ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

# Research on Optimization of Teaching Content and Curriculum System of “Basic Accounting” Based on Hybrid Algorithm

*Zhihong Shan*[1,*]

[1] Guangzhou Huali College, Guangzhou, Guangdong, 511325, China

**SUMMARY:** *To tackle such problems as the failure to consider diverse behaviors of students and improper dynamism of the curriculum system when teaching the topic of Fundamentals of Accounting, this paper presents a hybrid algorithm approach as the approach to optimize the teaching material and curriculum system. Through the integration of Gaussian mixture models and clickstream data analysis, this can be used to determine the characteristics of student learning behaviors and the model parameters are optimized using the Expectation-Maximization (EM) algorithm. According to the ARCS motivation model, the learning design is based on an all-encompassing teaching evaluation system including both formative and summative evaluations. With the help of empirical mode decomposition, students multi-dimensional behavioral time-frequency features were extracted with the use of 2022 Basic Accounting course at H University School of Accounting as an empirical subject. The connection between patterns of behavior and academic achievement was confirmed and compared the results of teaching in experimental and non-experimental classes. Results show that: The hybrid algorithm is capable of identifying the multimodal distribution features of student behavior. The non-experimental class mean (63.15), median (67), and pass rate (0.77) were significantly lower than the respective measures in the experimental class full sample. There was a significant correlation (0.201) between learning performance and formative assessment at the 1% statistical level.*

***KEYWORDS:*** *Basic Accounting Instruction; Gaussian Mixture Model; Expectation Maximization Algorithm; ARCS Motivation Model; Learning Behavior Analysis*

# 1 Introduction

Due to the fast-paced growth of the economy and the intensification of the globalization process, accounting has become an essential way of documenting the economic events of a company, and its position and function have been highlighted more frequently [1]. The literature [2] analyzed the significance of the basic accounting skills in the work of small and medium-sized enterprises (SME). Its survey results showed that the demands of the corporation need students to be able to manage cash journals, compute credit values, and balance reconciliation, which are crucial competencies in attaining sustainable development in SMEs. In relation to other courses offered to economics and management students, the role of the course titled, the Fundamentals of Accounting is fundamental and pioneering in its impact on subsequent courses and the development of the students’ accounting thinking and skills [3-5]. Literature [6] suggests a framework to help design an accounting course which would clarify the course objectives and ensure that they correspond to the course activities and assessments, thus being

*shzh151819@163.com
https://doi.org/10.65102/is2026472
Published: 30 April, 2026

helpful in developing the students accounting thinking skills effectively.

Nevertheless, the Fundamentals of Accounting course also has its own issues. The material is intricate, and the instructor must find a way to strike a balance between theoretical teaching and practical implementation during the limited time of a class. To the viewpoint of students, the course is seen as demanding, and there are problems after-class understanding and consolidation [7-10]. In terms of evaluation, end of term assessments fail to encourage regular student participation in the semester [11]. Reference [12] was meant to determine what challenges students have experienced in accounting classes and the reason behind them. Survey analysis found that whereas some students did not experience any comprehension problems, others had different opinions concerning the nature and explanations of their challenges. Reference [13] discussed the factors behind under-performance among students and teachers in university accounting education. The findings of questionnaire showed that there were huge differences in performance between students and teachers suggesting the establishment of an environment of teaching and learning that promotes effectiveness of instruction in accounting education. It is obvious that the best way to make the teaching and curriculum organization of the course Fundamentals of Accounting more effective is to optimize it.

The need to optimize teaching content involves the updating of the course material depending on the development of the field of accounting and market demand [14, 15].The focus is on the fundamental knowledge including the basic concepts of accounting, the elements of accounting, accounting subjects, accounting vouchers, the ledger, and financial statements and the development of analytical and practical skills of students using real-life case studies [16-19]. Curriculums optimization requires changes in teaching strategies and assessment models [20]. In the information era, there is a positive impact of digital teaching resources, including multimedia instruction and online classes, on the methods of pedagogy and the results of learning [21-24]. Creating online teaching services helps share resources and promotes student-led learning and collaboration [25, 26]. The reference [27] illustrates the effectiveness of experiential teaching methods in improving the results of basic accounting courses. It provides a teaching approach to basic accounting courses that uses an open teaching platform that is based on embedded Linux information processing technology, which greatly increases the quality of teaching. Reference [28] outlines a multimedia teaching system built upon the Dokeos and Bigbluebutton systems to be used in the course on the subject of the Principles of Accounting. This system has numerous functions of remote education that play a significant role in enhancing the quality of teaching. Literature [29] analyzed the attitudes of non-accounting majors towards the learning of online accounting courses and factors that influence them. The findings of questionnaires reveal that online accounting courses are positively received by students with the attributes of instructors and students being significant factors that define this process.

The importance of evaluating teaching is based on the identification of flaws in the teaching process by conducting thorough evaluations of teaching performance of experts, teachers, and learners in the field of teaching fundamentals of accounting so that improvement strategies can be applied [30-32]. Reference [33] examines the difficulties with university accounting education, highlighting the fact that in the big data environment, university accounting education should not only be directed at professional practical skills development and optimization of accounting course curricula but also develop an online teaching effectiveness assessment model. Reference [34] concludes in its study of how accounting courses are taught that students view accounting instruction to be above average and there is a high correlation between the ratings of the quality of accounting instruction and the ratings of e-learning materials.

The paper uses Gaussian mixture models and the Expectation Maximization algorithm to recognize learning motivation types among student groups. Combining clickstream data with self-determination theory it measures how strongly it is connected to learning motivation and behavior patterns. Using an evaluation system based on the ARCS model of motivation, it aims to alleviate the shortcomings of single-criterion assessment, which is limited to only grades. The implementation of teaching methods was done using the 2022 cohort of students enrolled at the School of Accounting at H University as study participants. Empirical Mode Decomposition and time-frequency feature extraction approaches were used to explore the temporal trends in the various behaviors of students. The integration of statistical analysis with machine learning models was utilized to confirm the causal relationships between learning behaviors and academic performance. Practical utility of the hybrid algorithm in optimizing teaching content and curriculum systems on such dimensions as academic achievement, correlation and multiple regression was tested through comparing grades of the experimental and non-experimental classes.

