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Retraction

Retracted: The Teaching Effect Evaluation Model of University Ideological and Political Theory under the Background of New Media and Big Data

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] J. Liu and Z. Madina, "The Teaching Effect Evaluation Model of University Ideological and Political Theory under the Background of New Media and Big Data," *Security and Communication Networks*, vol. 2022, Article ID 2404108, 11 pages, 2022.

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Research Article

The Teaching Effect Evaluation Model of University Ideological and Political Theory under the Background of New Media and Big Data

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This study uses new media technology and big data technology to build a teaching impact assessment model of university ideological and political theory based on new media and big data in order to enhance the effect of ideological and political teaching in colleges and universities. Furthermore, by specifying the instance distribution interval, this work explains the probable probability distribution of all instances of the tuple, ensuring the integrity of the data information of the clustering object and therefore boosting the algorithm's clustering accuracy. Furthermore, this research constructs an intelligent system frame structure by combining the real teaching requirements of ideology and politics. Finally, from the viewpoints of new media teaching efficiency and teaching impact assessment, this research develops experiments to validate system functionalities. The experimental research results show that the teaching effect evaluation model of university ideological and political theory constructed in this study based on new media and big data has a good teaching effect, and the effect of ideological and political teaching evaluation also meets the actual teaching needs.

1. Introduction

With the continuous development of the economy and society and the rapid development of information technology, our learning, living, and working methods are slowly changing. The rapid development of the information age has also profoundly affected the teaching methods of ideological and political education. Both developed and developing countries use various forms to study and explore how to use new media to implement ideological and political teaching [1]. With the continuous progress of ideological and political education reform, the party and the country have further requirements for the informatization of ideological and political education. Moreover, they clearly pointed out that it is necessary to rely on education informatization to promote the modernization of ideological and political education and indeed improve the ideological and political literacy of young people in new media. At the national level, in the past five years, a number of new media plans for ideological and political education have been introduced [2].

Most ideological and political instructors use more conventional teaching approaches when it comes to ideological and political education. The ideological and political instructors are the major source of instruction, and they educate in the form of ideological and political courses, with a relatively easy teaching approach. As a result, the ideological and political classroom is lifeless, unable to fully express students' subjectivity, and lacking in the spirit of inquiry and investigation. The rise of new media affords a number of choices for teaching ideological and political courses in this setting [3].

This paper combines big data technology to construct a teaching effect evaluation model of university ideological and political theory and conducts research on the effect of university ideological and political teaching through this model and provides a measurement tool for the subsequent improvement of teaching quality.

2. Related Work

The literature [4] referred to "electronic video" as "new media," from which the concept of new media was born. Nowadays, with the continuous development of digital media in the information age, there are more and more books on new media. The literature [5] proposed that the continuous division of mobile phones interacts with other cells to form a new organism. It is believed that mobile phones are a powerful spark plug that ignites the torch of technological progress and human development. Since then, new media has become a hot topic of the times, and people's attention to new media has gradually increased. The literature [6] believed that with the emergence of new media the relationship between humans and machines needs to be rethought. The continuous development of new media has already changed people's living habits. Moreover, foreign countries are gradually combining new media with education. With the advancement of the Internet age, new media education platforms, including TED open courses, continue to emerge, and the role of new media in education is getting more and more attention and development. In the process of combing the research related to foreign new media, we can draw such a conclusion. First of all, regarding the definition of new media, although there is no accurate conclusion, scholars generally believe that the definition of new media should be defined from the perspective of time development and technological development. Secondly, with regard to the influence of new media, the literature [7] believed that the influence of new media not only brings great changes to human communication activities, but also changes the way people live and socialize. The value provided by new media is not limited to the realm of communication; it has already had an impact on every aspect of society. Finally, the evolution of new media has an impact on the evolution of civic education. Furthermore, most nations have incorporated media literacy education as part of civic or moral education, and new media have been employed in the area of education on a constant basis. However, due to the different social, economic, political, and historical and cultural backgrounds of countries, there are few studies on the effective use of new media in the teaching of ideological and political courses in high schools in foreign academic circles.

The media environment has a special impact on contemporary high school ideological and political teaching due to its unique communication channels, presentation methods, and management modes. From the perspective of building an efficient political classroom, the literature [8] summarizes the impact as creating effective teaching situations, breaking the key and difficult points of teaching, improving the goals of emotional attitudes and values, and cultivating students' innovative ability. From the perspective of classroom application, the literature [9] summarizes the advantages of new media technology as conducive to improving classroom teaching efficiency, conducive to reforming teaching concepts and methods, and conducive to enhancing students' interest in political learning.

Literature [10] summarizes the advantages of the network as time advantages and space advantages and believes that the time resources and space resources of the network should be actively developed and summarized into two major aspects. One includes the use of the speed of the Internet to supplement current affairs knowledge in time, the use of the timeliness of the Internet to introduce the latest materials in a timely manner, the use of the real-time nature of the Internet to quickly obtain feedback information, the use of the practical flexibility of the Internet to extend classroom teaching, and the use of the Internet Virtuality, real-time experience activities. Literature [11] believes that the spatial advantages of the network are helpful to students' psychology, resource sharing, and home-school cooperation. By analyzing the characteristics of the new media environment and the status quo of the teaching of ideological and political courses in high schools, the opportunities brought by the new media environment to teaching resources can be summarized as follows: the source of educational resources has become open and diversified, and the form of teaching resources has become virtualized. Starting from the teaching process, the teaching process of high school ideological and political courses has increasingly shown the characteristics of combining virtual and real. Literature [12] believes that the use of new media technology can carry out high school political teaching reform; the specific methods include political teaching network, regular teacher demonstration network class, open class, student assessment results resource evaluation and analysis, etc. To better actualize the teaching process of merging virtual and real, new media and new technologies offer teaching approaches such as cloud platforms and online teaching resource libraries [13]. Starting from the characteristics of the new media environment, literature [14] believes that although the new media environment has its advantages, it has an impact on students' thinking and concepts due to its open and virtual characteristics. The knowledge taught by high school politics teachers is easy to be subverted by the information on the Internet. At the same time, because high school students are in adolescence and have weak discrimination and control ability, they are easy to be misled and denied in the face of bad information.

