

Research Article

Information Fusion and Its Intelligent Sensing for Learning Intervention Model of Educational Big Data

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With the continuous development of science and technology, a large number of devices containing high technology began to appear in people's lives. With the popularity of big data, it not only drives the development of the whole information industry in society but also leads to different degrees of innovation and development in the reform industry worldwide. The purpose of this paper is to study how to use information fusion and its intelligent sensing technology to play an active role in the education industry, to help students identify problems in the learning process, to give timely intervention and guidance, and to help students complete their learning tasks with high quality. This paper proposes to use information fusion and its intelligent sensing technology to take advantage of learning analytics to collect, organize, analyze, and guide the learning data generated by students in the learning process and then to generate interventions that can have an impact on learning and improve learning methods for students. The experimental results of this paper show that after the learning intervention, the students' frequency in discussion and communication was 72 in the first four weeks and reached 300 after the intervention, and the learning resources changed from 95 to 370 after the learning intervention, which is very significant progress.

1. Introduction

1.1. Background. Education is the cornerstone of national revitalization and national prosperity. In the Fifth Plenary Session of the 18th CPC Central Committee, the Party adopted the policy of "improving the quality of education," which makes improving the quality of learning the focus of current education work and spending time on internal construction, so that education can develop more qualitatively, efficiently, fairly, and sustainably. With the continuous development of science and technology, more and more teaching technologies have come into being, and the way of education and teaching has changed dramatically. Traditional classrooms have also integrated online learning, mobile learning, and blended learning modes, and the increasing number of learning methods and the networking of learning resources have made learning data more common, providing a data-

base for researchers to study students' learning behavior in depth; coupled with the information fusion sensing technology which continues to develop, integrating it with the education industry to continuously improve the quality of learning and optimize the learning process has become an urgent requirement at present.

1.2. Significance. The acquisition of sensing information is the premise of information fusion. This paper considers both the fusion function and the type of information hierarchy and realizes the use of a database for storing a large amount of sensing data, which makes the acquisition and conversion of information more convenient; combining education big data with learning intervention can understand the learning situation of learners, predict future learning behavior, provide students with personalized

intervention mode, and guide students to successfully complete their learning tasks.

1.3. Related Work. With the continuous advancement of technology, information fusion and intelligent sensing technologies have been developed and applied to several areas of life; education is an important resource for national development, and improving the quality of education is a dimension that cannot be ignored. Combining information fusion and educational big data can promote the development of the entire education industry, so a large number of researchers have explored both. Chu et al. propose a novel ILC design framework that learns not only from past trials but also from future trials predicted using plant model knowledge to update control inputs. It is shown that by including information from predicted future trials, the designed ILC controller is less short-sighted and therefore can achieve better performance. An analysis of the algorithm's characteristics reveals potential advantages in terms of convergence speed; the proposed algorithm also has significant robustness characteristics in terms of model uncertainty, and both numerical simulations and experimental results using nonminimum phase test equipment demonstrate the effectiveness of the proposed approach [1]. Li et al. proposed a nested coil-based dual-coil magnetic resonance sensing structure for sensing and tracking objects using electric and magnetic fields that allow intelligent interaction, automation, and adaptation of cyberphysical systems; the method is called iSense. iSense combines induced voltage information from multiple different coils distributed on a surface with a group-based interference mitigation mechanism between the coils to perform collaborative sensing to detect the type of object placed on a large surface and track its mobility [2]. Pouryazdan et al. proposed a game-theoretic approach to ensure the trustworthiness of user recruitment in mobile crowd sensing systems. The approach is a platform-centric framework consisting of three phases: user recruitment, collaborative decision-making with trust scores, and badge reward. In the proposed framework, users are incentivized by running subgame perfect balance and gamification techniques. Through simulations, we show that the proposed approach can achieve approximately 50% and at least 15% improvements in platform and user utility, respectively, compared to fully distributed and user-centered trusted crowd sensing [3]. Lin-Siegler et al. found that students' beliefs about themselves, their environment, and their intellectual pursuit of success can influence their motivation and, consequently, their school performance. This implies that shaping these beliefs has the potential to influence students' motivation and performance. Building on this insight demonstrates a promising but underexplored approach to improving student motivation and learning: designing and implementing psychologically informed instructional activities to change students' attitudes and beliefs, exploring motivational processes in schools and classrooms, and testing the effectiveness of interventions against rigorous control conditions [4]. Wu used a 2×2 factorial and between-subjects quasiexperimental design in which intervention type and teacher type were manipulated to produce four different ver-

sions of an experiment designed to investigate the effectiveness of two types of SEL interventions delivered by two different types of teachers to determine their effectiveness on SEL knowledge, learning anxiety, and intention to drop out. The results of the study indicated that while psychology teachers were more effective in increasing SEL knowledge and reducing intention to drop out, the regular teachers were more effective in reducing learning anxiety. The TASSEL intervention was more effective in increasing SEL knowledge and reducing intention to drop out, while the SEL regular intervention was more effective in reducing learning anxiety. However, within-group analyses showed that the combination of TASSEL and psychology teachers was the best combination in reducing intention to drop out, while the combination of SEL and psychology teachers was the best combination in reducing learning anxiety [4]. Rafiq et al. proposed that the purpose of the study was to determine the role of transformative interventions in developing an enabling learning environment for female adult learners in higher education and to consider their reparticipation and continuing their postcompulsory education learning process and used a qualitative approach with an interpretive case study. Semistructured, open-ended interviews were conducted with 16 purposively selected female participants. Two private universities and two public universities were selected for the experiment, where adult working students experienced transformative learning interventions in their programs. In addition, the experiences and responses highlighted the needs, barriers, and expectations of adult students in higher education, and they identified reflective activities including article review and reflective writing [5]. Di and Bo proposed and analyzed an educational intervention model for mental health of college students based on stress coping. The empirical results proved that a confident and optimistic attitude can effectively relieve stress and achieve self-regulation and stress intervention. It can be seen that the coping strategies of college students in the face of stress are crucial. Meanwhile, there are obvious differences in stress among students of different types, levels, and disciplines. In summary, according to the results of this study, educators should pay more attention to the stress situation of college students, tap and integrate mental health education resources, guide students to adopt positive coping strategies, and ultimately help students get rid of psychological problems from multiple perspectives [6]. The research study presented by Tele is aimed at determining the effect of using the 5E learning model in sociology on students' academic performance and students' perceptions. The study has been conducted in a secondary school in the center of Adiyaman in the 2019-2020 academic years, using the achievement test developed by the researcher in determining the academic achievement levels of the students. On the other hand, an open-ended questionnaire developed by the researcher was used in determining students' perceptions of the 5E learning model, and a parallel mixed-method research design was used in which data collected through qualitative and quantitative methods were assessed together. It can effectively enable learners to remain active throughout the education process and achieve meaningful learning [7].