# 2 Research on the Application of Hybrid Algorithms in Teaching “Fundamentals of Accounting”

The scientific rigor and versatility of the teaching material and structure of the curriculum of the course, which is called the Fundamentals of Accounting (the backbone of the finance and accounting programs) are directly related to the level of the formation of professional competence of students under the conditions of digital transformation in higher education. In the context of the accelerated development of educational big data and intelligent algorithm technologies, hybrid algorithms present new opportunities to map student learning behavior accurately and dynamically change teaching methods.

## 2.1 Learning Behavior Analysis Based on Gaussian Mixture Models

### 2.1.1 Theoretical Foundations of Gaussian Mixture Models

When analyzing student learning behaviors, Gaussian Mixture Models (GMM) are a flexible way to identify and model complex patterns of student behavior. The assumption behind GMM is that the data are mixtures of several Gaussian distributions, whereby each Gaussian distribution may represent a latent cluster or pattern in the data. This model is especially appropriate to capture the diversity in learning behaviors since it can represent the behavior of each student or group of students instead of putting all students behaviors into one distribution.

GMM is expressed mathematically as:

$$p(x)=\sum_{k=1}^{K}\pi_k N\left(x \mid \mu_k,\Sigma_k\right) \tag{1}$$

Here, $x$ represents the multidimensional data point to be modeled, $K$ denotes the number of Gaussian distributions, and $\pi_k$ is the mixture weight for the $k$ th Gaussian distribution, satisfying $\sum_{k=1}^{K}\pi_k=1$ and $\pi_k>0, N\left(x \mid \mu_k,\Sigma_k\right)$ is the probability density function of the $k$ th Gaussian distribution, where $\mu_k$ and $\Sigma_k$ denote the mean and covariance matrix of the $k$ th Gaussian distribution, respectively.

### 2.1.2 Model Construction and Parameter Optimization

The essence of building a GMM model is finding the best parameters, i.e., the mean, covariance matrix, and mixture weights of every Gaussian distribution. The optimization of these parameters is usually done through the Expectation-Maximization (EM) algorithm, which enhances the likelihood-based function value of the data iteratively up to convergence.

In the Expectation (E) step, the posterior probability of every data point being associated with every Gaussian distribution is calculated. Such probabilities indicate the contribution made by each data point to each Gaussian distribution. The Maximization (M) step updates the parameters of Gaussian distributions according to these contributions, allowing the model to be more fitted to the data.

The specific formula for parameter updates is as follows:

$$\pi_k = \tfrac{1}{N} \sum_{i=1}^{N} \gamma\left(z_{ik}\right) \tag{2}$$

$$\mu_k = \sum_{i=1}^{N} \gamma\left(z_{ik}\right) x_i \sum_{i=1}^{N} \gamma\left(z_{ik}\right) \tag{3}$$

$$\Sigma_k = \sum_{i=1}^{N} \gamma\left(z_{ik}\right)\left(x_i - \mu_k\right)\left(x_i - \mu_k\right)^T \sum_{i=1}^{N} \gamma\left(z_{ik}\right) \tag{4}$$

where $\gamma\left(z_{ik}\right)$ is the posterior probability that the $i$ nd data point belongs to the first Gaussian distribution.

### 2.1.3 Algorithm design and implementation

The specific flow of the Gaussian mixture model is shown in Fig. 1 and described as follows:

(1) Parameter initialization. Before constructing a Gaussian mixture model (GMM), parameter initialization is required first. This includes setting the number of data subsets $K'$ and the number of components of the GMM model $K$, as well as the initial mixing coefficients and covariance matrix of the model.

(2) Dataset $X$. The collected dataset $X$ is used as input, which will be used for subsequent SVD decomposition and GMM model training.

(3) SVD Decomposition of Data Matrix. Singular value decomposition (SVD) is performed on the data matrix to obtain the left singular matrix $U$, the singular value matrix $S$ and the right singular matrix $V^T$.SVD is a method to decompose the original data matrix into the product of three matrices, which helps in the downscaling and extraction of the main features of the data.

(4) Number of data subsets $K'$ and number of GMM model components $K$. After the SVD decomposition, the experiment can determine the number of data subsets $K'$ and the number of GMM model components $K$ based on the magnitude of the singular values. These parameters will directly affect the clustering effect of the GMM model.

(5) Parameter estimation. On the basis of parameter initialization and SVD decomposition, EM algorithm or VI algorithm is used to estimate the parameters of the GMM model, including the mixing coefficients and covariance matrices.EM algorithm is a commonly used iterative method to find the maximum likelihood estimation of the parameters of the probabilistic model in the presence of latent variables.

(6) Gaussian Mixture Model (GMM). Finally, the estimated parameters are used to construct a Gaussian mixture model, which will be employed to analyze and predict student learning behaviors.

Figure 1 clearly illustrates the entire process from parameter initialization to GMM model construction, including key steps such as data preprocessing (SVD decomposition) and parameter estimation (EM or VI algorithm). This process will allow educators to learn more about and utilize the role played by Gaussian mixture models in studying a student learning behavior.

This strategy allows GMM to be used not as a mere analytical instrument in research but also as a way of helping teachers acquire more profound knowledge on the actual structure of student behavior and hence offer direction in educational practice.