3. New Media Teaching Data Processing Algorithm

The algorithm first builds an interval number model of uncertain tuples to ensure the integrity of the distribution information of uncertain instances and avoid the decrease in accuracy of clustering results due to the loss of data information; then, calculate the interval number boundary distance of uncertain tuples, and compare the relationship between the extreme distance and the threshold. According to the comparison results of the two, the positional relationship between the uncertain tuples is judged, and the neighborhood density of the uncertain tuples is calculated. By comparing with the density threshold, it is judged whether the current tuple can be a core tuple, so as to realize the initial construction of the cluster. Next, the neighbor tuples around the core tuple are continuously merged until the high-density area formed by the core tuple and its neighbors cannot be expanded, and the current cluster construction is completed. Traverse the remaining uncertain tuples in the dataset to ensure that all uncertain tuples can be allocated to appropriate clusters to achieve density clustering of uncertain data [15].

Certain data clustering methods are unable to quantify the data information characterising the clustering objects due to the uncertainty of the data. Since it is a consequence, while constructing a clustering algorithm for uncertain data, we must evaluate how the algorithm-related concepts appropriately convey the data's uncertainty, as this has a direct impact on the algorithm's ultimate clustering outcome. The IN-DBSCAN algorithm is an extension of the traditional deterministic data clustering algorithm DBSCAN. It first supplements the related description of the uncertainty of data distribution and then redefines the basic concepts in the DBSCAN algorithm from the perspective of data probability distribution, ensuring density clustering [16].

Although uncertain objects cannot provide exact values, they can only describe the distribution information of uncertain instances through probability distribution functions, but it is often easy to determine the upper and lower limits of the instances, so the interval number model can be used to describe the uncertainty of the data. The interval number model of the uncertain tuple is based on the center and radius of the interval number to confirm the position information of the uncertain tuple, and the possible probability distribution of all instances of the tuple is described by describing the instance distribution interval to ensure the integrity of the data information of the clustering object, and then improve the clustering accuracy of the algorithm. At the same time, the interval number distance calculation method based on the possible value boundary of the instance can effectively avoid the meaningless distance calculation outside the boundary range, which provides the possibility to simplify the calculation process of the distance between uncertain objects and improve the operating efficiency of the algorithm. In summary, the uncertain data described by the interval number model can help improve the performance of the uncertain data clustering algorithm. Therefore, this article uses interval numbers to describe the instance distribution of uncertain objects [17].

For any uncertain tuple X_i, the value interval of the uncertain instance (x_{ij}, p_{ij}) is $[x_L, x_R]$. Then, the closed interval $I_{X_i} = [x_L, x_R] \in R$ of the real number set is called the interval number of the uncertain tuple X_i. Among them, x_L is the lower limit of the number of intervals I_{X_i}, and x_R is the upper limit of the number of intervals I_{X_i}. If and only if $x_L = x_R$, the interval number I_{X_i} is an accurate value; that is, the uncertain tuple X_i is a certain data.

For the interval number $I_{X_i} = [x_L, x_R]$ of any uncertain tuple X, we assume $x_L = m_{x_i} - r_{x_i}$, $x_R = m_{x_i} + r_{x_i}$, then $m_{x_i} = (x_L + x_R)/2$ is recorded as the center of interval number I_{X_i}, and $r_{x_i} = (x_R - x_L)/2$ is recorded as the radius of interval number I_{X_i}.

The interval number Ix is a real number interval on the number line, as shown in Figure 1(a). In order to represent uncertain tuples in different dimensions, we need to further expand the concept of interval numbers [18].

Uncertain tuple X_i is given, and the record value of its uncertain instance (x_{ij}, p_{ij}) is a k-dimensional vector, denoted as $x_{ij} = (x_{ij}^1, x_{ij}^2, \ldots, x_{ij}^k)$. The value interval of the value x_{ij}^k in any dimension in x_{ij} is $[x_L^k, x_R^k]$; then the set of real closed intervals $I_{x_i} = \{[x_L^1, x_R^1], [x_L^2, x_R^2], \ldots, [x_L^k, x_R^k]\}$ is called the k-dimensional interval number of the uncertain tuple X_i. Among them, x_L^k is the lower limit of the interval number I_{X_i}, which represents the minimum value of x_{ij}^k in different dimensions. x_R^k is the upper limit of the interval number I_{X_i}, which represents the maximum value of x_{ij}^k in different dimensions. If and only if $x_L^k = x_R^k$, the uncertain tuple X_i is an exact vector [19].

The k-dimensional interval number $I_{x_i} = \{[x_L^1, x_R^1], [x_L^2, x_R^2], \ldots, [x_L^k, x_R^k]\}$ is given. If there is $x_L^k = m_{x_i}^k - r_{x_i}^k$ and $x_R^k = m_{x_i}^k + r_{x_i}^k$, $m_{X_i} = \left\{(m_{X_i}^1, m_{X_i}^2, \ldots, m_{X_i}^k) | m_{X_i}^k = (x_L^k + x_R^k)\right.$ $\left./2\right\}$ is the center of the interval number I_{X_i} , and $r_{X_i} = \left\{(r_{X_i}^1, r_{X_i}^2, \ldots, r_{X_i}^k) | r_{X_i}^k = (r_R^k - r_L^k)/2\right\}$ is the radius of the interval number I_{X_i} .

The spatial representation of the k-dimensional interval number I_{X_i} of the uncertain tuple is shown in Figure 1(a). When there is $k = 2$, the interval number I_{X_i} is a rectangular area in the plane in the Cartesian coordinate system, as shown in Figure 1(b). When there is $k = 3$, the interval number I_{X_i} is a cube space in the spatial rectangular coordinate system; as shown in Figure 1(c), k is extended to any positive integer n; at this time, Ix is a multidimensional spatial data, expressed as a hyperbox space in the spatial coordinate system.

