

## Retraction

# Retracted: Research on the Integration of Preschool Language Education Resources Based on Metadata Storage

### Journal of Mathematics

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

- [1] S. Weiwei, "Research on the Integration of Preschool Language Education Resources Based on Metadata Storage," *Journal of Mathematics*, vol. 2022, Article ID 4802381, 8 pages, 2022.

## Research Article

# Research on the Integration of Preschool Language Education Resources Based on Metadata Storage

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Aiming at the problems of high redundancy and slow integration speed in the existing education resource data integration methods, a new preschool language education resource integration method based on metadata warehouse is designed. The metadata warehouse is designed, and the advantages of the integrated database are analyzed. On this basis, the sample data of preschool language education resources are classified with the help of cost matrix, and the constraints of different types of classification are set. The data collector of preschool language education resources is set up by using random forest algorithm to complete the data collection of preschool language education resources. The data of preschool language education resources are processed consistently, and the convergence of the data is calculated by edge function. On this basis, the redundant data in preschool language education data resources are characterized with the help of discourse, and the redundant data are removed to complete the data preprocessing of preschool language education resources. We determine the dimension distance between preschool language education resource data and complete the clustering integration of preschool language education resource data with the help of fuzzy mean clustering algorithm. The experimental results show that the integration method designed in this paper can reduce the redundancy in the integrated data, and the integration speed is fast.

## 1. Introduction

The early stage of language learning is the key period of human language germination. The habits formed in language learning in this period will affect people's life. As a key tool for human communication, the resource data in the process of language learning have a key impact on it. Preschool language education resources are the first language resources that children come into contact with in their learning. The representation and understanding of these resources play a key guiding role in children's growth [1]. The quantity of data in preschool language instruction materials is expanding as electronic information technology advances; however, there are various data kinds, and fish eyes mistake pearls [2]. The importance of language education in early infancy cannot be overstated. As a result, boosting the quality of instructional materials is beneficial to children's language acquisition. As a result, current research in this sector is focusing on the successful integration of

preschool language instruction materials [3], removing unnecessary information from the data to increase its usefulness. A variety of approaches have been tested, and some results have been obtained. Xiao [4] proposed an educational information fusion method based on intelligent data acquisition and processing. This method first represents the relevant education data, then maps the relationship according to different characteristic data, constructs the education information database by Protégé software, and finally effectively fuses the semantic information of education resource data. This method improves the speed of information fusion of educational resources, but the redundancy of data in data fusion is not considered. Wang et al. [5] suggested a machine learning-based parallel integration solution for tiny database datasets. This technique uses a Bayesian algorithm to generate a priori independent hypotheses for relatively unrelated data and then categorizes the educational resource data efficiently. It examines the volatility of data characteristics based on categorization and

utilizes MapReduce parallel processing to finish the integration of education data. This technology has minimal integrated data redundancy and increases the quality of resource data, but the operation procedure is difficult and has certain limitations.

In order to make up for the shortcomings of the above methods, this paper designs a new preschool language education resource integration method based on metadata warehouse. The main technical lines of this method are as follows.

*Step 1.* Design the metadata warehouse and analyze the advantages of changing the integrated database.

*Step 2.* Classify the samples of preschool language education resource data with the help of cost matrix, set the constraints of different types of classification, and set the preschool language education resource data collector with random forest algorithm to complete the data collection of preschool language education resources.

*Step 3.* Perform consistency processing on the data of preschool language education resources and use the edge function to calculate the convergence of the data.

*Step 4.* On this basis, characterize the redundant data characteristics in preschool language education data resources with the help of discourse, remove the redundant data, and complete the data preprocessing of preschool language education resources. Determine the dimension distance between preschool language education resource data and complete the clustering integration of preschool language education resource data with the help of fuzzy mean clustering algorithm.

*Step 5.* Conduct experimental analysis.

## 2. Metadata Storage and Data Integration of Preschool Language Education Resources

*2.1. Metadata Warehouse Analysis.* This article investigates the use of cloud data warehousing technologies in the integration of preschool language instruction materials. As a result, the metadata warehouse is intended to store the preschool language resource data in the cloud data warehouse database of preschool language education resource integration. It is necessary to extract the metadata of preschool language education resources, deposit the metadata of different preschool language education resources according to certain teaching needs, and store the precipitated data in order to improve the data information of preschool language education resources and collect these resource data into the metadata warehouse [6]. Through excellent integrated retrieval of preschool language education materials, the metadata repository established in this study delivers data services for preschool language instruction.

