{v \in N_i(u)} \operatorname{sim}(u, v) R_{v,i}}{|\operatorname{sim}(u, v)|}. \quad (5)$$

Among them, $N_i(u)$ is the preschooler's neighbor set composed of K preschoolers who have evaluated game i and have the highest similarity with preschooler u, sim(u,v) represents the similarity between preschooler u and preschooler v.

Based on the game-based collaborative filtering algorithm, we estimate the current preschool children's score for the game by referring to the score records of the preschool children's games with the neighbors of the predicted game. The neighbor game here refers to a game that is highly similar to the predicted game. The calculation of preschooler u's prediction score for game i is shown in formula (6) [20]:

$$P(u, i) = \frac{\sum_{v \in N_i(i)} \operatorname{sim}(i, j) R_{v,i}}{\sum_{v \in N_i(i)} \operatorname{sim}(i, j)}. \quad (6)$$

Among them, $N_u(i)$ is the game neighbor set composed of K games with the highest similarity to game i among the games evaluated by preschooler u, and sim(i,j) represents the similarity between preschooler i and preschooler j.

Commonly used similarity measurement methods in collaborative filtering algorithms mainly include Cosine Similarity and Pearson Correlation. The cosine similarity method is often used in game-based collaborative filtering algorithms. This method represents objects as vectors and obtains the similarity between objects by calculating the cosine angle between the vectors:

$$\operatorname{sim}(i, j) = \frac{\sum_{u \in U_{i,j}} R_{u,i} R_{u,j}}{\sqrt{\sum_{u \in U_{i,j}} R_{u,j}^2 \sum_{u \in U_{i,j}} R_{u,j}^2}}. \quad (7)$$

Since this similarity measurement method does not consider the difference between preschool children's scores and their average scores, we use Adjusted Cosine Similarity, as shown in formula (8) [21]:

$$\operatorname{sim}(i, j) = \frac{\sum_{u \in U_{i,j}} \left(R_{u,i} - \overline{R_u}\right)\left(R_{u,j} - \overline{R_u}\right)}{\sqrt{\sum_{u \in U_{i,j}} \left(R_{u,i} - \overline{R_u}\right) \sum_{u \in U_{i,j}} \left(R_{u,j} - \overline{R_u}\right)}}. \quad (8)$$

Among them, $\overline{R_u}$ represents the average value of the sum of u scores of preschool children. It shows that adjusting the cosine similarity is more suitable for use in game-based methods than the Pearson correlation coefficient. In contrast, the Pearson correlation coefficient has better results in the method based on preschool children, which is shown in formula (9) [22]:

$$\operatorname{sim}(i, j) = \frac{\sum_{u \in I_{iu,v}} \left(R_{u,i} - \overline{R_u}\right)\left(R_{v,j} - \overline{R_u}\right)}{\sqrt{\sum_{u \in I_{u,v}} \left(R_{u,i} - \overline{R_u}\right) \sum_{u \in I_{u,v}} \left(R_{v,j} - \overline{R_u}\right)}}. \quad (9)$$

In the actual scoring process, the evaluation criteria of each preschool child are different. Some preschool children are more relaxed and tend to give most games 4 or even 5 points, and some preschool children are stricter and more cautious and tend to give most games less than 3 points. In other words, if a score record is 4 points, it does not necessarily mean that preschoolers like the game. For relaxed preschoolers, maybe 5 points are really liked. However, for strict preschool children, a score of 4 has already indicated the preschool children's tendency to be interested or like it. Therefore, the average score of preschool children is introduced here to measure whether a certain preschool child's score record is a positive or negative tendency score, as shown in formula :