The various theories above have explored different aspects of information integration and big data education to varying degrees, but there is no systematic combination and specific use is yet to be explored.

1.4. Innovation Points. In this paper, we combine information fusion and intelligent sensing technology with big data in education, so that the increasingly accumulated big data in the field of education can play its role, and in this paper, we propose learning analytics, which refers to the use of a variety of methods and tools to collect learning data, analyze and answer them, and then fully explore the hidden value information behind the data, to understand and optimize learning and its context in all aspects, and to provide in-depth learning for students and diversification for teachers. It supports students' in-depth learning, teachers' diversified teaching, and administrators' scientific decision-making to promote the real realization of personalized learning and the steady improvement of education and teaching quality.

2. Information Fusion and Its Intelligent Sensing for Learning Intervention Model of Education Big Data Research Methods

2.1. Information Fusion and Intelligent Sensing. Human perception of objective things is usually acquired through various organs such as vision, hearing, smell, and taste, and in this way, information of different dimensions is obtained, and then, the acquired information is analyzed and processed according to experience and their own knowledge, and finally, they form their own understanding of the acquired information [8]. Intelligent sensing information fusion is to imitate the human understanding process, to analyze and process the different information acquired according to some rules, and finally to obtain the correct cognitive information. Figure 1 shows the schematic diagram of intelligent sensing information fusion.

Information fusion was first applied in the military field, where the U.S. military used it for sonar signal processing, and as science and technology continued to advance, communication and sensor technologies also developed rapidly [9]. The prototype theory of information fusion was proposed in 1973, namely, the theory of probabilistic data interconnection filters, with which the U.S. used to process sonar signals and subsequently succeeded in locating enemy positions. Due to the successful utilization of the theory in practical cases, it was highly valued by domestic and foreign scholars and has been continuously developed since then [10].

At the end of the last century, foreign scholars have explored the information fusion theory in depth, comprehensively depicted the principles and concepts of information fusion, made relevant elaborations on the model of multitarget information fusion, and carried out simulation implementations of relevant arithmetic cases. Due to the continuous in-depth development of information fusion theory, Western countries have developed various military systems that can perform target identification and monitoring, missile guidance and missile defense, as well as threat

assessment and situational assessment to achieve the goals of intelligence gathering and target identification, and battlefield situation assessment. Technological powerhouses such as Russia have also developed numerous military data fusion systems [11, 12].

The research on information fusion theory in China started late compared to foreign countries, and the first academic work on information fusion was published in 1994. Because of the great offensive nature of information fusion technology within the military domain, the government and related departments have set up special funds for information fusion [13]. Due to the government's attention, many domestic universities and related R&D institutions have also paid high attention to it, and scholars in related fields have made it their own R&D direction. Because of the general environmental factors in China, information fusion technology has achieved abundant results in a short period of time. The basic theories and specific practices have also been published. With the continuous follow-up of information fusion theory, multi-sensor information fusion systems for target tracking, identification, and battlefield situational assessment have been continuously developed [14].

There is a lot of research on information fusion, but no consensus on a broad definition has emerged. The information fusion levels analyzed from the information perspective involve data layer and decision layer algorithms, and the D-S evidence theory belongs to the decision layer information fusion, which has many advantages in theory but still has many problems in practical application. The data layer unites the individual sensors and is rich in information and accurate in results but is computationally intensive and requires homogeneous or equally accurate sensors. The decision layer is where the individual sensor judgements form the final reasoning and decision and is highly flexible but requires preprocessing. The solution given is mainly to normalize it, which targets the practice of simply discarding the behavior of previous conflicting information, i.e., reassigning conflicting information; there is also the view that the scheme itself has a strong computational basis, and if conflicting information is generated, it can be repaired first and then calculated using the group sum formula [16].

2.2. Information Fusion Techniques. Information fusion belongs to the formal organization, which mainly uses mathematical methods for its intervention. In order to obtain effective information, it is necessary to deal with multiple aspects. There are also more subject areas involved, such as neural networks and artificial intelligence. In recent years, with the development of science and technology, new ways of information fusion have emerged, which further promote the progress of information fusion techniques [15].