Metadata warehouse is an effective way to realize the integration of preschool language education resources. Its key role is to store all kinds of basic metadata information of

preschool language education resources [7]. The implementation flow of its storage is shown in Figure 1.

The metadata warehouse mainly includes the collection, storage, and integration of preschool language education resource data. By extracting these data and integrating preschool language education resources through the set specific interface, it supports the retrieval and various forms of display of preschool language education resources. The repository supports the mainstream relational preschool language education resource data and the standard of preschool language education resource data through index storage. Preschool language teaching resource data are gathered, preprocessed, and eventually incorporated into the metadata warehouse in a follow-up study to increase the application impact of preschool language teaching resource data [8].

*2.2. Data Collection of Preschool Language Education Resources.* Based on the metadata warehouse of preschool language education resources designed above, in order to integrate the integrated preschool language education resource data into the database [9], firstly, we need to effectively collect the resource data of preschool language education and take the collected resource data as the basis of the research to realize the research of methods. Because there are many types of preschool language education resource data and the amount of data is complex, these relevant data are classified before data collection of preschool language education resources to reduce the difficulty of data collection [10].

In the data classification of preschool language education resources, firstly, the data samples of preschool language education resources are classified into a category with its cost by means of cost matrix, that is, minimizing the expected generation value [11]. According to the basic original of the matrix, an arbitrary preschool education resource data sample  $a$  is divided into the expected cost  $Q(j|a)$  of class  $j$ , yielding

$$Q(j|a) = \sum_{j=1} y(j|a) \times b(i, j), \quad (1)$$

where  $y(j|a)$  represents the possibility that any sample of the preschool language education resource can be divided into class  $j$  species occurrence.

- (1) After determining the probability that preschool language education resource data will be divided, set the divided constraints. After meeting the conditions, classify the qualified preschool language education resource data [12], and the set constraints are as follows.

Conditions that the preschool language education resource data were classified into positive classes were set to

$$q(0|a)c(1, 0) + q(1|a)c(1, 1) \leq q(0|a)c(0, 0), \quad (2)$$

where  $c$  represents the positive class coefficient of preschool language education resources and  $q$  represents the probability estimation coefficient.

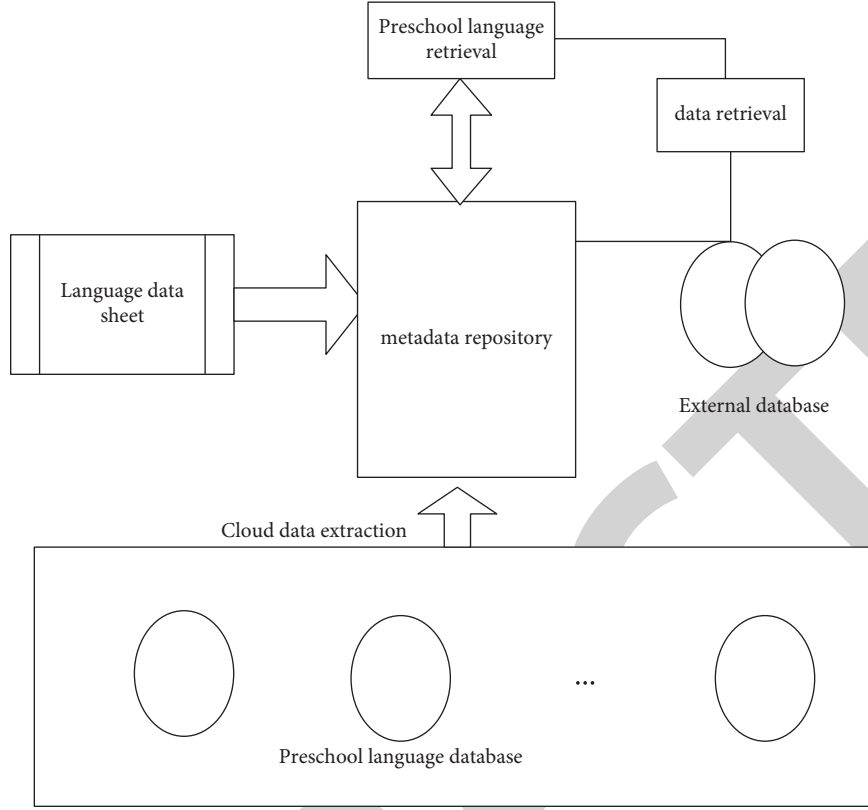


FIGURE 1: Schematic diagram of implementation process of metadata warehouse of preschool language education resources.