In order to meet the needs of practical problems, researchers have successively proposed a variety of interval number distance calculation formulas. Among them, P-distance and Hausdorff distance are commonly used distance calculation formulas for theoretical research on interval numbers. Their calculation process is as follows [20]:

$$\begin{aligned} d_p(\tilde{a}, \tilde{b}) &= \sqrt[p]{\left|b^L - a^L\right|^p + \left|b^U - a^U\right|^p}, \quad p \geq 1, \\ d_H(\tilde{a}, \tilde{b}) &= \max\left\{\left|b^L - a^L\right|, \left|b^U - a^U\right|\right\}, \end{aligned} \tag{1}$$

where $\tilde{a}$ and $\tilde{b}$ are two interval numbers, a^U and b^U represent the lower limit of the interval number, and a^L and b^L represent the upper limit of the interval number. We can find that these two distance formulas only consider the deviation of the corresponding limit of the interval number. The data in the interval's distribution information is lost. As a result, the aforementioned method is ineffective for calculating the interval number distance of the uncertain tuple. In addition, based on the expected value and width of the interval number, Bao Yu'e et al. proposed a more general meaning interval number distance formula-EW-type distance; the calculation process is as follows:

$$d_{EW}(\tilde{a}, \tilde{b}) = c\sqrt[p]{|E(\tilde{a}) - E(\tilde{b})|^p + \frac{1}{3}|W(\tilde{a}) - W(\tilde{b})|^p}, \quad p \geq 1. \tag{2}$$

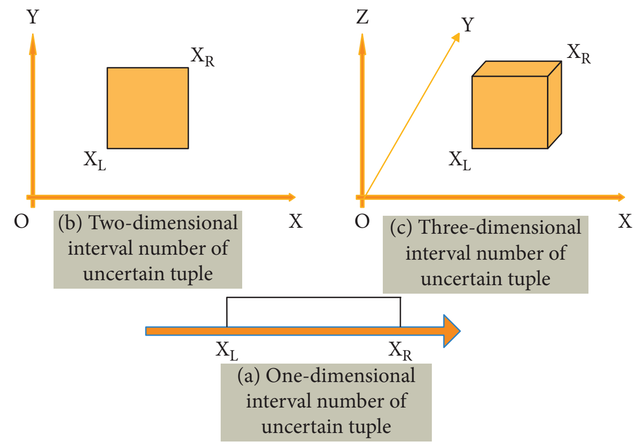

FIGURE 1: K-dimensional interval number of uncertain tuple. (a) One-dimensional interval number of uncertain tuple. (b) Two-dimensional interval number of uncertain tuple. (c) Three-dimensional interval number of uncertain tuple.

In the formula, $E(\tilde{a}) = a^L + a^U/2$ represents the expected value of $\tilde{a}$, and $W(\tilde{a}) = a^U - a^L/2$ represents the width of $\tilde{a}$. Compared with the P-distance and the Hausdorff distance, the EW-type distance considers the width difference of the interval number and the expected difference of the interval number, which effectively improves the utilization of data information, and the interval number distance is more comprehensive and detailed. The calculation result is more in line with people's intuitive judgment. However, the data in the default interval of the EW-type distance obeys a uniform distribution, and the EW-type distance cannot provide a satisfactory result for the data of other probability density distributions. Therefore, we need to design a more efficient interval number distance calculation strategy to calculate the distance between uncertain tuples [21].

If it is assumed that the one-dimensional interval numbers of any two uncertain tuples X and X; are $I_{x_i} = [m_{x_i} - r_{x_i}, m_{x_i} + r_{x_i}]$ and $I_{x_j} = [m_{x_j} - r_{x_j}, m_{x_j} + r_{x_j}]$, respectively; then, the positional relationship between I_{x_i} and I_{x_j} on the real number axis is shown in the four distance states shown in Figure 2: connected state, overlapping state, and containment state. We stipulate that the distance states of the other three interval numbers except for the distance state are non-separation states, and define the distance calculation formulas for I_{x_i} and I_{x_j}. If the distance between the interval numbers I_{x_i} and I_{x_j} is separated, the maximum value of the two distances is $d_{\max} = |m_{x_i} - m_{x_j}| + r_{x_i} + r_{x_j}$, and the minimum value of the two distances is $d_{\min} = |m_{x_i} - m_{x_j}| - r_{x_i} - r_{x_j}$. If the distance between the number of intervals I_{x_i} and I_{x_j} is not separated, the maximum value of the two distances is $d_{\max} = |m_{x_i} - m_{x_j}| + r_{x_i} + r_{x_j}$, and the minimum value of the two distances is 0. Therefore, for any two one-dimensional interval numbers, the distance between them is $d = [d_{\min}, d_{\max}]$; among them, there is

$$d_{\min} = \begin{cases} \left|m_{x_i} - m_{x_j}\right| - r_{x_i} - r_{x_j} \left|m_{x_i} - m_{x_j}\right| - r_{x_i} - r_{x_j} > 0, \\ 0 \left|m_{x_i} - m_{x_j}\right| - r_{x_i} - r_{x_j} \leq 0, \end{cases}$$
$$d_{\max} = \left|m_{x_i} - m_{x_j}\right| + r_{x_i} + r_{x_j}, \tag{3}$$

The distance calculation method is extended to the number of k-dimensional intervals, and the distance $D = [D_{\min}, D_{\max}]$ between the uncertain tuples can be obtained, where

$$D_{\min} = \sqrt{\sum_{j=1}^{k} d_{j\min}^2},$$
$$D_{\max} = \sqrt{\sum_{j=1}^{k} d_{j\max}^2}. \tag{4}$$

The above distance formula effectively utilizes the data information contained in the interval number center and radius and calculates the boundary distance between any two uncertain tuples of k-dimensional interval numbers. However, in the process of clustering, the distance threshold may be between the minimum boundary distance and the maximum boundary distance. At this time, it is necessary to calculate the probability distribution of instances that meet the distance threshold in the interval number of uncertain tuples. Therefore, we define the distance distribution of uncertain tuples as follows [22].