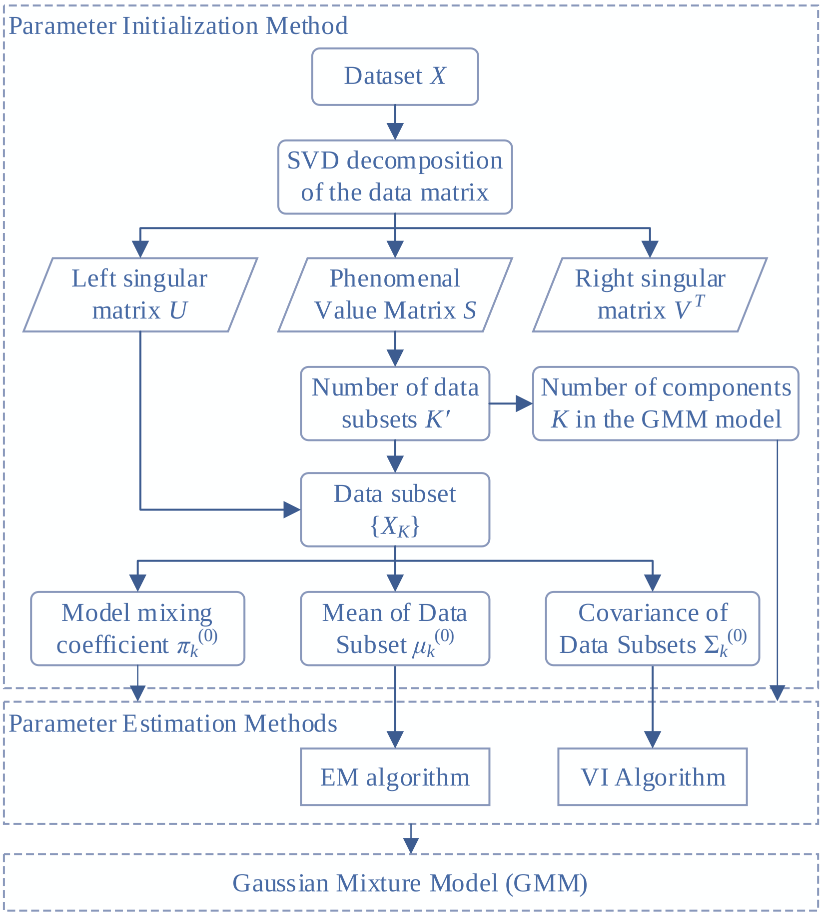



*Figure 1: Gaussian mixture model process*

## 2.2 Learning Behavior Modeling Based on Clickstream Data

### 2.2.1 Main Modeling Process and Introduction

A key part of building a data-driven learning motivation analysis model includes three main steps, which are acquiring data on online learning, processing data, and analyzing learning motivation. The general flow is shown in Figure 2. We initially gather clickstream data followed by extraction of features connected with learning motivation. Transformation of the features is done to have the feature vectors needed to conduct further analysis. After preparing the feature data, we conduct clustering analysis and statistical analysis. Descriptive statistics are used to characterize the potential relationships between learning behaviors and different learning motivations. The constructed features are further analyzed using the deep clustering model proposed in this paper to examine the learning motivations of different student groups. The following sections provide a detailed explanation of this modeling process.

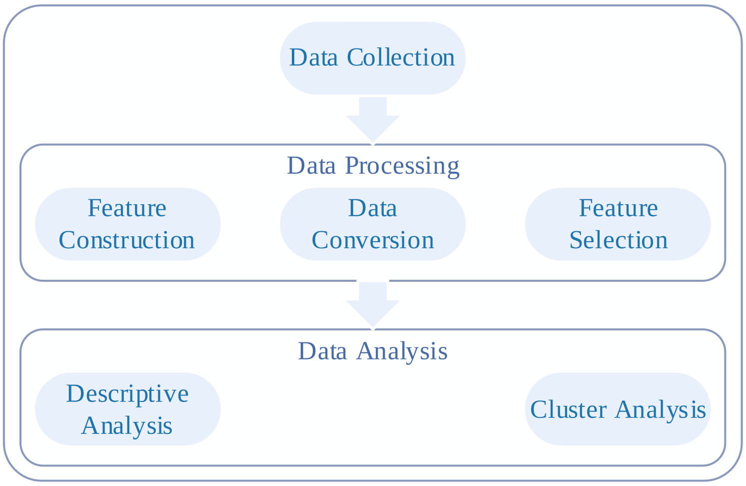



*Figure 2: Overall process*

The dataset used in this study was collected and organized by researchers at X University, one of the world's largest providers of online courses. At this university, course content and materials are delivered through a Virtual Learning Environment (VLE). This platform collects certain demographic information about students, along with clickstream interaction data recorded within the online learning platform. Lectures, exercises, and other course materials are sent to students via the VLE. All user interactions with course materials or other users on the platform are logged and kept in the university data warehouse.

The common course layout is represented by Figure 3. Most courses are nine months long. Before the course starts, administrators will activate the online educational services on the learning platform, and upload the appropriate course materials to the online educational platform. They may be enrolled into courses a few weeks before the official start date. The online users have an opportunity to pick and enrol on particular courses depending on their choices until the registration deadline is reached two weeks later after the course has started. After registration is closed, there is no more registration, and the process of learning the course starts. An ordinary sequence of courses consists of a number of in-class quizzes over the course of the semester, which act as indicators to gauge the understanding of course materials by users. The last exam completes the course.

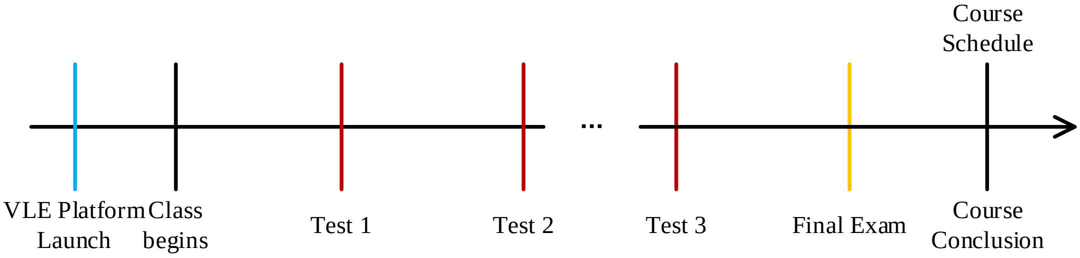



*Figure 3: The typical structure of a certain course*

### 2.2.2 Modeling and Analysis of Learning Motivation Data

The present research explores two different courses, A and B, taken out of X University. Each of the courses was about 38 weeks long. The materials of all lessons were made available a few days before the commencement of the class. Each course included three in-class assignments, one midterm exam, and one final exam. Students' final grades were measured based on their overall performance in both in-class assignments and exams. Generally, final grades serve as a good indicator of student motivation. However, for enrolled students who failed the course or withdrew early, we cannot solely judge their motivation based on their final grades. Therefore, we categorized students based on a combination of learning activity patterns and final grade characteristics within the dataset. The feature symbols used in the study are as follows:

$S$ represents the entire student body, and the number of students is $|S| = N$.