- (2) The condition that preschool language education resource data are divided into negative categories is set as

$$q(0|a)v(1,0) - q(1|a)c(1,1) \leq r(0|a)c(1,0), \quad (3)$$

where  $v$  represents the data resource conversion coefficient and  $r$  represents the range of classification proportion, and the value is  $[0, 1]$ .

After determining the above classification constraints of preschool language education resources, it is necessary to balance the classified preschool language education resources to ensure the effectiveness of data resource collection [13]. The calculation formula of resource data balance is

$$E = \frac{p(1,0)v}{d(1) - d(0)}, \quad (4)$$

where  $d(1)$  represents the prior probability of positive class data in the original data of the initial preschool language education data,  $d(0)$  represents the prior probability [14] of negative class data in the initial preschool language education data, and  $c$  represents the data balance factor. The effective classification process of preschool language education resource data is shown in Figure 2.

On the basis of data classification, through the effective collection of positive data and negative data, presecondary language education data were found. In data collection, the data in different types of datasets are collected through random forest. Through multiple training of data in different

types of datasets [15], the data collector is constructed to complete data collection, namely:

$$W(x) = \arg \max \sum_{i=1}^n K(h_i), \quad (5)$$

where  $W(x)$  represents preschool language education resource data collector,  $K$  represents a single base collector,  $h_i$  represents the target data acquisition, and  $\arg$  represents the collection function.

First, the samples of preschool language education resources data are categorized using a cost matrix, and the restrictions of several forms of categorization are established. On this foundation, the data collector for preschool language education resources is set up, and the data collection of preschool language education resources is completed using the random forest method.

In the data collection of preschool language education resources, firstly, the samples of preschool language education resources data are classified with the help of cost matrix, and the constraints of different types of classification are set. On this basis, the data collector of preschool language education resources is set up by using random forest algorithm to complete the data collection of preschool language education resources.

**2.3. Data Preprocessing of Preschool Language Education Resources.** There are various duplicate data and granularity information conflicting with the integration of the