Any two uncertain tuples X_i and X_j in the dataset D are given, and the probability $P_{d(x_i,x_j)\leq\varepsilon}$ that the distance between the two is less than or equal to the distance threshold ε can be expressed as

$$P_{d\left(x_i,x_j\right)\leq\varepsilon} = \sum_{k=1}^{s}\sum_{l=1}^{s} \delta\left[d\left(x_{ik}, x_{jl}\right) \leq \varepsilon\right] \cdot p_{ik} \cdot p_{jt}. \tag{5}$$

Formula (5) counts the overall probability that the instance distance in the uncertain tuple is less than the distance threshold. Among them, e is a distance threshold, which is used to judge the distance relationship between two uncertain objects. $\delta[d(x_{ik}, x_{jl}) \leq \varepsilon]$ is a logical judgment function, which is used to judge whether the distance d between the uncertain instances (x_{ik}, p_{ik}) and (x_{jl}, p_{jl}) meets the requirement of the threshold ε. If there is $d(x_{ik}, x_{jl}) \leq \varepsilon$, there is $\delta[d(x_{ik}, x_{jl}) \leq \varepsilon] = 0$; otherwise, there is $\delta[d(x_{ik}, x_{jl}) \leq \varepsilon] = 1$.

This study introduces the IN-DBSCAN algorithm, a novel clustering technique for uncertain data based on the interval number model of doubtful data and the computation method of interval number distance. The IN-DBSCAN method enhances and extends the traditional clustering algorithm DBSCAN to accomplish density clustering of uncertain data due to the benefits of density-based clustering techniques in detecting nonspherical clusters. The

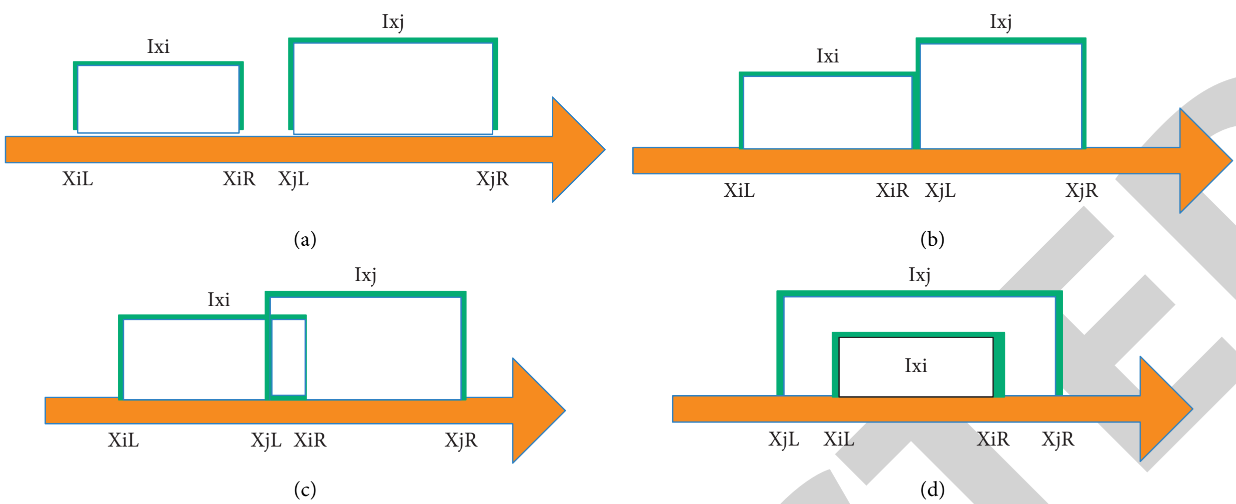

Figure 2: Four positional relationships of interval numbers. (a) Separated state. (b) Overlapped state. (c) Connected state. (d) Contained state.

main idea of the algorithm is to compare the relationship between the number of neighbors of the object and the density threshold by calculating the neighborhood density of the uncertain object and then merge the surrounding uncertain objects to expand the range of a given cluster and realize the segmentation of high density by low-density points. The basic flow of IN-DBSCAN algorithm is shown as in Figure 3 [23].

X is an uncertain tuple in data set D. For any uncertain tuple X_j in D, the probability that it is located in the neighborhood of X_i (that is, the probability that X_j becomes a neighbor tuple of X_i) is $P_{d(x_i,x_j)\le\varepsilon}$; then the set of probabilistic neighbors in the $\varepsilon-$ neighborhood of X_i can be expressed as

$$\text{PNeighbor}(X_i) = \left\{X_j | P_{d(x_i,x_j)\le\varepsilon} > 0\right\}. \tag{6}$$

Among them, ε is a distance threshold, which represents the range of the neighborhood of X_i, and $P_{d(x_i,x_j)\le\varepsilon}$ represents the probability of the distance distribution between the uncertain tuples X_i and X_j.

X_i is an uncertain tuple in the dataset D. For any uncertain tuple X_j in D, $P_{d(x_i,x_j)\le\varepsilon}$ represents $X_j{}'$ ' s support for X_i, denoted as $\text{support}_{\text{degree}}(X_i, X_j)$. Then, the overall support $\text{total}_{\text{degree}}(X_i)$ of X_i can be defined as

$$\begin{aligned}\text{total}_{\text{degree}}(X_i) &= \sum_{X_j\epsilon P\text{Nelghbor}(X_i)} \text{support}_{\text{degree}}(X_i, X_j),\\ &= \sum_{X_j\epsilon \text{PNelghbor}(X_i)} P_{d(x_i,x_j)\le\varepsilon}.\end{aligned} \tag{7}$$

The degree of support is a necessary condition for discriminating the core uncertain tuples. A parameter threshold u is given, which represents the minimum support that a certain uncertainty element composition needs to satisfy as the core uncertainty element group. If there is $\text{total}_{\text{degree}}(X_i) \ge \mu$, X_i is considered a core uncertain tuple.

We stipulate that $\text{average}_{\text{degree}}(X_i)$ represents the average support of X_i; then there is $\text{average}_{\text{degree}}(X_i) = \text{total}_{\text{degree}}(X_i)/|\text{PNeighbor}(X_i)|$. Among them, $|\text{PNeighbor}(X_i)|$ represents the number of uncertain tuples in the $\varepsilon-$ neighborhood of X_i. If X_i is the core uncertain tuple. Since there is $\text{average}_{\text{degree}}(X_i) \le \max(P_{d(x_i,x_j)\le\varepsilon}) \le 1$, we can draw the conclusion of $|\text{PNeighbor}(X_i)| \ge \mu$. That is, μ can be considered as the minimum number of neighbor tuples that should be included in the $\varepsilon-$ neighborhood of the core uncertain tuple.