Bayesian theory is classified as a statistical theory of systems; Bayes' theorem is a theorem about the conditional probability (or marginal probability) of random events A and B , where $P(A|B)$ is the probability that A will occur if B occurs. Bayes' theorem is also called Bayesian inference. As early as the 18th century, British scholar Bayes (1702~1763) proposed a formula for calculating conditional probability to solve the following types of problems:

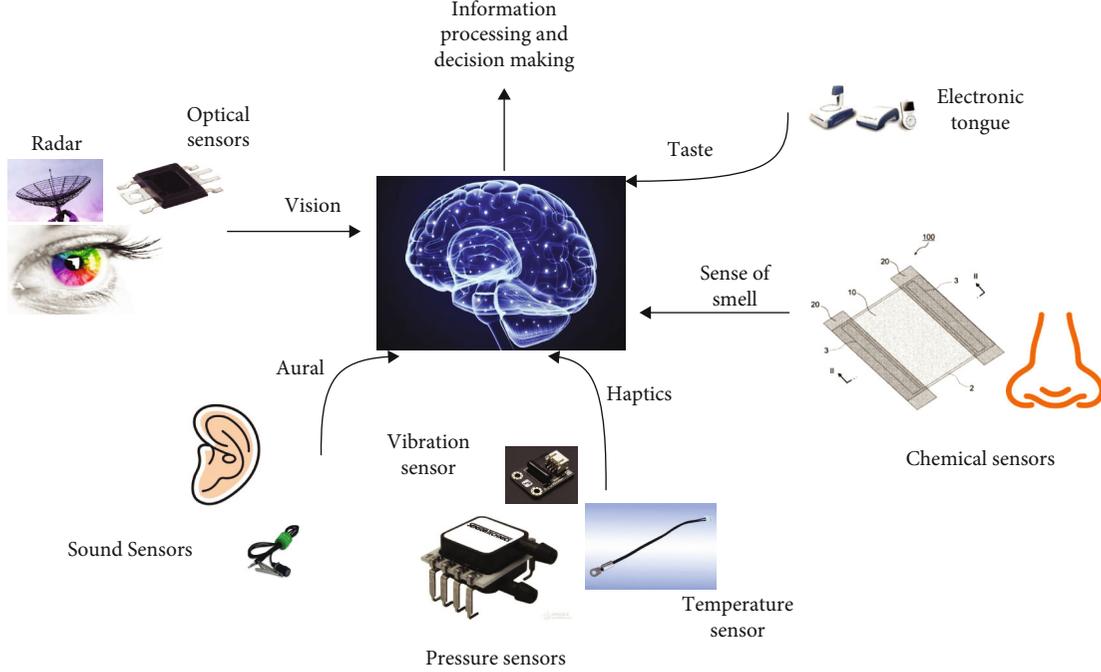


FIGURE 1: Intelligent sensing information fusion diagram.

Hypothesis $H[1], H[2], \dots, H[n]$ are mutually exclusive and constitute a complete event. Knowing their probability $P(H[i]), i = 1, 2, \dots, n$, some events A and $H[1]$ are now observed, $H[2], \dots, H[n]$ is accompanied by a machine, and the conditional probability $P(A/H[i])$ is known, find $P(H[i]/A)$, which requires the following qualifications:

$$Q_a \cap Q_z = \alpha (a \neq z), \quad (1)$$

$$Q_a \cup Q_z \cup \dots \cup Q_n = W, \quad (2)$$

$$R(Q_a) > 0 (a = 1, 2, \dots, n). \quad (3)$$

Among them, Q_1, Q_2, \dots, Q_n represents a subset; the expression can get the following formula for any event greater than zero:

$$T(Q_a|U) = \frac{T(U|Q_a)T(Q_a)}{\sum_{z=1}^n T(U|Q_z)T(Q_z)}. \quad (4)$$

In practical applications, we consider the subsets of the space to be mutually independent, and if the system decision is Q_1, Q_2, \dots, Q_n , the posterior probabilities can be obtained after testing the probabilities and conditional probabilities, which can be expressed as follows:

$$T(Q_a|S_1 \Lambda S_2 \dots \Lambda S_m) = \frac{\prod_{i=1}^m T(S_i|Q_a)T(Q_a)}{\sum_{z=1}^n \prod_{i=1}^m T(S_i|Q_z)T(Q_z)}. \quad (5)$$

When the results are checked, each subset is independent of each other when target identification is performed, but when too few targets are detected, the resulting results

do not accurately describe the problem, and the information fusion process is shown in Figure 2.

S evidence theory is one of the commonly used methods for information fusion, which can effectively deal with the uncertainty of information, overcome the limitations of the YeBES theory, and require no prior intervention in the calculation process, making it more convenient in practical use, but when there is highly conflicting evidence, the output will show the opposite conclusion from common sense. We express it as follows:

$$y(\varphi) = 0, \quad (6)$$

$$\sum_{S \subset \vartheta} y(S) = 1, \quad (7)$$

$$\text{Bel}(S) = \sum_{A \subset S} y(A) (\forall S \subset \chi). \quad (8)$$

Among them, $\text{Bel}(s)$ represents the trust function, which is the sum of the basic probabilities of all the subsets of proposition S . The Bel function is the lowest estimate of the assumed level of trust, from which we obtain

$$\text{Bel}(\varphi) = y(\varphi) = 0, \quad (9)$$

$$\text{Bel}(\theta) = \sum_{A \subset \theta} y(A) = 1. \quad (10)$$

When θ is the discriminative frame, the domain of definition is 0-1, which is obtained as

$$\text{pl}(S) = 1 - \text{Bel}(\bar{B}) = \sum_{A \cap S \neq \varphi} y(A). \quad (11)$$

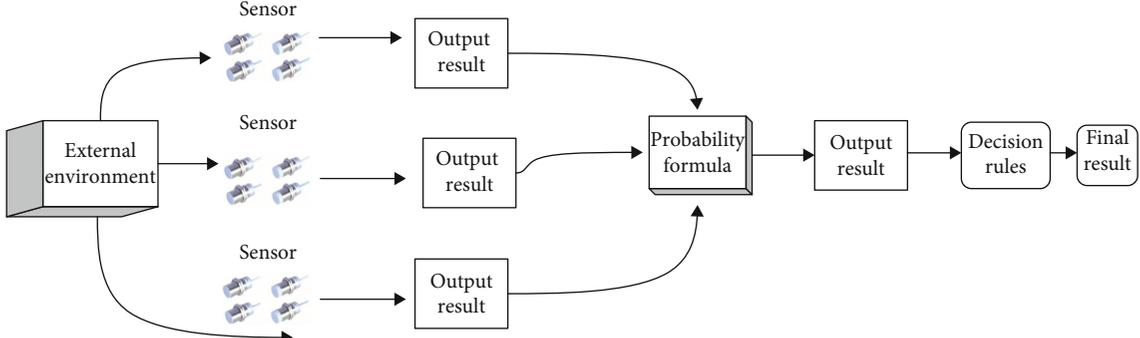


FIGURE 2: Schematic diagram of the information fusion process.