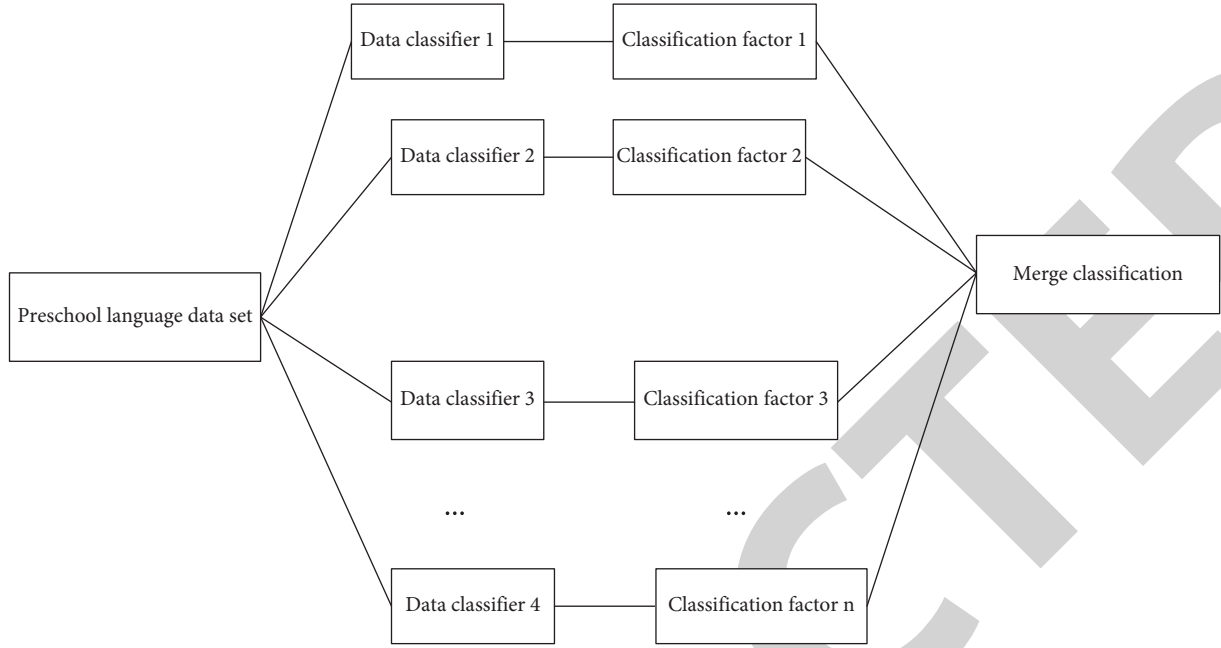


FIGURE 2: Data classification process of preschool language education resources.

aforementioned obtained preschool language education resource data [16]. To increase the efficacy of the study approach in this work, it is required to properly preprocess the preschool language education resource data. In light of the above-mentioned education resource data convergence, it is required to process the education resource data consistently in order to provide suitable data integration. The edge function is introduced to control the convergence of educational resource data [17], that is:

$$S = t_l \sum \text{arg}h_i \times T, \quad (6)$$

where  $\text{arg}h_i$  represents the edge function,  $T$  represents the mean function, and  $t_l$  represents the degree of the convergence of educational resource data.

The edge function can improve the reliability of preschool language education resource data, but the generalization error needs to be further improved, that is:

$$f = px(L(a, b) < 0), \quad (7)$$

where  $px$  represents the probability that preschool language education resource data exist in space.

After solving the consistency of preschool language education resource data, it is necessary to remove the redundant information in the education resource data [18]. The granularity generation process of preschool language education resource data is a kind of granulation process. The redundant data generated in the granulation process become the interference data affecting the integration. At this time, the generated redundant data are regarded as a universe [19] in a space and set as a quadruple, that is:

$$O = \{e, s, H, g\}, \quad (8)$$

where  $e$  represents the redundant data attribute values of the educational resource data,  $s$  represents the value domain of

the redundant data, and  $H$  represents the information function.

At this time, the redundant representation of any educational resource data in this domain [20] is

$$U \sum Ra \in e, \quad a \in H, \quad (9)$$

where  $R$  represents the redundant database and  $U$  represents the information function.

The redundant data of education resource data are reflected by formula (10), and this type of data is removed to obtain

$$Q(x) = \rho \frac{1}{2} |U_i|, \quad (10)$$

where  $Q(x)$  represents processed results,  $U_i$  represents redundant data features, and the data removal ratio is  $\rho$ .

In the preprocessing of preschool language education resource data, firstly, the consistency of preschool language education resource data is processed, and the convergence of data is calculated by edge function. On this basis, with the help of discourse, the redundant data characteristics in preschool language education data resources are characterized, and the redundant data are removed to complete the data preprocessing of preschool language education resources.

**2.4. Data Integration of Preschool Language Education Resources.** Based on the preprocessing of preschool education resource data after the above preprocessing, the data are effectively integrated. In the integration, first of all, it is necessary to determine the dimensional distance between preschool language education resource data. The effective measurement of this distance is conducive to data integration and improve the speed of integration methods [21].



Set the dataset of preschool language education resources as

$$D = \{d_1, d_2, \dots, d_n\}, \quad (11)$$

where  $d_n$  represents the full space dimension value of the annual data of preschool language education resources and  $D$  represents the set of constrained information in the set.

Then, educational resource data in the set dataset are randomly selected to generate a subspace [22]:

$$Z = \{z^1, z^2, \dots, z^B\}, \quad (12)$$

where  $z^B$  represents the random eigenvalues in the subspace.

At this time, the distance [23] between the subspatial dimension of preschool educational resource data and educational resource data is

$$\text{dis}(a, b) = \sum \frac{D(a_i, b_i)}{|v|}, \quad (13)$$

where  $|v|$  represents the data similarity in the subspace set and  $D(a_i, b_i)$  represents the constraints.

After determining the dimension distance of preschool language education resource data, the similar data are effectively clustered. This paper completes the clustering integration of preschool language education resource data with the help of fuzzy mean clustering algorithm. The algorithm is a soft clustering algorithm, which replaces the same type of data after effective fuzziness, reduces the difficulty of data integration [24], and can adhere to the influence of uncertain factors on data in the integration process. The integration process is as follows.