X_i is an uncertain tuple in the dataset D, then the probability of X_i becoming the core uncertain tuple is $p^{\text{core}}_{\varepsilon,\mu,D}(X_i)$, and the calculation process can be expressed as

$$p^{\text{core}}_{\varepsilon,\mu,D}(X_i) = 1 - \left(\sum_{A\subseteq\text{PNeighbor}(X_i)} \prod_{X_j\in A}\left(1 - P_{d(X_i,X_j)\le\varepsilon}\right) \prod_{X_j\notin A}\left(1 - P_{d(X_i,X_j)\le\varepsilon}\right) \prod_{\text{PNeighbor}(X_i)} P_{d(X_i,X_j)\le\varepsilon}\right). \tag{8}$$

Among them, A is a subset of PNeighbor (X_i), s is a distance threshold, and u is the minimum number of neighbors that can be contained in the neighborhood of the core uncertain tuple.

In the process of calculating $p^{\text{core}}_{\varepsilon,\mu,D}(X_i)$, we did not directly count all possible cases where the number of neighbor tuples in the e-neighborhood of the uncertain tuple X; is greater than or equal to the density threshold u. Instead, we

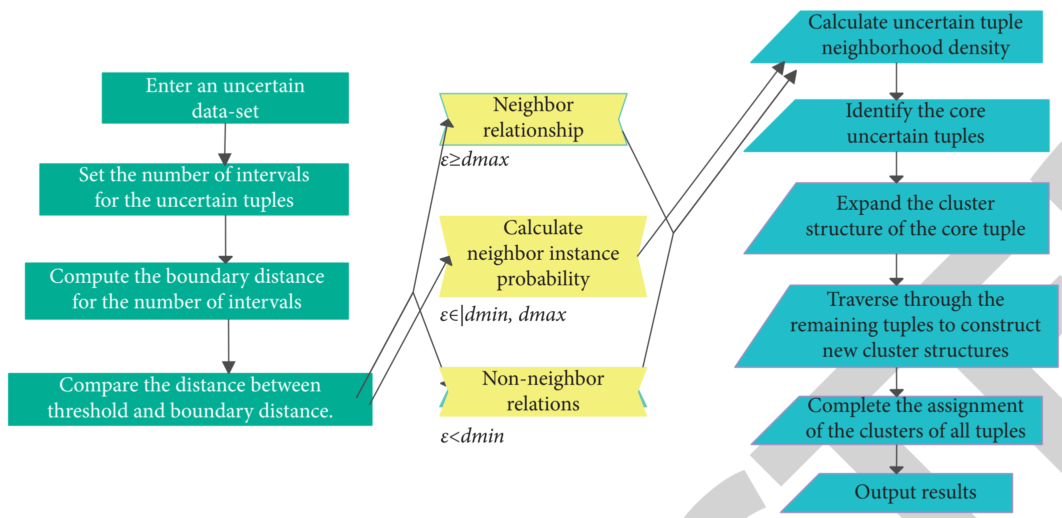

Figure 3: The basic flow of the algorithm.

indirectly calculate the probability sum of the case where the number of neighbor tuples in the e-neighborhood is less than the density threshold u, and then perform the inversion operation to obtain the probability that X becomes the core uncertain tuple. At this time, the value of density threshold u is usually very small, the number of adjacent tuples is greater than or equal to the density threshold, and much greater than the number of adjacent tuples and less than the density threshold. The use of indirect calculation methods can effectively reduce the computational complexity, thereby improving the operating efficiency of the algorithm.

In order to further optimize the calculation efficiency of $p^{\text{core}}_{\varepsilon,\mu,D}(X_i)$, we sort the uncertain tuples in the PNeighbor(X) set in descending order according to the size of $p^{\text{core}}_{\varepsilon,\mu,D}(X_i)$ and then query the distance distribution probability of the uth tuple in the set. If there is $p^{\text{core}}_{\varepsilon,\mu,D}(X_i) = 1$, it means that there must be u neighbor tuples in the neighborhood of X. At this time, X must be the core uncertain tuple, we set $p^{\text{core}}_{\varepsilon,\mu,D}(X_i) = 1$ directly. If there is $P_{d(X_i,X_j)\le\varepsilon} < 1$, we are specifically expanding the calculation of $p^{\text{core}}_{\varepsilon,\mu,D}(X_i)$.

In the dataset D, any two uncertain tuples Xi and Xj are given, and the directly reachable probability $p^{\text{dir-reach}}_{\varepsilon,\mu,D}(X_i,X_j)$ of X, relative to X, is specified, and the calculation process is as follows:

$$p^{\text{dir-reach}}_{\varepsilon,\mu,D}\left(X_i,X_j\right) = p^{\text{dir-reach}}_{\varepsilon,\mu,D\setminus\left\{X_j\right\}}\left(X_i\right)\cdot P_{d\left(X_i,X_j\right)\le\varepsilon}. \tag{9}$$

Among them, $p^{\text{dir-reach}}_{\varepsilon,\mu,D\setminus\{X_j\}}(X_i)$ represents the probability that the neighborhood of X_i contains at least u-1 neighboring tuples in addition to the uncertain tuple X, and $P_{d(X_i,X_j)\le\varepsilon}$ represents the probability that the distance between Xi and Xj is less than or equal to the threshold e. These two events are independent of each other and do not affect each other. Therefore, the product of the two probabilities indicates that when the density threshold is u, the uncertainty tuple Xi is the neighbor probability of the core uncertainty tuple Xi with respect to the neighborhood of i.

Similar to the DBSCAN algorithm, the quality of the clustering results of the IN-DBSCAN algorithm depends on the value of the neighborhood radius E and the density threshold MinPts. Under normal circumstances, the parameters and MinPts settings are derived from experience and knowledge, which is difficult to determine. The IN-DBSCAN algorithm is very sensitive to these parameter values, and different values may lead to very different clustering results.