We refer to the above expression as the likelihood function, whose result represents the degree of trust, and the pl function represents the highest estimate of the assumed degree of trust. Accordingly, we can obtain

$$pl(S) \geq Bel(S)(\forall S \subset \varphi). \quad (12)$$

Synthesizing the evidence for the identification framework yields the following expression:

$$y(S) = y_1 \oplus y_2 = 0 \begin{cases} \sum_{h,j} h_j & y_1(S_h)y_2(A_j) \\ \frac{S_h \cap A_j}{1-u} & \forall S \subset \varphi, A \neq \varphi. \\ 0 & \end{cases} \quad (13)$$

Among them, u reflects the degree of conflict between various evidences, which we call the conflict factor. $y(s)$ represents the highest estimate of the trust levels of the two, A represents a constant, and y_1, y_2 represents different assumed trust levels.

If multiple evidences are combined, we define its expression as

$$y(S) = y_1 \oplus y_2 \oplus \dots \oplus y_n = \begin{cases} \frac{\sum_{S_j=S} \Pi y_h(S_j)}{1 - \sum_{S_j \neq \varphi} \Pi y_h(S_j)} & \forall S \subset \varphi, S \neq \varphi. \\ 0 & \end{cases} \quad (14)$$

Suppose that $S_1, S_2 \subset \varphi$, satisfies the following conditions:

$$y(S_1) = \max \{y(S_h), S_h \subset \varphi\}, \quad (15)$$

$$y(S_2) = \max \{y(S_h), S_h \subset \varphi, S_h \neq S_1\}. \quad (16)$$

If

$$y(S_1) - y(S_2) > \mu_1, \quad (17)$$

$$y(W) < \mu_2, \quad (18)$$

$$y(S_1) > y(W). \quad (19)$$

This is the final result, and μ_1, μ_2 represents the threshold value.

When the specific conflicting part is uncertain, then the obtained conflicting evidence loses its value, so an improved method has been proposed, which is to remove the normalization process from the evidence theory and recognize the conflicting evidence as an unknown proposition completely, so that we can get

$$y(S) = \sum_{S_h \cup A_j \cup C_i \dots = S} y_1(S_h)y_2(B_j)y_3(C_j)\dots, \quad \forall S \subset \varphi, S \neq \varphi. \quad (20)$$

Among them, when $y(S) < 1$, we consider it as a conflicting factor of evidence.

2.3. Education Big Data

2.3.1. Data. There is no uniform definition of data because it has different roles in different fields. A narrow understanding is a numerical value. With the continuous development of science and technology, data has continuously expanded its connotation, and it not only can be exponential values but also be used to represent symbols with rules, so we consider that what is processed by certain coding is data [16]. Therefore, in today's world of evolving scientific and technological development, it is necessary to acquire and use data. Data in a broad sense have the following main characteristics.

- (1) *Time-Sensitive.* That is, all data can only produce its maximum value within a certain time frame, and once the optimal point in time has passed, it will lose its use value.
- (2) *Dispersion.* That is, data does not have a constant place of generation, mainly scattered distribution; data collection has a certain degree of difficulty.
- (3) *Measurability.* That is, all data are numbers and have measurable characteristics.

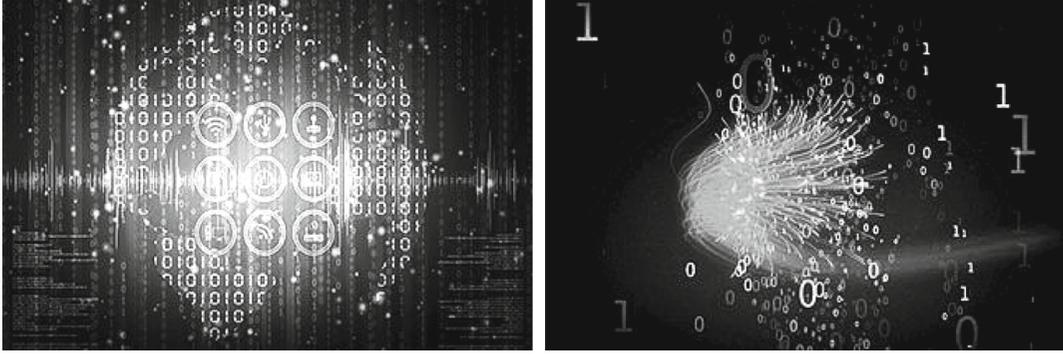


FIGURE 3: Big data diagram.

2.3.2. *Big Data*. The origin of big data can be traced back to the end of the last century at the earliest, and relevant scholars mentioned in their works that artificially encoded information would appear in human life instead of natural information. Since big data was only used in a small part of the field in the environment at that time, it did not have a wide impact. The main applications of big data are in the following: (1) Understanding and targeting customers. This is by far the most widely known application area of big data. Many companies are keen to use social media data, browser logs, text mining, and other types of datasets to create predictive models through big data technologies to gain a more comprehensive understanding of their customers and their behaviors and preferences. (2) Improving healthcare and public health. The power of big data analytics can decode entire DNA sequences in minutes, helping us find new treatments and better understand and predict disease patterns. (3) Provide personalized services. Big data applies not only to companies and governments but also to each of us, for example, by benefiting from data collected by wearable devices such as smart watches or smart bracelets. It was not until 2008 when the concept of “big data” was first proposed, that big data was developed in a real sense, and during this period, the definition of big data was proposed: a data population whose data size exceeds that of traditional database software to capture, store, manage, and analyze [17]. Figure 3 shows the schematic diagram of big data, which is generally considered to have the following characteristics.