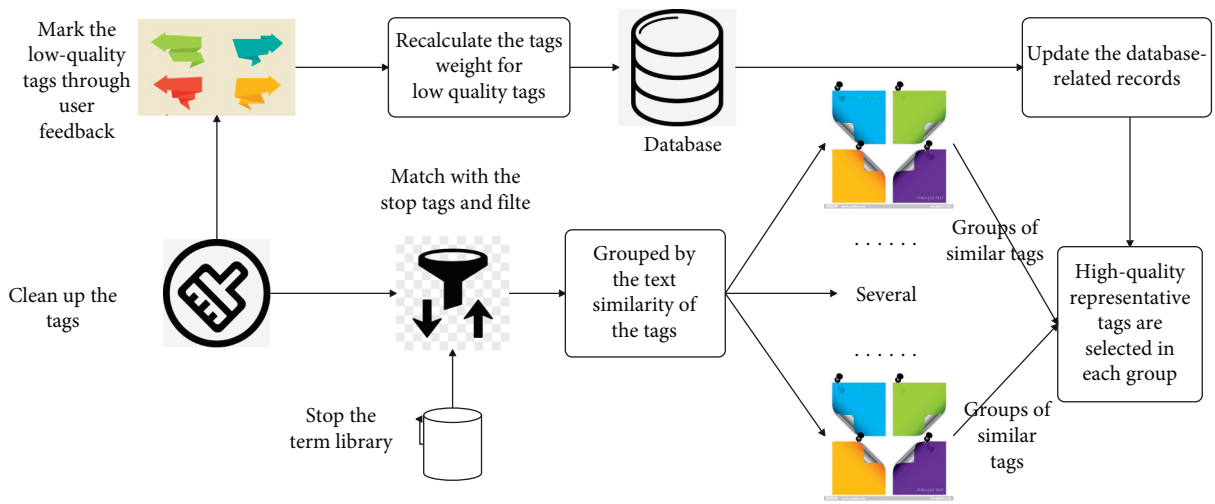

Figure 2: Label cleaning process.

$$P(u,i) = \overline{R_u} + \frac{\sum_{v \in N_i(u)} \mathrm{sim}(u,v)\left(R_{v,i} - \overline{R_v}\right)}{\sum_{v \in N_i(u)} \mathrm{sim}(u,v)}. \quad (10)$$

Game-based methods can also be similarly processed by introducing average game scores, as shown in formula :

$$P(u,i) = \overline{R_t} + \frac{\sum_{v \in N_u(i)} \mathrm{sim}(i,j)\left(R_{u,j} - \overline{R_j}\right)}{\sum_{v \in N_u(i)} \mathrm{sim}(i,j)}. \quad (11)$$

In the practical application of the recommender system, the total number of score records is much smaller than the product of preschool children and the number of games. The score matrix for preschool children and games contains a large number of zero-value elements (indicating that preschool children have not rated the game or preschool children have not purchased the game). Such a scoring matrix has the problem of data sparsity. The definition of the sparsity of the scoring matrix is shown in formula :

$$\mathrm{Sparsity}(M_R) = \frac{|R|}{|U||I|}. \quad (12)$$

When calculating the similarity of preschoolers based on a sparse scoring matrix, it is likely that only a few scores are involved. When these scores are exactly similar or even equal, this group of preschool children will be considered completely similar (the similarity is close to 1). In fact, because the number of common scores is too small, this phenomenon may be just a coincidence, but it will cause dissimilar preschoolers to have too high recommendation weights in the recommendation calculation process, and ultimately unreliable recommendation results.

Aiming at the data sparsity problem in the collaborative filtering algorithm, a feasible solution strategy is to reduce the similarity obtained by only a small number of scores. The improved similarity of preschool children is shown in formula :

$$\mathrm{sim}\prime(u,v) = \frac{\min\left\{\left|I_{u,v}\right|, \gamma\right\}}{\gamma} \times \mathrm{sim}(u,v). \quad (13)$$

Similarly, the improved game similarity is shown in formula :

$$\mathrm{sim}'(u,v) = \frac{\min\left\{\left|I_{u,v}\right|, \gamma\right\}}{\gamma} \times \mathrm{sim}(u,v). \quad (14)$$

This method penalizes the similarity calculated involving the number of ratings less than the specified number y. The y value varies according to the data set, and cross-validation is required to determine the best y value.

This paper proposes another solution to the data sparsity problem, which increases the number of available scores by improving the similarity calculation process. Carefully analyze the calculation process of the similarity of preschool children. No matter which similarity calculation formula is used, the accuracy bottleneck lies in the size of the $|I_{u,v}|$. In the traditional similarity calculation method, the calculation of $I_{u,v}$ is done by exact matching, that is, only those games that match exactly in the game set evaluated by preschooler u and preschooler v will be used to calculate the similarity between the two spend. Now, we consider the following situation: preschooler u rated game i with 5 points, preschooler v rated game j with 5 points, preschooler u did not rate j, and preschooler v did not rate game i. There is no score intersection between u and preschooler v. It is known that the similarity between game i and game j is 0.9 (very similar). According to the aforementioned description, because the exact match result of the game is an empty set, the traditional similarity calculation method cannot calculate the similarity between the preschooler u and the preschooler v.