A MinPts value is supplied, as seen in Figure 4. If the value of z is too big, the noise points may be divided into a single cluster, or data items previously belonging to multiple clusters may be combined. If the value of c is too small, the cluster may be split, and the data objects originally belonging to the same cluster are divided into multiple separate clusters. In the case of a given c value, if the value of MinPts is too large, the number of data objects that meet the core uncertain tuple condition will be reduced, and the uncertain tuples originally belonging to the same cluster are marked as noise points. If the value of MinPts is too small, it will lead to an increase in the number of data objects that meet the core uncertain tuple conditions, and the uncertain tuples that are originally noise points may be divided into a certain cluster. Therefore, how to avoid the manual input of parameters in the IN-DBSCAN algorithm and enable it to automatically input parameters through explicit query to achieve adaptive density clustering of uncertain data is an important problem that we need to solve.

4. University Ideological and Political Teaching Effect Evaluation Model Based on New Media and Big Data Technology

This study reforms the ideological and political classroom teaching mode, merges the varied evaluation mechanism, and achieves the teaching evaluation aimed at assessing the core competency based on the learning characteristics of college students. With the help of information technology, this paper develops an Internet + classroom teaching platform suitable for college students to provide technical

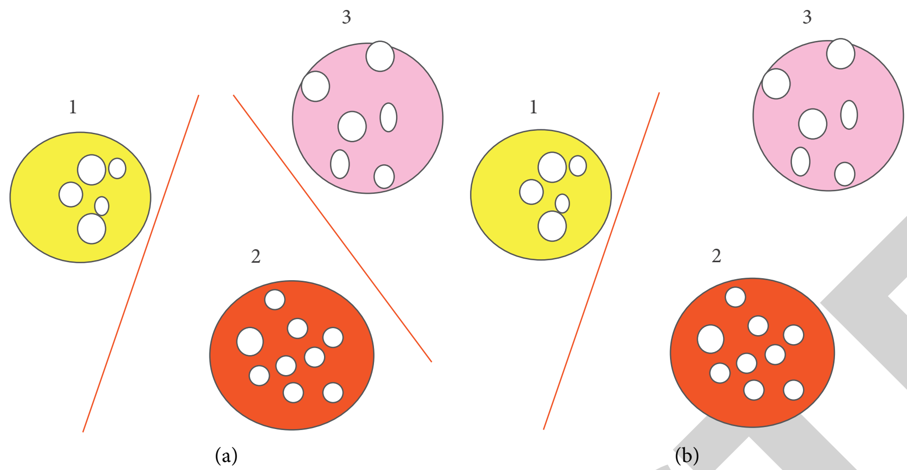

Figure 4: Different parameter values lead to different division results of the algorithm. (a) EPS = 2, MinPts = 5, (b) EPS = 6, MinPts = 2.

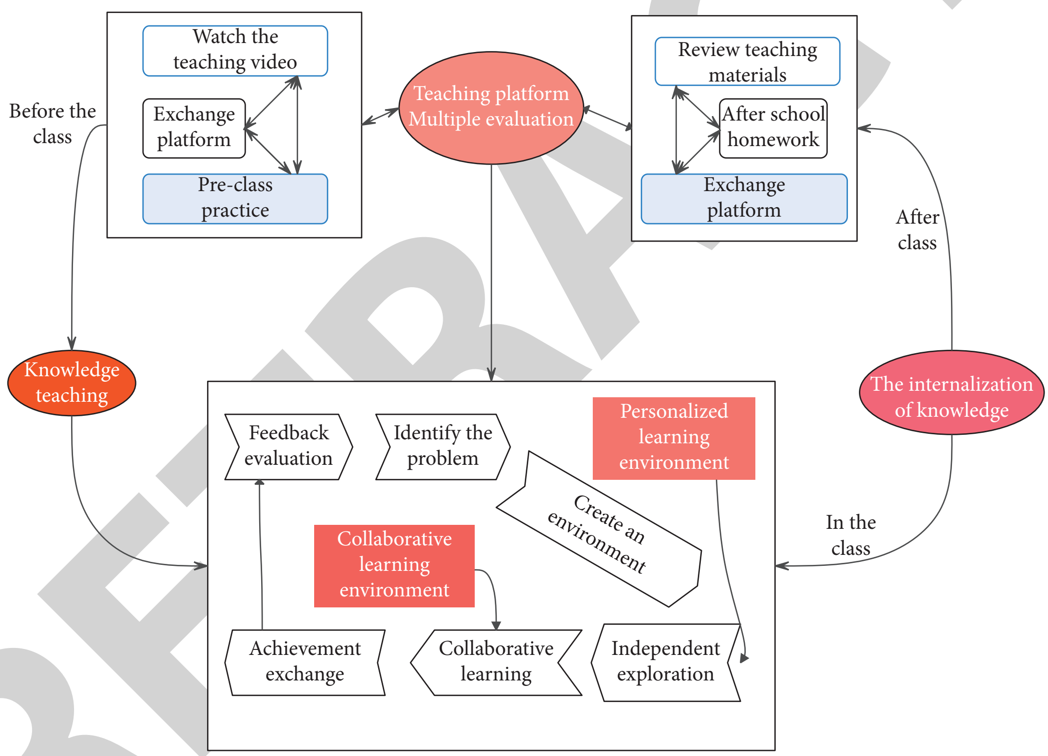

Figure 5: Implementation model diagram of ideological and political multi-evaluation.

support for the realization of political classroom teaching reforms and the diversified teaching evaluation of "doing what it says". Figure 5 shows the implementation model of ideological and political classroom teaching evaluation.

The Internet + classroom ideological and political teaching platform can be divided into five modules: online resource management, online learning, communication and discussion, diversified evaluation, and system maintenance. According to the needs of each system user for system functions, the five modules can be subdivided into multiple submodules, as shown in Figure 6.

The HTML5-based Internet + classroom ideological and political new media teaching platform for colleges and universities is a set of Internet + classroom teaching platform based on "pre-class online learning as the forerunner, flipped classroom teaching as the core, online communication and discussion as the auxiliary, and diversified teaching evaluation as the driving force." The platform linkage relationship is shown in Figure 7.