- (1) *Technological*. If you want to use big data, you must use high technology such as visual analysis and predictive analysis capability to process the data in order to get the value of big data. Visualization is the theory, methods, and techniques of converting data into graphs or images for display on-screen and interactive processing using computer graphics and image processing techniques. Predictive analysis is the process of mining data to draw valuable and meaningful conclusions. There are many principles that need to be followed in data analysis, and some of the data analysis models that have been developed

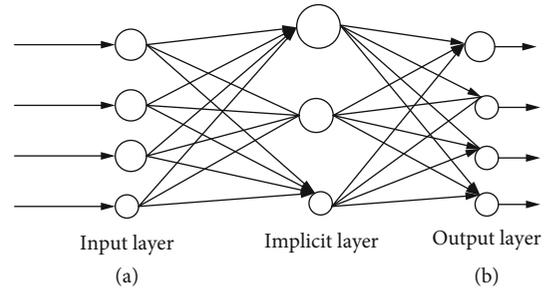


FIGURE 4: Network neural structure.

TABLE 1: Basic information of survey respondents.

Variables	Category	Number of people	Proportion (%)
Gender	Male	298	71
	Female	122	29
Specialty	Arts	120	29
	Sciences	300	71
Grade	Freshman year	105	25
	Sophomore	96	22.8
	Junior	147	35
	Senior year	72	17.2

over 100 years include pattern recognition, big data statistics, machine learning, artificial intelligence, and data mining.

- (2) *Capability*. Big data can find the intrinsic value and connection in the huge amount of information and also has the ability of innovation and prediction.
- (3) *Conceptual*. Respect data, break the fixed thinking that data is power, open data, realize the open sharing of data, and cultivate the concept of speaking with data.
- (4) *Large Quantity*. In today’s information explosion, the whole society is generating data all the time. The number of data is growing by thousands of times.
- (5) *Many Types*. At the same time as the massive amount of big data, data types are becoming more

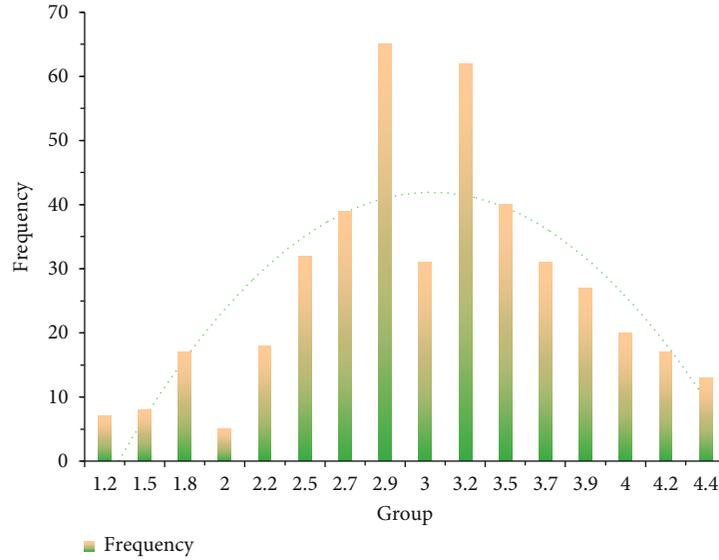


FIGURE 5: Student learning frequency chart.

and more diversified, and unstructured data occupies an important proportion. The types of big data can be broadly divided into three categories: (1) traditional enterprise data: including consumer data from CRM systems, traditional ERP data, inventory data, and account numbers; (2) machine-generated/sensor data: including call detail records, smart meters, industrial equipment sensors, equipment logs (usually digital exhaust), and transaction data; (3) social data: including user behavior records and feedback data and social media platforms such as Twitter and Facebook.

- (6) *Efficient Computing*. Big data uses cluster high-speed computing and storage to realize distributed operation systems, which improve the transmission rate of access data and can quickly extract key information.
- (7) *Value*. Valuable information can be generated during the integration of big data.

2.3.3. Education Big Data. Educational big data is a collection of data generated in the whole educational activities and used for educational development. Educational big data mainly comes from teaching activities and management activities and of course also includes related activities such as student meal data. With the continuous development of educational information technology, the collection of data is increasing, and all activities surrounding big data become educational big data [18]. The main characteristics of educational big data are as follows.

- (1) *Real-Time*. Traditional educational big data is mainly collected by human hands for a long period, while big data has highly personalized characteristics, which can focus on individual performance and can only reach real-time individual information.

TABLE 2: Distribution of dimensional means and standard deviations.

Categories	Average value	Standard deviation
Continuous learning	3.05	0.5
Curiosity level	2.8	0.61
Classroom attitude	3.32	0.57
Learning initiative	2.17	0.80
Perception of learning purpose	3.29	0.81
Categories	3.67	0.85

- (2) *Fine Granularity*. Traditional data is mostly collected in stages, and the information is also mostly questionnaires. The granularity is coarse. The information of big data is often process and instant data collection. The granularity is fine.
- (3) *High Authenticity*. Traditional data collection is often obtained with the knowledge of the subject collecting the data; then, this data has a deliberate nature; in the era of big data, the data collection will not affect the daily life of students, and the data will be more realistic.
- (4) *Difficult to Process*. Big data has a complex structure and requires the use of cloud computing, visualization, network neural structure, and other high tech, and the processing is more complex. Figure 4 shows the schematic diagram of the network neural structure.
- (5) *Strong Decision-Making*. The main role of traditional data is to carry out the overall interpretation of the

TABLE 3: Distribution of differences in dimensions in different situations.