The set of high-scoring games for preschool children u is the User Favorite Item Set (User Favorite Item Set). By accumulating the similarity between each group of successfully matched game pairs and taking the average, the result is the set similarity between $I^+{}_u$ and $I^+{}_v$. To get closer to the similarity of the real game set, try to avoid the situation where the same game is matched multiple times (as shown in Figure 3). Especially, when the game similarity is calculated based on the collaborative filtering similarity algorithm, the similarity between popular games and other games is

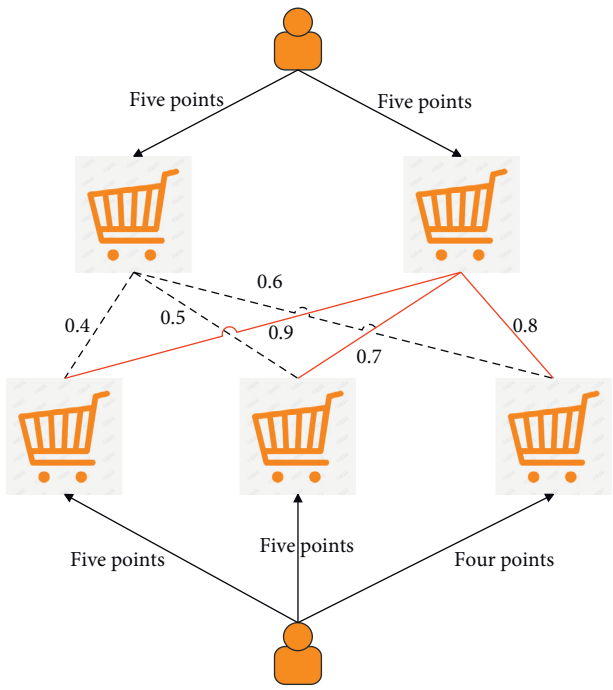

Figure 3: An example where a game is matched multiple times in the calculation of set similarity.

generally high, which will cause the calculated set similarity to not well reflect the preschool children's degree of similarity between interests.

Therefore, the weight reduction penalty should be imposed on games that have been matched more than once. Considering that the result range of cosine similarity or Pearson's correlation coefficient is [-1,1], different penalty mechanisms are adopted for positive and negative similarity, although in theory it is difficult for games with negative correlation to be the best match. The penalty strategy is to reduce all similarities related to the game when calculating the similarity according to the number of times the game has been matched.

In addition, for each game i, the game i^* that is most similar to game i in the set of scored games for each preschooler u can be calculated, that is, $\{i^* \in I_u, \mathrm{sim}(i, i^*) = \max_{i \in I_u} \mathrm{sim}(i, i^*)\}$. The collaborative filtering method based on preschool children can be extended with formula :

$$P(u, i) = \frac{\sum_{v \in N_i(i)} \mathrm{sim}(u, v) \mathrm{sim}(i, j) R_{v,j}}{\sum_{v \in N_i(i)} |\mathrm{sim}(u, v)||\mathrm{sim}(i, j)|}. \quad (15)$$

The advantage of using this expansion formula to calculate is that for different prediction games, even if the number of reliable neighbors for preschoolers is insufficient, we can expand enough neighbors and scores by looking for approximate games, thereby solving data sparseness to a certain extent. Improve the reliability of prediction results.

4. Analysis of Game Teaching Method in Preschool Education Based on Big Data Technology

Users can obtain information based on their existing knowledge, perception, and thinking through the intuitive interactive interface provided by the machine and react through the interactive interface. The machine processes the received information and then transmits it to the user through the man-machine interface or makes other forms of feedback. The human–computer interaction process can be summarized as consisting of four basic functions: information receiving function, information storage function, information processing and decision-making function, and execution function, as shown in the following Figure 4:

The memory storage model is the three-level memory model of memory. This model divides the process of memory into three stages according to the time sequence of memory. Sensory memory is the initial stage, followed by short-term memory, and finally long-term memory. The model can be shown in Figure 5:

It can be seen from the model in Figure 5 that people first obtain information from the environment through sensory memory, such as vision and hearing. Some information will be lost in this process. Then, when the information gets attention, the human brain begins to perform the next stage of memory, which is short-term memory. When performing short-term memory, the human brain processes and reorganizes information and responds. To achieve this process, the human brain also needs to call up the knowledge in long-term memory. When the information is retold and strengthened, the information can be stored in long-term memory. The arrows on the way indicate the flow of information.