As a help, the C/S design mode is used in this article. The desktop version of the teaching platform apps may be swiftly generated by encapsulating HTML5 pages, and screen recording, electronic blackboard writing, and automated file uploading features can be added at the same time. The system structure diagram of the platform is shown in Figure 8.

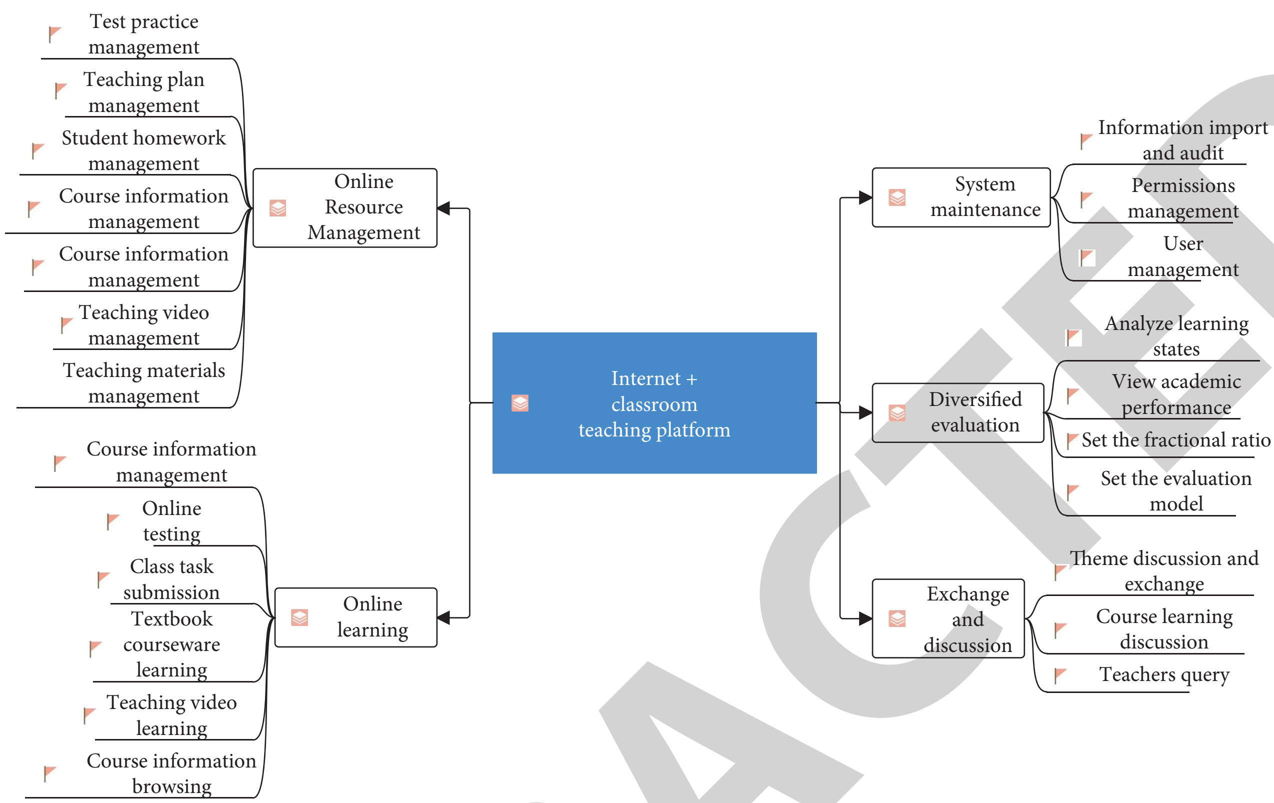

Figure 6: The overall function module diagram of the system.

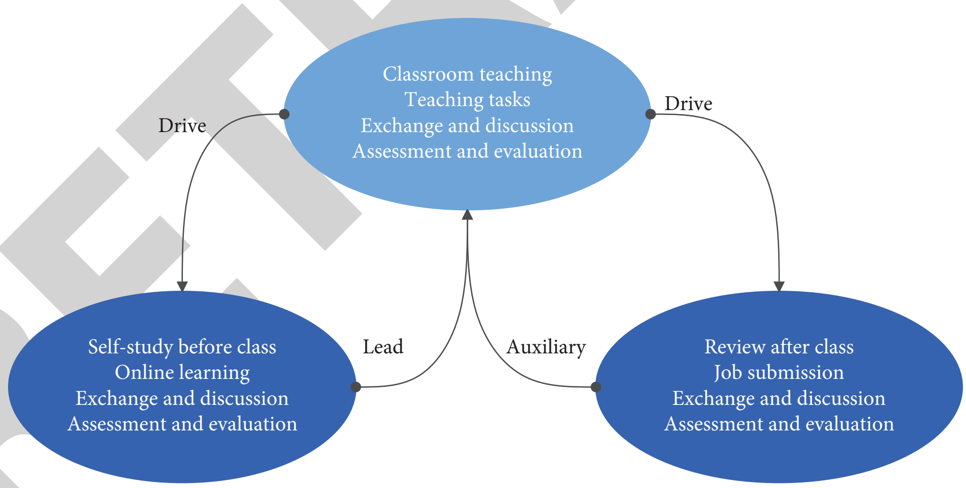

Figure 7: The linkage diagram of the ideological and political teaching platform.

On the basis of the above analysis, the effect of the teaching effect evaluation model of university ideological and political theory based on new media and big data constructed in this paper is verified. When designing the experiment, this paper mainly starts from the two perspectives of new media teaching efficiency and teaching effect evaluation and obtains the results shown in Table 1 and Figure 9.