Categories	Gender		Only child		Single-parent children	
	Male	Female	Yes	No	Yes	No
Continuous learning	2.94	2.93	2.91	2.96	2.76	2.83
Curiosity level	3.29	3.35	3.17	3.15	3.35	3.36
Classroom attitude	2.35	2.16	2.25	2.51	2.19	2.26
Learning initiative	3.35	3.51	3.29	3.51	3.31	3.33
Perception of learning purpose	3.57	3.65	3.55	3.58	3.62	3.51

TABLE 4: Differences in learning dimensions by grade level.

Categories	Freshman	Sophomore	Junior	Senior
Continuous learning	2.87	2.9	2.95	2.93
Curiosity level	3.54	3.25	3.29	3.32
Classroom attitude	2.46	2.34	2.15	2.41
Learning initiative	3.53	3.42	3.34	3.31
Perception of learning purpose	3.6	3.52	3.01	3.49

situation, but due to its inherent shortcomings, results can only be used as a basis for decision-making and cannot be overrelied on; while the results of big data analysis are more complete, understanding is also more in-depth and has higher decision-making function.

- (6) *Outstanding Security*. The security of education data is more private compared with other information, especially students' information, and the community is more concerned about it, fearing that someone will use students' information for illegal activities. In the era of big data, this situation is more serious than traditional data, and information is more easily accessible, making information theft more rampant.

3. Information Fusion and Its Intelligent Sensing on Education Big Data for Learning Intervention Model Research Experiments

3.1. Experimental Subjects. This experiment adopts a random sampling method to conduct a big data survey on students in a university. A total of 500 questionnaires were distributed, 420 data were recovered, 80 invalid questionnaires were removed, and the effective rate reached 84%.

As shown in Table 1, we have mainly classified gender, major, and grade level in the whole survey subjects to specifically sort out the proportion of the survey subjects in the whole sample, and according to the overall data, it can be seen that the proportion of male students is high, the scientific sex group is larger, and among the four grades, the number of survey subjects is the most in the junior year and the least in the senior year for the reason of internship [19].

3.2. Experimental Tools. In this investigation, the inquiry of the respondents was divided into five dimensions: continu-

TABLE 5: Differences in home location.

Categories	Rural	County	City
Continuous learning	2.88	2.91	3.01
Curiosity level	3.31	3.32	3.32
Classroom attitude	2.4	2.25	2.41
Learning initiative	3.41	3.35	3.45
Perception of learning purpose	3.52	3.57	3.64

ous learning, curiosity level, classroom attitude, learning initiative, and perception of learning purpose. Persistent learning is the ability to enter the learning state for a long time; the curiosity level is the motivation to produce learning, which is expressed as their own interest in learning; classroom attitude is the different emotions of students during the class; learning initiative is the active learning; and learning purpose perception is the view of learning, which is commonly known as why they learn [20, 21]. The five dimensions were investigated in terms of cognitive dimension, affective dimension, and dispositions of students, and throughout the survey, the higher the score, the better the whole learning.

We use a scoring system in our survey, with 3 being the theoretical value, and the higher the score, the better the learning situation. According to the data in Figure 5, it can be seen that, as a whole, the students' learning situation is positively distributed, and according to the calculation, the overall learning situation is at about 3.12, which is close to the theoretical value, and the whole situation is close to the general level, but there are still some students who are below the theoretical value [22].

3.3. Data Collection. According to the data in Table 2, the mean and standard deviation of the survey dimensions were calculated in the experiment, and the highest score in the survey was the perception of learning purpose, which

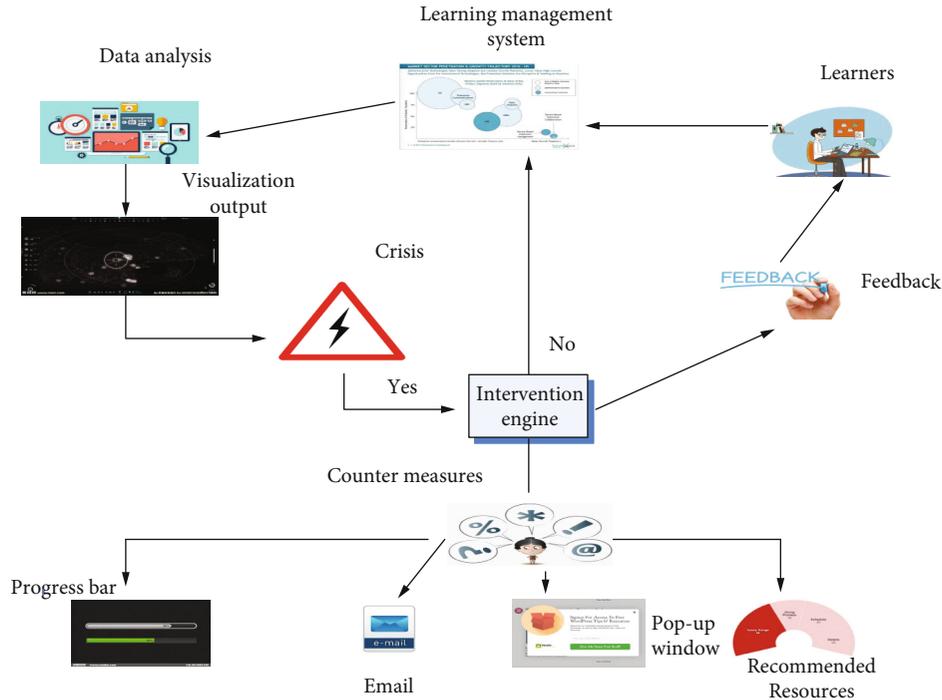


FIGURE 6: Schematic diagram of the intervention learning model.

reached 3.67; the second-ranked was the degree of curiosity, with a mean value of 3.32; learning initiative ranked third, with a mean value of 3.29, and the lowest score was the classroom attitude, which was only 2.17, and the persistent learning score was also relatively low [23].