$$g_i(1, 2, \cdots N) \tag{5}$$

As shown in formula (5), $g_i$ represents the score of the first assignment submitted by the student.

$$d_{i,j}(i = 1, 2, \cdots, N;\ j = 1, 2, 3) \tag{6}$$

In formula (6), $d_{i,j}$ denotes the number of days delayed for student i's jth assignment.

varClicks is the variance of a specific student's clickstream within a given time period. It represents the frequency of shifts in online learning behavior across different learning resources.

avgDelay denotes the average number of days a student delays submitting three assignments. Negative values indicate the number of days a student submits assignments ahead of deadlines, while positive values indicate the number of days delayed. As shown in formula (7).

$$avgDelay = \frac{\sum_{i,j=1}^{3} d_{i,j}}{3} \tag{7}$$

This paper categorizes students into three groups based on Self-Determination Theory (SDT): intrinsically motivated, extrinsically motivated, and those without clear motivation. The following is a set of criteria and procedures on how to classify a student based on his or her type of motivation.

Intrinsically motivated students (IMS) are those who perceive the course material to be truly interesting. They do not aim at necessarily passing the course, since they are interested in what they do. Therefore, intrinsically motivated learners can also be divided into two groups: those who pass the course (IMPS) and those who do not (IMFS). The exact meanings are given below:

$$\begin{aligned} IMPS = \{\forall s \in S \,|\, & [(g \geq 60) \,\&\, (g \leq 80) \,\&\, (avgDelay \leq 8)] \\ & |\, [(\mathrm{var}Clicks \geq 150) \,\&\, (\mathrm{var}Clicks \leq 300)]\} \end{aligned} \tag{8}$$

$$\begin{aligned} IMFS = \{\forall s \in S \,|\, & [(g \geq 40) \,\&\, (g \leq 59)] \\ & |\, [(\mathrm{avgDelay} \geq 3) \,\&\, (avgDelay \leq 14) \,\&\, (\mathrm{var}Clicks \leq 200)]\} \end{aligned} \tag{9}$$

The students, having external motivation (EMS), have a deep intention to learn and acquire knowledge in a specific area of interest towards achieving the ultimate objective of awarding a certificate or prize at last. The majority of students in this group hope to receive a certificate at the end of the course to validate their learning achievements. Students in this group can be classified according to formula (10). As shown by formula (10), students with external motivation tend to achieve higher assignment scores and rarely exhibit delayed submission of assignments.

$$EMS = \{\forall s \in S \,|\, [((g \geq 75) \,|\, (avgDelay < 3))\&(\mathrm{var}Clicks \geq 20)]\} \tag{10}$$

Students with no apparent motivation (UMS) refer to those who drop out of courses or exhibit minimal learning behavior. Specifically, as shown in Equation (11), students lacking clear learning motivation receive low assignment scores and submit work with significant delays.

$$UMS = \{\forall s \in S \mid [((g \le 30) \mid (avgDelay \ge 14)) \,\&\, (avgClicks \le 250)]\} \tag{11}$$

## 2.3 Instructional Evaluation Based on the ARCS Motivation Model

The instructional assessment design based on the ARCS motivation model, as shown in Figure 4, advocates for diverse assessment methods and emphasizes the role of formative assessment. It evaluates students' classroom performance, such as participation levels, frequency of responses, and the quality of their answers. Summative assessments primarily evaluate homework completion and knowledge mastery. However, grades should not be the sole criterion for judging students. The ARCS motivation theory emphasizes stimulating students' learning motivation and helping them achieve satisfaction. Therefore, whether conducting formative or summative evaluations, teachers should prioritize encouraging students and guiding their attributions.

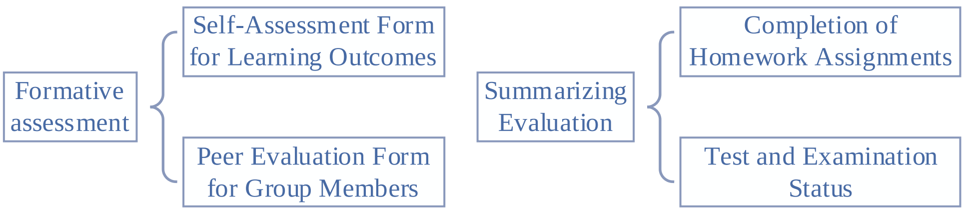



*Figure 4: Teaching evaluation design*

The Learning Effectiveness Self-Assessment Form enables students to evaluate their own learning progress, covering aspects such as learning interest, learning ability, and collaborative skills. Through this self-assessment process, students can gauge their learning outcomes for the current lesson, gaining a concrete and tangible sense of their progress and classroom gains. When students recognize positive learning outcomes, they build confidence in their studies. This approach also serves as an effective method for helping students achieve learning satisfaction. For teachers, the self-assessment form provides insight into students' self-evaluations. When identifying instances of misattribution or dissatisfaction with learning outcomes, teachers can promptly guide students toward rational attribution and monitor their psychological state outside of class to prevent the development of negative attitudes.

The peer evaluation form is used for students to assess their group collaborators. Based on the satisfaction strategies of the ARCS motivation model and students' physical and psychological development characteristics, peer evaluations significantly influence students' learning satisfaction. Therefore, peer evaluations help students understand how they are perceived by others. When receiving positive feedback, students gain learning satisfaction, thereby enhancing their motivation and confidence.

# 3 Case Study on Teaching Optimization of "Fundamentals of Accounting" Based on Hybrid Algorithms

All experimental data in this chapter are derived from the teaching practice of the "Fundamentals of Accounting" course for the Class of 2022 at the School of Accounting, H

University. The course used a blended learning approach which comprised both online and offline teaching as well as a learning platform created independently by the university. The experimental group structure involved the implementation of an optimized teaching content and curriculum system in the experimental classes (Classes 1-3) based on a hybrid algorithm, whereas non-experimental classes (Classes 4-6) were taught under the conventional educational framework with the same pace of work.

## 3.1 Extraction of Multi-Behavioral Time-Frequency Features for Students

### 3.1.1 Empirical Mode Decomposition

Initially, the multi-behavioral student data of the fused form are subjected to preprocessing. The Empirical Mode Decomposition (EMD) is used to decompose the signal into different intrinsic mode functions (IMFs), converting multi-behavioral student data into several linearly stationary components.