The experimental research results show that the teaching effect evaluation model of university ideological

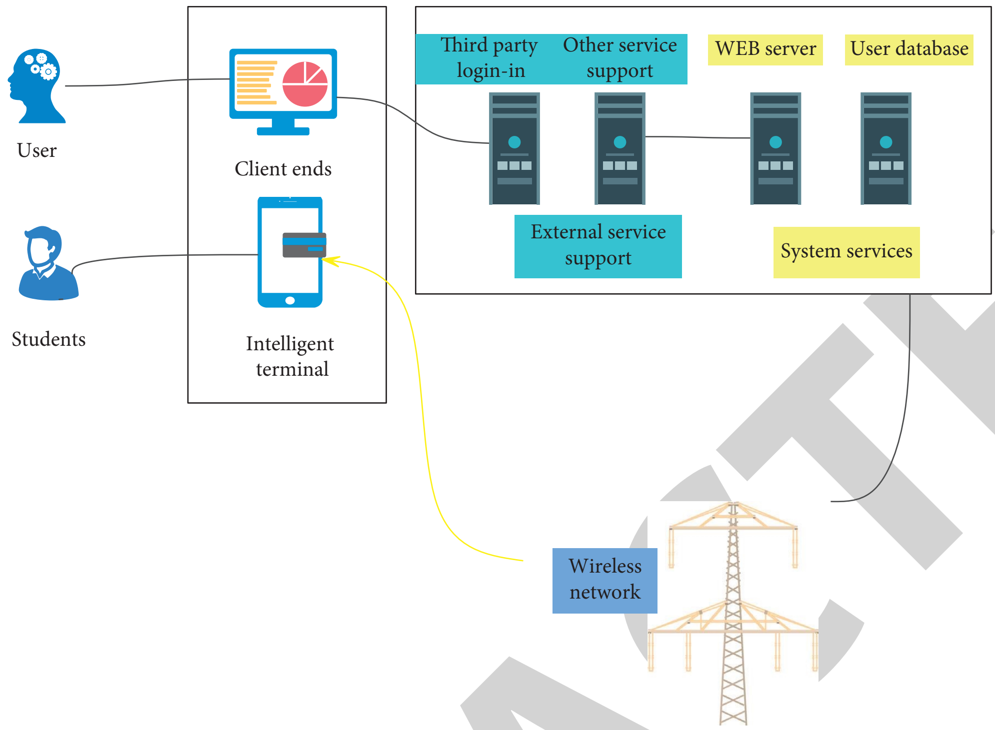

Figure 8: Schematic diagram of system structure.

Table 1: Performance verification of teaching effect evaluation model of university ideological and political theory based on new media and big data.

NO	Teaching efficiency	Teaching evaluation	NO	Teaching efficiency	Teaching evaluation	NO	Teaching efficiency	Teaching evaluation
1	93.0	81.3	21	81.5	85.6	41	86.4	89.9
2	81.1	83.3	22	81.4	76.2	42	82.3	80.6
3	92.4	80.4	23	88.3	88.7	43	86.7	85.2
4	81.8	76.7	24	86.8	91.7	44	81.5	78.3
5	93.4	85.1	25	85.7	80.3	45	83.1	85.5
6	87.9	87.0	26	90.3	80.0	46	88.6	85.1
7	91.4	90.3	27	92.1	83.3	47	93.0	76.7
8	92.2	89.2	28	85.8	82.4	48	83.8	89.2
9	92.4	79.0	29	88.4	75.2	49	93.9	77.1
10	83.1	86.0	30	93.3	82.8	50	85.7	87.4
11	94.0	78.2	31	84.0	85.1	51	83.6	88.5
12	89.9	85.6	32	89.7	90.1	52	85.2	83.9
13	88.6	90.6	33	85.3	88.1	53	93.8	85.9
14	85.7	80.6	34	83.9	78.5	54	89.0	79.0
15	88.5	79.5	35	85.9	90.7	55	85.3	79.5
16	86.0	78.4	36	89.1	75.7	56	86.8	83.7
17	85.9	83.7	37	92.3	79.3	57	92.0	77.0
18	86.5	81.6	38	85.0	75.5	58	87.9	86.8
19	90.1	85.5	39	90.8	89.4	59	91.4	87.0
20	88.2	85.0	40	81.5	77.8			

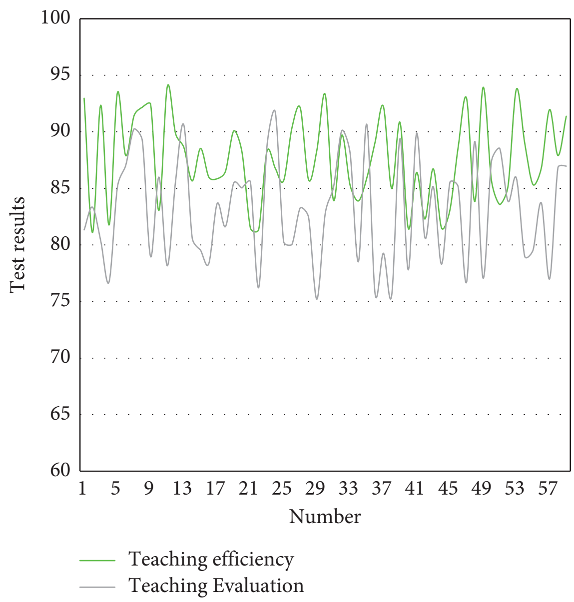

Figure 9: Statistical diagram of experimental results.

and political theory constructed in this paper based on new media and big data has a good teaching effect, and the effect of ideological and political teaching evaluation also meets the actual teaching needs.

5. Conclusion

With the rapid development of new media technology and the popularization of applications, college students have become one of the main applications of new media. Students must not only study professional skills in college, but also have high moral character, philosophy, and behaviour habits. Students have lost the original function of new media as a result of inadequate use of new media by professors, and they are unable to fully exploit the influence of new media in the teaching of ideological and political courses. As a result, the study presented in this article on the use of new media in college curriculum teaching may help to enhance and improve current ideological and political education theories, as well as give reference value and guidance for university ideological and political education. In a practical sense, the application of new media in the teaching of ideological and political courses is conducive to improving the ideological and political awareness of college teachers and students. Therefore, mastering reasonable and effective new media tools (such as micro-classes) for ideological and political teaching is conducive to improving the teaching quality of ideological and political courses, increasing students' interest in ideological and political courses, and making students' course knowledge learning more solid.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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