According to the data in Table 3, it can be seen that the conditions of influence of different learning dimensions were investigated during the experiment, and the students' gender and single-parent and only-child status were explored. According to the data, there was a slight difference between the different genders on the learning dimensions, but the effect was not significant; on whether they were the only child and whether they have single parents, although there was a difference in the total score, the gap was not significant throughout the learning process [24].

In order to investigate the differences in learning among different grades, a one-way ANOVA was conducted with the dimensions of college students' learning attitudes and the total score as the dependent variable and the grade as the independent variable, as shown in Table 4, according to which it was found that there was no significant difference in the learning dimensions among students of different grades [25].

In the survey in order to explore the impact of home location on the learning dimensions produced by students, we analyzed three locations: rural, county, and urban, and according to the data in Table 5, it is clear that the dimensions and overall levels of learning attitudes of college students whose home locations are in rural, county, and urban areas differ, with urban scores being the highest, rural the second-highest, and county the lowest, but the differences between them are not significant [26].

4. Information Fusion and Its Intelligent Sensing on Learning Intervention Model of Educational Big Data

4.1. Learning Behavior Performance. In order to conduct an objective analysis of students' learning behavior, we retrieved students' submission of assignments and other information from their learning management system and conducted the corresponding statistics and analysis, expecting to obtain the students' completion before and after the implementation of the intervention-guided support service. Figure 6 shows a schematic diagram of the intervention learning model.

According to the data in Figure 7, it is clear that the first four weeks and the last four weeks produced different results through the intervention. According to the survey, before the learning intervention, the number of submitted assignments was 275, but after the intervention, the number of submissions reached 352, and the same change was found in self-evaluation and others' evaluation, which changed from 172 to 300, and self-evaluation changed from 233 to 349. In terms of discussion and communication, it was 72 in the first four weeks, but after the intervention, it reached 300, and learning resources changed from 95 to 370, a very significant improvement, and after investigating online testing, it was found that the first four weeks were only 125, but the use of the online testing system reached 315 after the intervention, and through these data, it can be shown that although the period of investigation is different, it can be seen from the improvement of students' learning programs that the intervention guidance is very helpful in serving students and can help them to complete their learning tasks effectively [27].

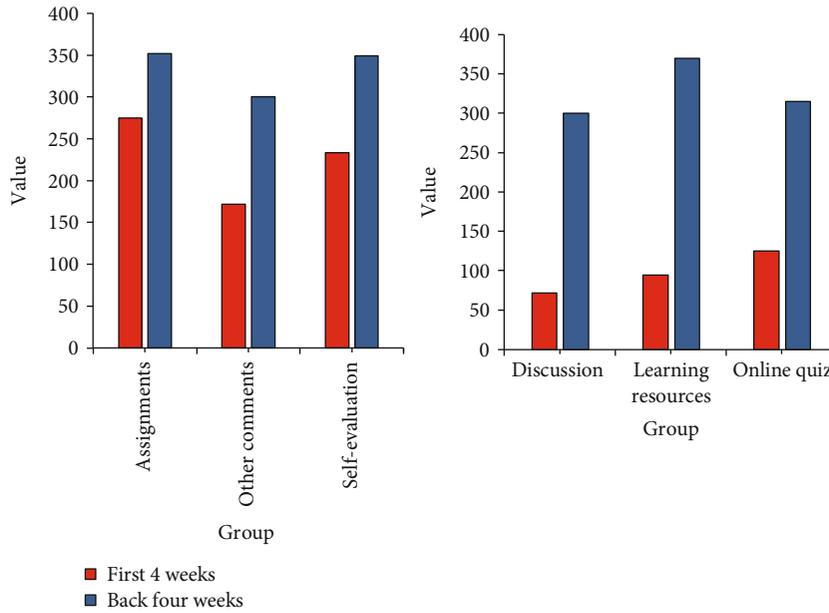


FIGURE 7: Survey of online learning platform situation.

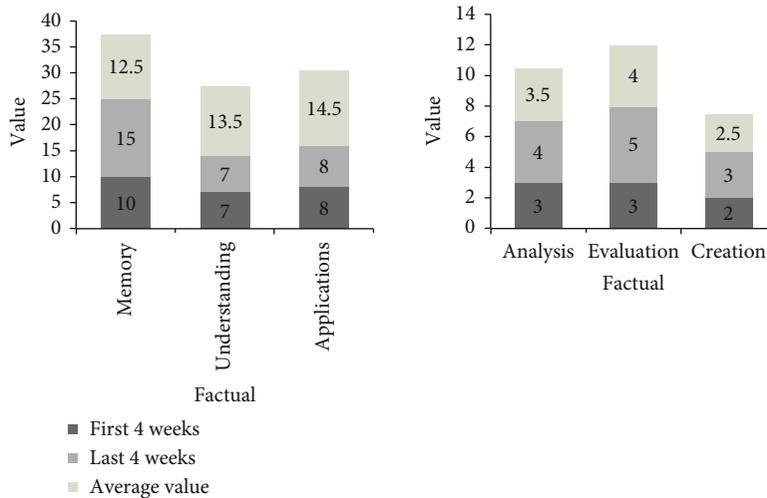


FIGURE 8: Statistics of factual knowledge content.

4.2. *Knowledge Learning Analysis.* In order to investigate the students’ knowledge acquisition, we investigated the content and main points of students’ learning in the fixed cycle and divided them into different modules of knowledge for separate investigation.