The human–computer interaction function diagram clearly describes the flow of information: information input, reception, processing, storage and output, and so on can know the goal and structure of the information, but does not reflect the roles of the three modules of the user's memory. In the process of using handheld mobile devices, in addition to the user's memory, the three modules affect all aspects of the information circulation process, the interactive design of the device, the difficulty of game tasks, and the user's information cognitive ability also affect the effect of information transmission. Based on the mutual influence of the aforementioned elements, a design model of instructional games supported by mobile devices has been researched, as shown in Figure 6.

The multisensory and multidimensional interactive virtual reality environment composed of sensors-controllers (chips)-virtual worlds (computers) will have a better immersive effect than virtual reality where computers are solely used as visual and auditory output. This research will combine the multisensory and multidimensional

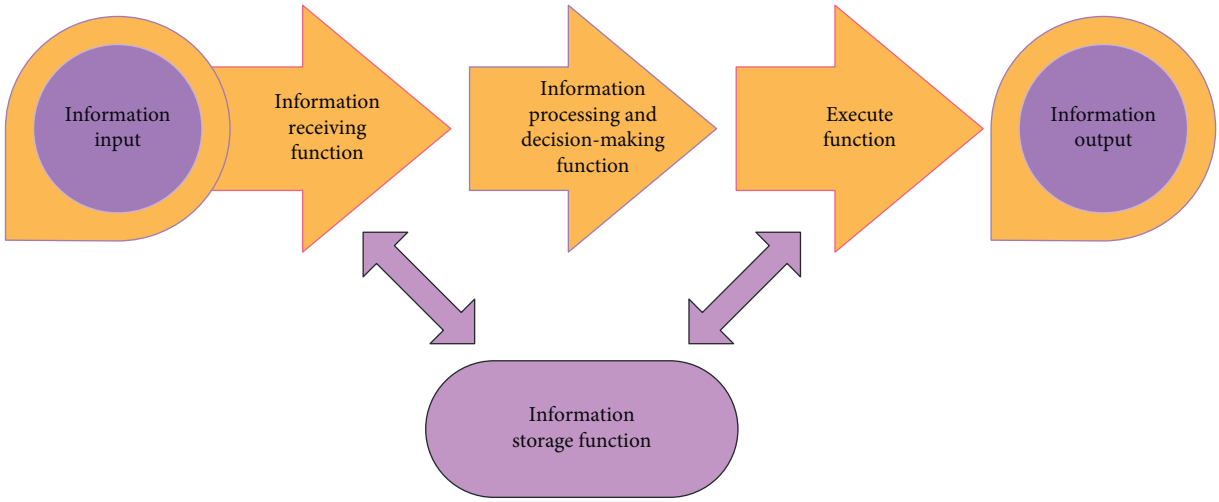

Figure 4: Basic functions of human-computer interaction.

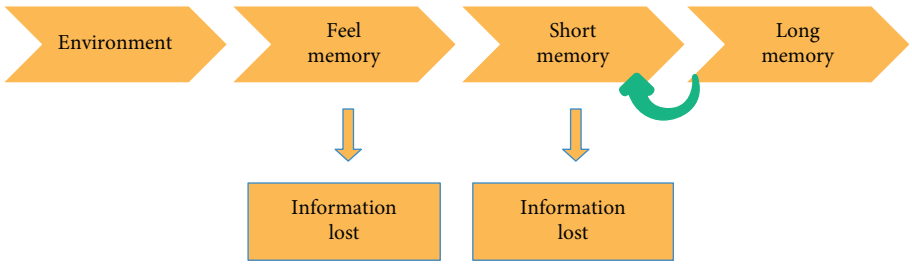

Figure 5: Three-storage model of memory.