With respect to the behavioral data of Student A in the experimental class on March 1st as a sample case, the initial signal is decomposed into EMD. This decomposition output is presented in Figure 5.It is evident that Student A's attention fluctuated significantly throughout the day, with nearly constant variation except for a brief period in the middle.

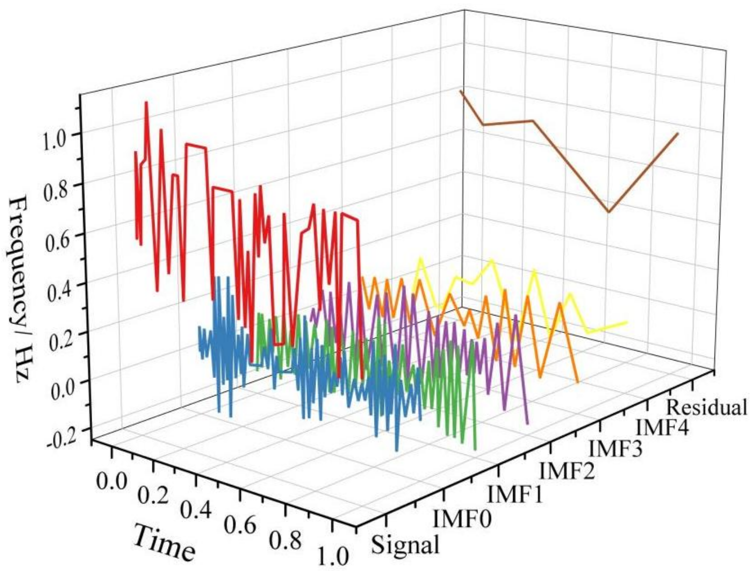



*Figure 5: Results of EMD Decomposition*

### 3.1.2 Time-Frequency Feature Extraction

Although the IMF has extracted local features of the signal, they remain time-domain signals. The Hilbert transform, however, can convert a time-domain signal into a phase signal moving in the complex plane, thereby obtaining its instantaneous frequency and instantaneous amplitude information. The time-frequency features of Student A's behavioral data are shown in Figure 6, with the effective information primarily concentrated in the frequency range between 0 and 10 Hz.

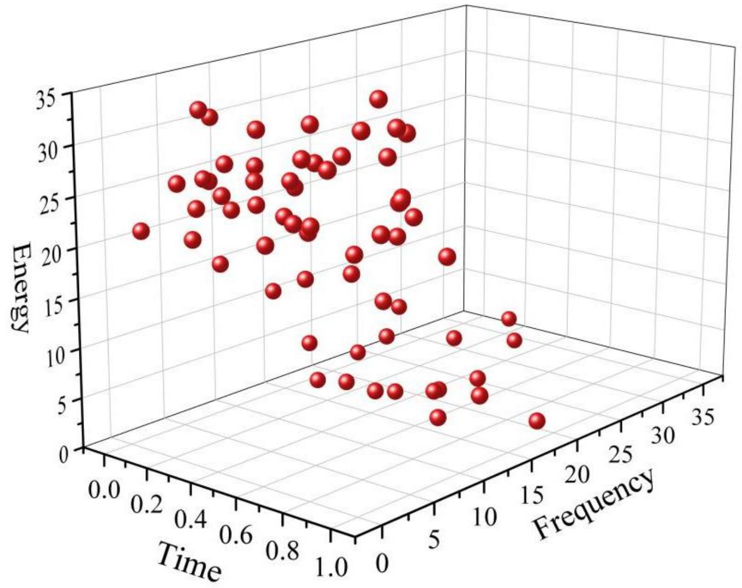



*Figure 6: The time-frequency characteristics of the behavior data of student A*

To filter out irrelevant information, only features within the 0–10 Hz frequency range need to be extracted. After performing time-frequency feature dimensionality reduction, the extracted time-frequency features are shown in Figure 7, with energy intensity concentrated between 15 and 35 dB.