According to the examination of factual knowledge in Figure 8, our investigation divided it into six modules: memory, comprehension, application, analysis, evaluation, and creation, and according to the data, it is clear that in memory, there is a relatively significant improvement from 10 to 15 after the learning intervention; in analysis and evaluation creation, there is an improvement, but it is not significant, and in comprehension and application, the learning intervention has almost no effect. Combining the data, it is clear that the use of learning interventions can have an effect on mnemonic knowledge [28].

According to the examination of metacognitive knowledge in Figure 9, as with factual knowledge, it was divided into six modules: memorization, comprehension, application, analysis, evaluation, and creation. According to the data, it is known that in memorization, the decline was more pronounced through the learning intervention, and there was no change in comprehension, no significant impact in application, no significant change in the analysis level, an increase in evaluation, and a decrease in creation. In summary, it is known that the learning intervention is not suitable for memory and innovation of metacognitive knowledge.

4.3. *The Effect of the Application of the Learning Intervention.* After conducting a series of analyses, the feedback on the evaluation of the application effect of the

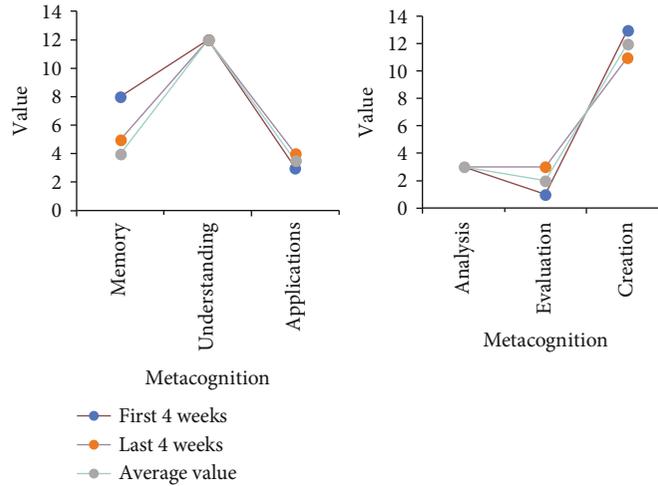


FIGURE 9: Metacognitive knowledge statistics.

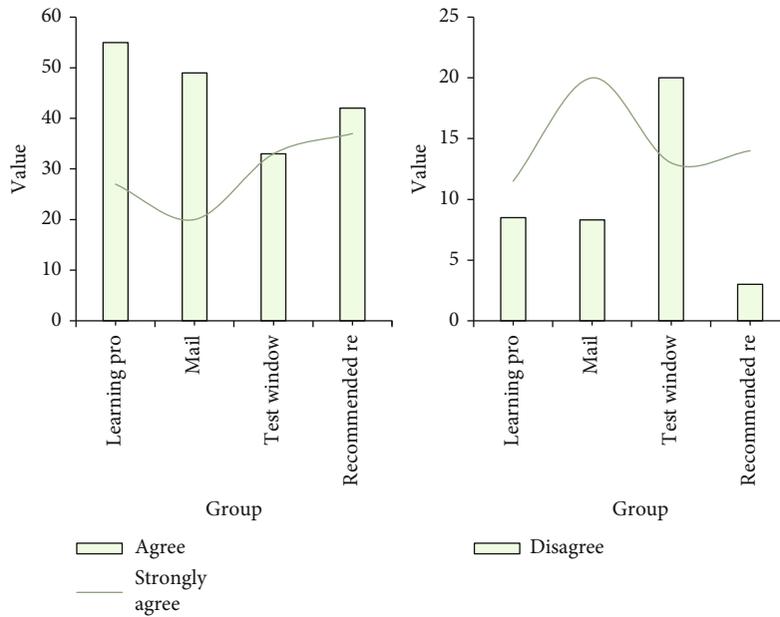


FIGURE 10: Evaluation of the effect of using the learning model.

learning intervention Murray was finally formed, which data also originated from the electronic questionnaire. Details are as follows.

According to the data in Figure 10, it can be seen that the percentage of those who agree or strongly agree that accessing the learning progress bar is conducive to promoting students' learning reaches more than 50%, the percentage of those who strongly agree is about 28%, those who disagree is 9%, and those who have an indifferent attitude is about 10%. About 50% agreed to use email to supervise themselves, 32% to use the test window, and about 40% to use the resource recommendation. Overall, the number of those who disagreed to use the resource recommendation was low, and the number of those who disagreed to use the test window was the highest, reaching 20%.

5. Conclusions

This paper focuses on the study of learning intervention models for educational big data using information fusion and its intelligent sensing, and the exploration process is dedicated to functional sensing skills to capture educational big data for learning interventions, aiming to facilitate students to complete teaching and learning tasks with high quality. This paper accomplishes the following: (1) The paper analyzes the levels of information fusion from the perspective of information, and the algorithms of data layer, feature layer, and decision layer are described separately to identify the discord in conflicting evidence and then compute them. (2) An improved algorithm based on the trust factor of evidence is proposed. The information fusion function is enhanced by assigning corresponding weights to the

evidence according to its distance from the evidence set. (3) The feedback on the use of different learning intervention models is explored to find out reasonable intervention methods. Meanwhile, this paper has many shortcomings: (1) Although the experiments are as identical as possible in the intervention time period, the experimental periods are different, which does not control the variables to some extent and leads to unscientific results. (2) In terms of sensing information collection, the use of transmitters was not considered and the interface and sensors were not networked. (3) The researcher's energy and ability are limited, and the investigation of college students' learning attitudes is limited to a particular school, and further investigation and analysis are needed to determine whether the results represent the overall situation of college students' learning attitudes in the region.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors state that this article has no conflict of interest.

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