Set the preschool education resource dataset to be integrated as

$$M = \{m_1, m_2, \dots, m_n\}, \quad (14)$$

where  $M$  represents the number of data from integrated preschool resources and  $m_n$  represents the dimension of data elements.

The above dataset to be integrated is divided into  $C$  class clusters, when the set class cluster membership matrix is represented as

$$\gamma = [\delta_{ij}]_{a \times b}, \quad (15)$$

where  $\gamma$  represents the degree of membership.

All integrated data were summed with a membership value of 1, that is:

$$\sum_{i=1}^n \delta_{ij} < k. \quad (16)$$

When the membership value of the calculated integrated data is closer to 1, it represents a higher probability of this type of data being easily integrated.

At this time, set the objective function of preschool education resource data and further determine the key data in the preschool language education resource data integration data through the objective function [25], namely:

$$\varepsilon(a, b) = \sigma \sum_{a=1, b=1}^n [\delta_{ij}]_{a \times b}, \quad (17)$$

where  $\varepsilon(a, b)$  represents the objective integration function and  $\sigma$  is the weight factor.

After the objective function determines the data weight of preschool language education resources, the effective data integration is completed. The data integration model is as follows:

$$\vartheta = \sigma \sum_{a=1, b=1}^n [\delta_{ij}]_{a \times b} p + \omega \left(1 - \sum \delta_{ij}\right), \quad (18)$$

where  $\omega$  represents the Lagrangian multiplier,  $\vartheta$  represents the final integration result, and  $p$  represents the compactness after data integration.

In the data integration of preschool language education resources, the dimensional distance between preschool language education resource data is determined, and the clustering integration of preschool language education resource data is completed with the help of fuzzy mean clustering algorithm.

### 3. Experimental Analysis

**3.1. Experimental Scheme.** Following the completion of the design of the preschool language education resource integration approach, a simulation experiment is conducted to confirm the practicality of the proposed technique. The resource database for children's language training in MySQL database is chosen as the study object, with 1000 data selected as the experimental sample data, 300 data having some redundancy, and the other data being unclassified data. The research data are successfully trained to fulfill the experiment's needs in order to assure the experiment's efficacy. SPSS13.0 was used to examine the experimental data statistically.

**3.2. Experimental Index Design.** In the experiment, the methods in this paper, literature [4], and literature [5] are compared, mainly comparing the redundancy processing of integrated data by different integration methods, the accuracy of data integration, and the time cost of data integration.

**3.3. Analysis of Experimental Results.** Firstly, the experiment analyzes the redundancy processing of sample preschool language education resource data by this method and the methods in [4, 5]. Among them, the lower the data redundancy after processing, the better the effect of the representative method. On the contrary, the processing effect of the representative method has some shortcomings and needs further improvement. The experimental results are shown in Figure 3.

Using the methodology of this work, literature [4], and literature [5], it is possible to show that there are certain variances in the redundancy in the sample preschool language education resource data in Figure 3. The data redundancy drops dramatically and is always lower than that of the other two approaches when the sample data are integrated using the method described in this research.

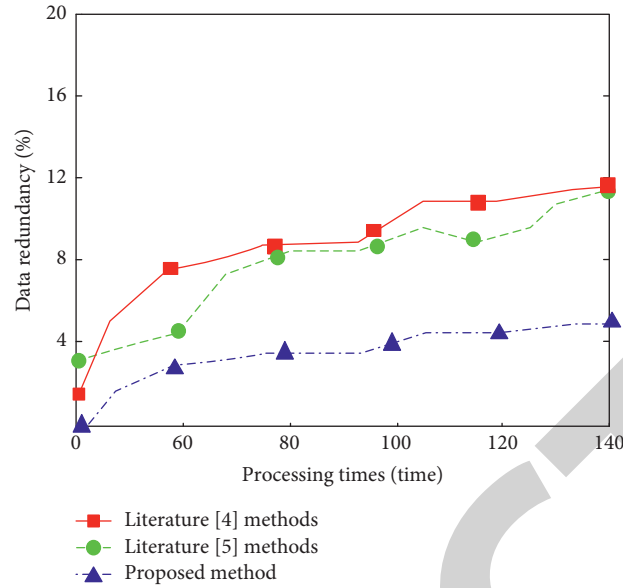


FIGURE 3: Data redundancy analysis results after integration of different methods.