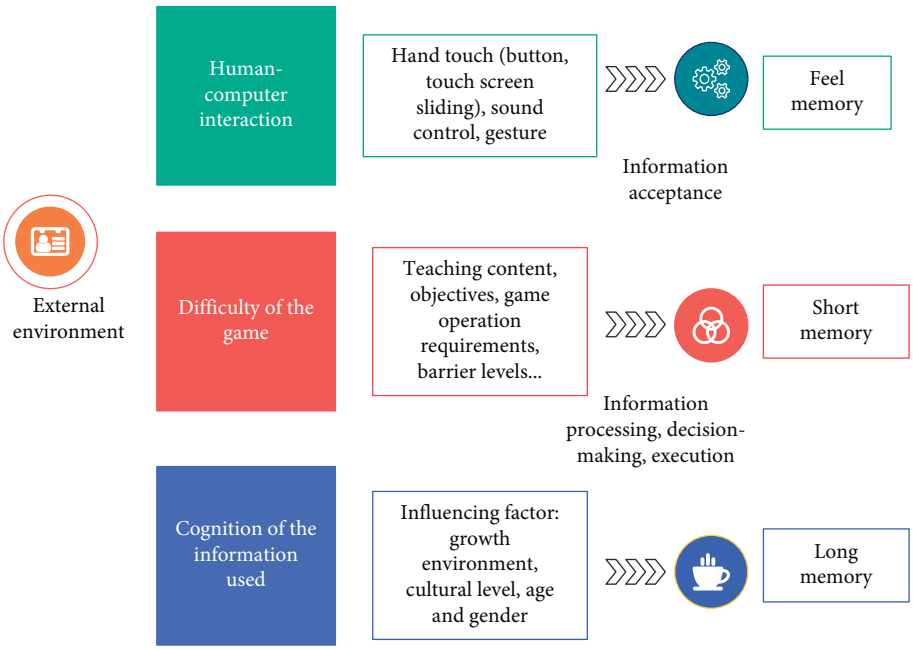

Figure 6: Teaching game design model supported by mobile devices.

interaction concept of sensor-controller (chip)-virtual world (computer) to design a virtual reality psychological relaxation game suitable for preschool students, as shown in Figure 7.

After constructing the aforementioned model, the performance of the model is verified. The model built in this paper is mainly used in preschool education, and it uses big data recommendation algorithms to recommend