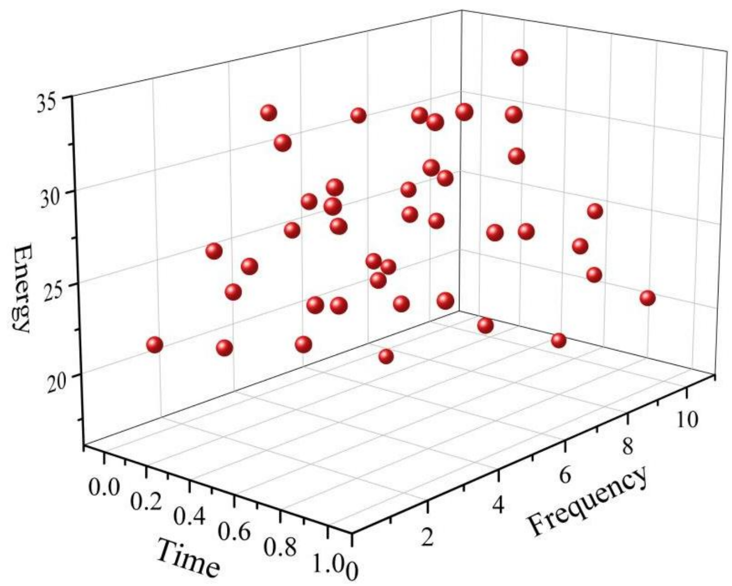



*Figure 7: Time-frequency features after dimension reduction*

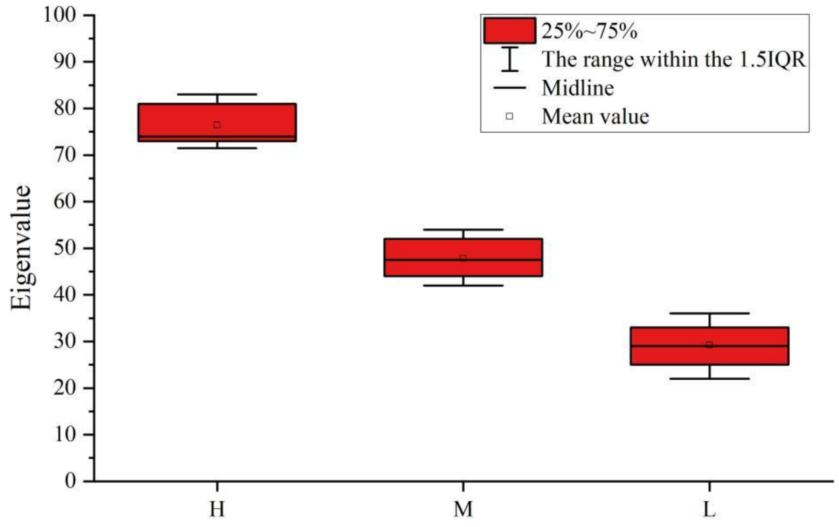
## 3.2 Analysis of Learning Behavior

### 3.2.1 Statistical Analysis of Behavioral Status and Academic Performance

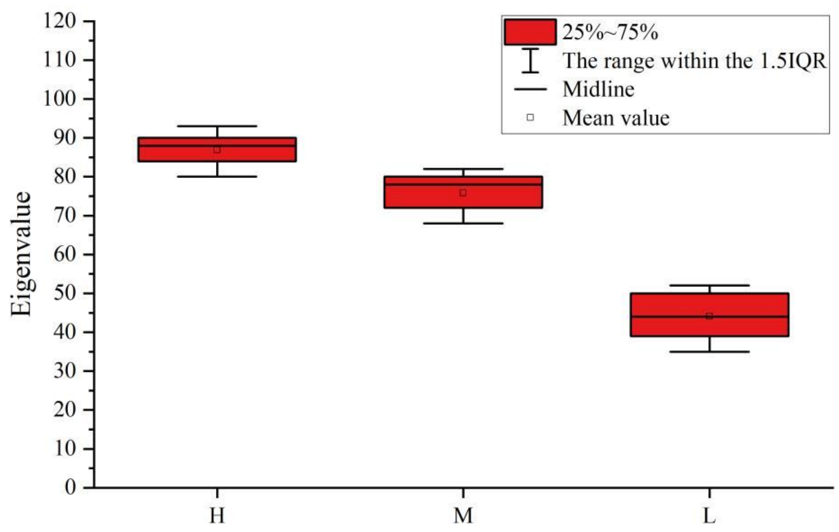
The box plots were used in order to investigate the dispersion patterns and the exact relationships between every one of the behavioral characteristics and the academic performance of the students in the experimental group.

The findings of this data analysis are demonstrated in Figure 8 (a-d). In comparison with

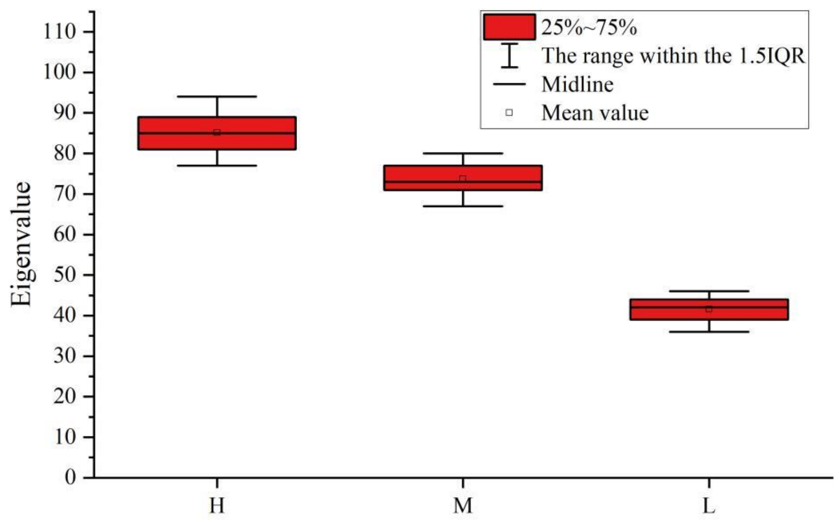
Figure 8 it can be seen that the data distributions and correlation rates of Learning (searching of study materials), Check (attendance), Test (chapter quizzes) and Discuss (discussion/Q&A) all have different levels of difference. The scores of the student academic performance were classified into three groups to facilitate their analysis: High (H), Medium (M), and Low (L). The most salient feature is that the distribution of Discuss has a relatively constant form and is the only one of the four that does not contain outliers. Concurrently, each of the four traits shows positive correlations with various levels of performance. It means that high-performing students are more involved in course-related actions, medium-performing students have different views on these actions, and low-performing students show a moderate level of involvement in course-related actions.



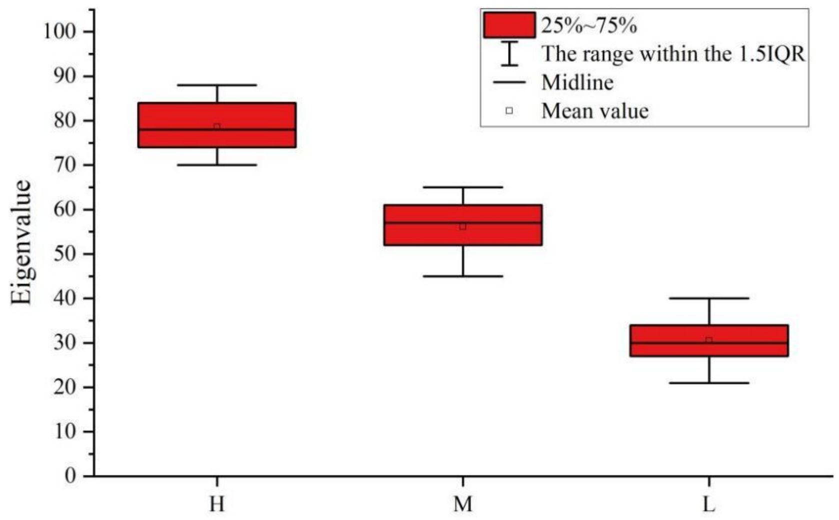

(a)Learning




(b)Check




(c)Test




(d)Discuss

*Figure 8: Results of data statistical analysis*

### 3.2.2 Model Validity Verification

(1) Univariate Feature Fitting Experiment

The next part of this chapter uses a grouped strategy to create Gaussian function models based on samples of various groups in the experimental cohort. Firstly, students are divided into three groups (H, M and L) according to their overall academic performance grades based on different intervals in a certain semester and the experiments are performed on each group independently. Next, the univariate Gaussian function fitting experiment chooses the number of student discussion Q&A sessions as the input feature. At last, the numerical values of the discussion participation features of the three groups were organized into a sequence sample which served as an input. Functional approximation was done in order to determine the final grade prediction fitting results using the Gaussian function fitting model. In order to show the fitting performance of the GM-GF model, the curve_fit method was utilized in order to visualize the results graphically. Figure 9 presents the grouped experimental findings. The tendency of the predicted values of the GM-GF model is close to the real ones, which means that the model has a high level of precision in its predictions.