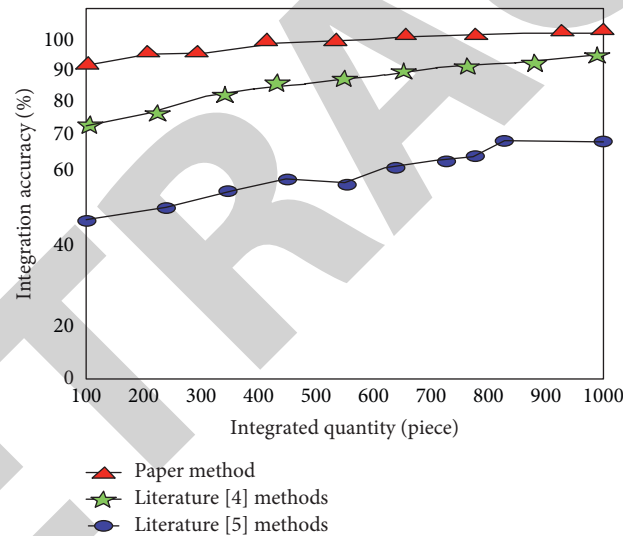


FIGURE 4: Integration accuracy results of sample data of different methods.

Although the other two approaches' data redundancy is within a respectable range, it is nevertheless larger than that of the method described in this work. This is due to the fact that the data redundancy in this method's dataset is handled in depth, increasing the method's efficacy [31, 32].

The experiment analyzes the accuracy of data integration of sample preschool language education resources by the methods of this paper, literature [4], and literature [5]. The results are shown in Figure 4.

By analyzing the experimental result data in Figure 4, it can be seen that the accuracy of data integration of sample preschool language education resources using this method and the methods in [4] is different. Among them, the data accuracy of this method is always higher than 90%, while the integration accuracy of the other two

methods fluctuates greatly and is lower than that of this method. The effectiveness of the proposed method is verified.

In order to further verify the effectiveness of the proposed method, the time cost of data integration of sample preschool language education resources by this method and the methods in literature [4] method and literature [5] method is experimentally analyzed. The results are shown in Table 1.

By analyzing the experimental results in Table 1, it can be seen that with the continuous change of the number of samples, there is a certain gap in the time cost of data integration of sample preschool language education resources by the methods in this paper, literature [4], and literature [5]. Among them, when the data volume is 600, the integration

TABLE 1: Time cost of data integration of sample preschool language education resources by different methods (s).

Number of samples/bars	The method of this paper	The method in [4]	The method in [5]
200	0.51	1.26	1.34
400	0.53	1.43	1.46
600	0.57	1.62	1.48
800	0.61	1.57	1.66
1000	0.65	1.69	1.87

time overhead of the method in this paper is about 0.57 s, the integration time overhead of the method in literature [4] is about 1.62 s, and the integration time overhead of the method in literature [5] is about 1.48 s. When the amount of data is 1000, the integration time overhead of the method in this paper is about 0.65 s, the integration time overhead of the method in literature [4] is about 1.69 s, and the integration time overhead of the method in literature [5] is about 1.87 s. In contrast, the time cost of data integration in this method is low, which verifies the effectiveness of this method.

#### 4. Conclusion

Preschool is the key period for children to learn language, and the influence of language education resources is more important. In order to solve the problem of poor integration effect in data integration methods, a new method of preschool language education resource integration based on metadata warehouse is designed. The metadata warehouse is designed, and the advantages of changing the integrated database are analyzed. The sample data of preschool language education resources are classified with the help of cost matrix, and the constraints of different types of classification are set. The data collector of preschool language education resources is set up by using random forest algorithm to complete the data collection of preschool language education resources. The data of preschool language education resources are processed consistently, and the convergence of the data is calculated by edge function. With the help of discourse, the characteristics of redundant data in preschool language education data resources are characterized, and the redundant data are removed to complete the data pre-processing of preschool language education resources. We determine the dimension distance between preschool language education resource data and complete the clustering integration of preschool language education resource data with the help of fuzzy mean clustering algorithm. The experimental results show that the integration method designed in this paper can reduce the redundancy in the integrated data, and the integration speed is fast.

#### Data Availability

The data used to support the findings of this study are included within the article.

#### Conflicts of Interest

The author declares that there are no conflicts of interest.

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