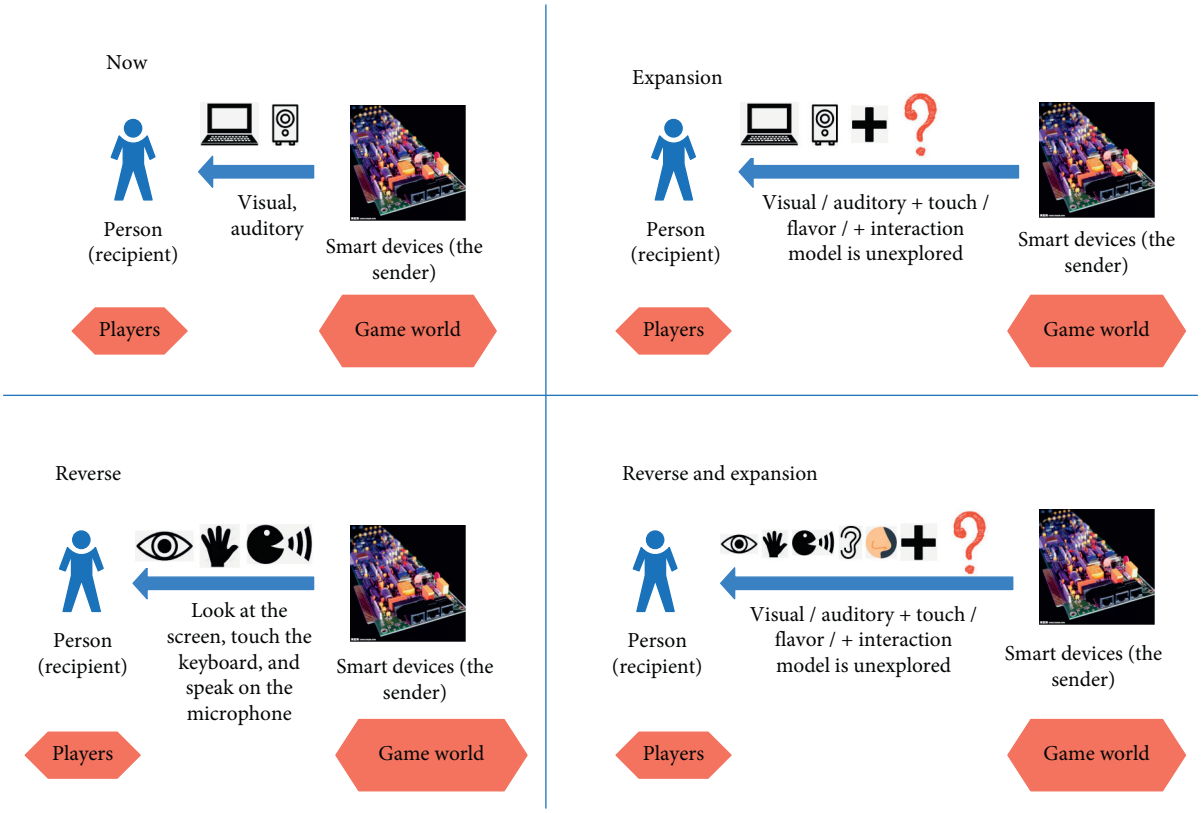

Figure 7: Game teaching mode in preschool education.

Table 1: Preschool education data mining and game recommendation effects.

Number	Data mining	Game recommendation
1	92.6	80.0
2	85.5	85.7
3	93.9	77.6
4	89.2	90.0
5	82.3	84.5
6	85.1	90.0
7	84.9	87.3
8	81.7	88.4
9	88.3	89.5
10	91.3	88.9
11	89.6	78.2
12	89.5	84.9
13	82.7	76.8
14	86.2	88.7
15	90.9	76.3
16	86.8	90.8
17	88.1	82.0
18	89.2	82.8
19	84.2	89.2
20	83.0	87.5
21	93.1	76.9
22	92.3	87.9
23	82.1	87.4
24	90.5	81.9
25	90.8	88.1
26	87.1	76.9
27	89.3	83.1
28	82.5	84.5

Table 1: Continued.

Number	Data mining	Game recommendation
29	89.7	87.9
30	81.9	79.3
31	89.2	90.8
32	88.1	88.8
33	85.8	89.1
34	82.7	88.4
35	93.9	88.1
36	90.6	85.0
37	87.0	81.4
38	93.2	76.5
39	90.0	76.1
40	92.7	87.9
41	89.5	76.4
42	87.3	82.3
43	86.6	88.0
44	84.0	76.4
45	89.9	78.9
46	82.7	90.2

Table 2: Evaluation of the teaching effect.

Number	Teaching effect
1	91.3
2	89.8
3	88.2
4	87.1
5	80.8
6	85.9
7	90.1
8	80.9
9	88.5
10	81.5
11	85.3
12	80.9
13	92.0
14	88.6
15	87.4
16	81.6
17	85.1
18	86.7
19	81.9
20	82.5
21	80.7
22	89.7
23	81.2
24	88.4
25	88.9
26	86.9
27	91.6
28	81.6
29	86.4
30	88.2
31	89.2
32	86.7
33	82.6
34	84.1
35	82.2
36	92.3
37	85.7

Table 2: Continued.

Number	Teaching effect
38	86.5
39	84.3
40	85.8
41	89.3
42	88.8
43	92.1
44	89.3
45	87.2
46	90.1

appropriate games and uses data mining algorithms to mine students' learning conditions and improve real-time teaching.

Therefore, this paper first designs experiments to conduct preschool education data mining and game recommendation effect verification and obtain relevant experimental data through multiple sets of simulation data. The results are shown in Table 1 below.

From the experimental results in Table 1, the game teaching method in preschool education based on big data technology proposed in this paper can effectively conduct preschool education data mining and can recommend suitable games for preschool education. After that, this paper evaluates the teaching effect, and the results are shown in Table 2.

From the above research, the game teaching method in preschool education based on big data technology proposed in this paper has good teaching effects and can play a certain role in preschool education.

5. Conclusion

Games and teaching are two important means of modern preschool education practice, and there is a close relationship between them. The implementation of preschool game education must be based on a scientific understanding of the relationship between the two. With the continuous reform and development of preschool education, the kindergarten preschool education has undergone earth-shaking changes, including adjustments to educational content, teaching methods, and educational goals. In particular, it emphasizes that kindergarten education should be based on games. This adjustment not only conforms to the children's physical and mental development law and age characteristics but also realizes the teaching mode of "children as the main body and teachers as the leading" in the game. Modern educational psychology research shows that children's learning is a proactive process of knowledge construction, and teachers should pay full attention to children's subjective status. This paper combines big data technology to evaluate the effect of game teaching method in preschool education, analyzes the teaching effect of game teaching method in preschool education, and combines big data technology to discover problematic teaching points, so as to further improve the teaching effect of preschool education.

Data Availability

The labeled dataset used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no competing interests.

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