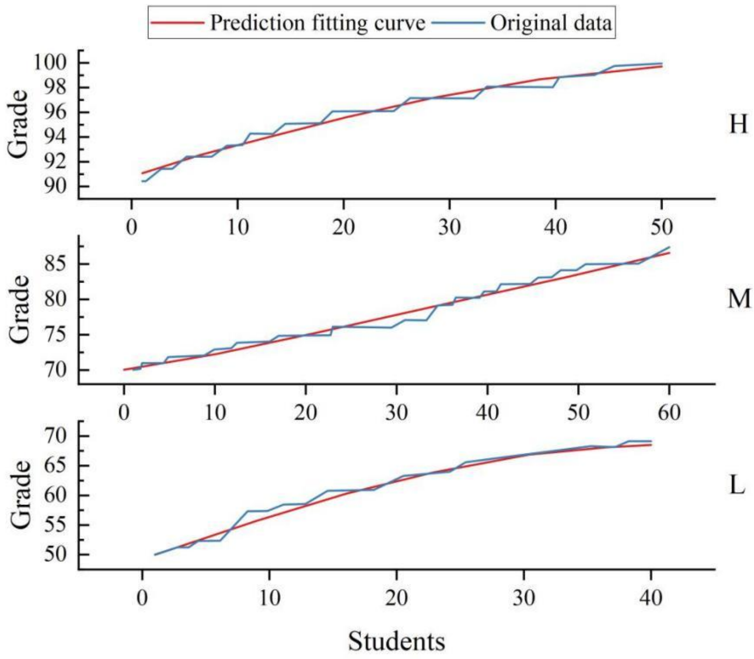



*Figure 9: Curve-fitting results of the grouped experiments*

(2) Comparative Experiments on Multi-Gaussian Model Mixture Fitting

The experiment values were normalized and scaled to the interval [-1,1]. Figure 10 shows the results of GMM fitting. As it can be seen, GMM is capable of capturing the multimodal distribution characteristics of data in three-dimensional space quite well, and provides accurate fitting to complex data distributions. In comparison with other older single-distribution assumption models like the single Gaussian model, GMM is more flexible and fits accurately to characterize both heterogeneous and multi-peak properties of sample data due to its mixture of Gaussian elements.

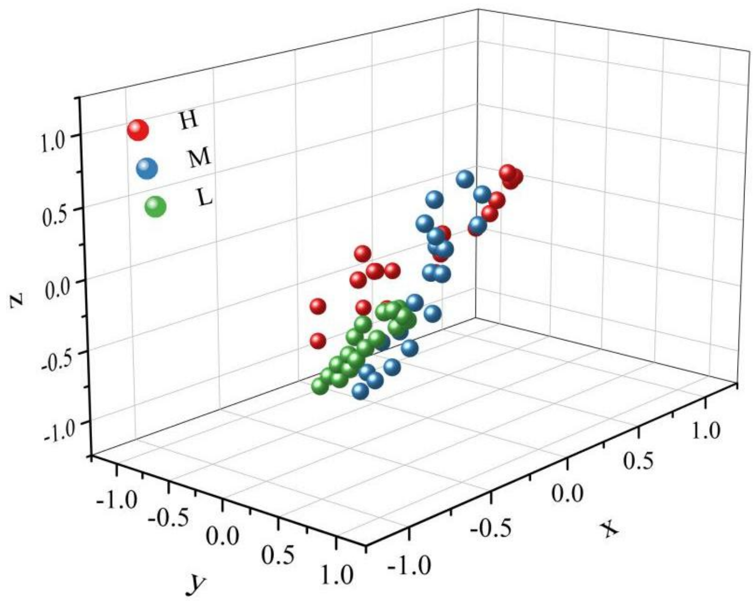



*Figure 10: Experimental results of GMM fitting*

## 3.3 Application Effect Analysis

### 3.3.1 Comparison of Academic Performance Results

For analytical and comparative purposes, this study divides the final scores of the research sample into two groups based on the time period: the experimental period and the comparison period. These groups are further segmented into six intervals by class. Descriptive statistics are then applied to the scores within each interval, followed by interval-specific descriptive statistical analysis. The students' academic performance results are presented in Table 1. It can be observed that the scores between the experimental class and the non-experimental class during the comparison period show little difference. During the comparison period, the experimental class's mean, median, and pass rate showed no significant numerical differences compared to the non-experimental class, corroborating the notion that student quality was comparable. Descriptive statistics for the full samples of both experimental and non-experimental classes reveal that the experimental class's full sample mean (88.35) , median (91), and pass rate (0.93) of the experimental class's full sample were significantly higher than the corresponding values for the non-experimental class's full sample. This provides preliminary validation for the assertion that algorithm-assisted instruction enhances teaching effectiveness in “Fundamentals of Accounting.” The experimental class's mean score and pass rate during the experimental period exceeded those of the comparison period by over 10%, further indicating that algorithm-assisted instruction contributes to improved teaching outcomes.

*Table 1: Results of students' academic performance*

| | | Experimental Class | | | | Non-experimental class | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | The entire sample | 4 | 5 | 6 | The entire sample |
| Experimental period | Mean value | 89.38 | 88.16 | 87.52 | 88.35 | 75.62 | 77.12 | 76.44 | 76.39 |
| | Median | 92 | 91 | 90 | 91 | 78 | 80 | 79 | 79 |
| | SD | 12.54 | 11.09 | 10.22 | 11.28 | 15.22 | 14.37 | 12.41 | 14.01 |
| | Max. | 100 | 100 | 100 | 100 | 100 | 98 | 99 | 100 |
| | Min. | 46 | 41 | 52 | 41 | 34 | 42 | 48 | 34 |
| | Pass rate | 0.94 | 0.91 | 0.93 | 0.93 | 0.83 | 0.82 | 0.85 | 0.83 |
| | Sample size | 100 | 100 | 100 | 300 | 100 | 100 | 100 | 300 |
| Non-experimental period | Mean value | 77.32 | 76.14 | 75.06 | 76.17 | 75.12 | 77.04 | 76.13 | 76.10 |
| | Median | 77 | 77 | 76 | 76.67 | 76 | 77 | 76 | 76.33 |
| | SD | 18.27 | 19.03 | 19.22 | 18.84 | 19.02 | 18.41 | 18.93 | 18.79 |
| | Max. | 98 | 99 | 100 | 99 | 99 | 99 | 99 | 99 |
| | Min. | 23 | 31 | 26 | 23 | 26 | 27 | 24 | 24 |
| | Pass rate | 0.82 | 0.79 | 0.81 | 0.81 | 0.82 | 0.82 | 0.84 | 0.83 |
| | Sample size | 100 | 100 | 100 | 300 | 100 | 100 | 100 | 300 |

### 3.3.2 Correlation Analysis

The hybrid algorithm that has been suggested in this paper can ensure the formative assessment process in the Fundamentals of Accounting course is optimized in a targeted manner using the data-driven precision interventions. In order to determine how this teaching model impacts academic performance, we also explore how formative assessment scores and final grades interact, assuming all other factors are equal. Also, the study identified four dimensions highly correlated with formative assessment, i.e., learning resources scores, attendance scores, chapter test scores, and discussion/Q&A scores, to evaluate their relative contribution to the total grades and the inner workings once they have been affected by the hybrid algorithm. Table 2 shows Pearson correlation test findings. In particular, there is a correlation coefficient (final grades/formative assessment) of 0.201 which is statistically significant at 1 percent. It implies that increased formative assessment scores tend to go hand-in-hand with higher final grades. Besides, the correlation coefficients of study material scores, attendance scores, chapter test scores, and discussion/Q&A scores were 0.235, 0.152, 0.164, and 0.125 respectively, all significant. This means that larger values of each indicator are associated with higher final grades.

*Table 2: Results of pearson correlation test*

| | Grade | Process evaluation | Learning | Check | Test | Discuss |
|---|---|---|---|---|---|---|
| Grade | 1 | | | | | |
| Process evaluation | 0.201 *** | 1 | | | | |
| Learning | 0.235 *** | 0.716 *** | 1 | | | |
| Check | 0.152 ** | 0.694 *** | 0.431 *** | 1 | | |
| Test | 0.164 *** | 0.778 *** | 0.504 *** | 0.422 *** | 1 | |
| Discuss | 0.125 ** | 0.803 *** | 0.487 *** | 0.403 *** | 0.572 *** | 1 |

### 3.3.3 Multiple Regression Analysis

In order to demonstrate more deeply the degree and the statistical significance of the effect of different formative assessment indicators on final learning results in the Fundamentals of Accounting course, the study used a multiple linear regression model. Final student grades were used as the dependent variable, whereas the four most important formative assessment indicators were used as independent variable to build the regression equation. Table 3 summarizes the overall model fit and regression findings per variable. All of the chosen formative assessment indicators explained some 32.2% of the variation in final grades which indicates that the model has explanatory ability. The F-statistic value was 20.048 which is statistically significant at 1 percent level (p less than 0.01) which confirms the overall validity of this regression model.

In terms of the regression coefficients of each variable, the chapter test scores had the highest impact on the final grades, with a regression coefficient of 0.162, which is statistically significant at the 1% level. It means that chapter tests, being direct measures of student knowledge acquisition at certain points in time, have a high positive correlation with final grades and are an important component of the overall learning results. The regression coefficients of study materials scores, attendance scores, and discussion/Q&A scores were 0.072, 0.033, and 0.094 respectively and were all significant at the 5 percent significance level.

As it is stated in the results of the multiple regression analysis, both chapter tests and discussion/Q&A sessions are found to be significant positively influential measures of the formative assessment system of the “Fundamentals of Accounting" course and contribute to the final learning outcomes, and chapter tests scores are the most effective ones. This result is consistent with the efficiency of the hybrid algorithm to correctly determine the important indicators of assessment and optimize dynamically the teaching material and the methods of assessment.

*Table 3: Regression results*

| Variable | Model | VIF |
|---|---|---|
| Intercept | 28.497*** | - |
| Learning | 0.072** | 1.635 |
| Check | 0.033** | 1.331 |
| Test | 0.162*** | 1.524 |
| Discuss | 0.094** | 1.973 |
| Adj-$R^2$ | 0.322 | - |
| F | 20.048*** | - |

# 4 Conclusion

This paper explores optimization pathways for the teaching content and curriculum system of "Fundamentals of Accounting" based on a hybrid algorithm. Teaching practice results indicate that the mean (88.35), median (91), and pass rate (0.93) of the entire sample in the experimental class were significantly higher than the corresponding metrics of the entire sample in the non-experimental class. The correlation coefficient between learning achievement and formative assessment was 0.201, significant at the 1% statistical level. Chapter test scores exerted the most significant influence on final grades, with a regression coefficient of 0.162, significant at the 1% level. The regression coefficients for learning materials scores, attendance scores, and discussion/Q&A scores were 0.072, 0.033, and 0.094, respectively, all significant at the 5% significance level. Hybrid algorithm greatly contributes to the efficiency of lessons in the course of Fundamentals of Accounting as it helps to determine the areas of weakness in students with high accuracy and to modify the content of instruction and evaluation approaches dynamically.

# Funding

Fund Project: Research on Optimization of the Teaching Content and Curriculum System for Basic Accounting from the Knowledge Graph Perspective (2024 School level Teaching and Research Reform Project).

# About the Author

Shan Zhihong, (1978-10) female, Han Chinese, Hengyang, Hunan Province, master's degree, associate professor, research direction is extensive in digital-intelligen accounting, accounting theories and practices.

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