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iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 18 No. 16 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijet.v18i16.42701

PAPER

A Model to Predict and Analyze Students' Learning Preferences and their Cognitive Development through Educational Big Data

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ABSTRACT

Underpinned by the accelerated progression of information technology, the role of educational big data in information gathering and analysis has been underscored, particularly so in finance, a discipline embedded in logic and analysis. Patterns in student learning and behavioral data, when examined, can afford educators invaluable insights to shape efficacious teaching strategies. Contemporary research probing into the dynamics of student learning preference evolution and cognitive advancement appears to over-depend on static data, often falling short of effectively addressing the intricate data structures in educational big data. In this light, it becomes imperative to delve into the temporal shifts in student learning preferences and their link to cognitive advancement. In this context, a novel dynamic trust-aware preference evolution model is brought to the fore, with the potential to precisely track variations in learning preferences of finance students and elucidate their correlation with cognitive advancement. A correlation model is erected, laying bare the reciprocal interaction between the metamorphosis of student learning preferences and cognitive progression. This pioneering approach eclipses the constraints inherent in extant research methodologies, rendering deeper comprehension to educators. Findings from regression analysis divulge the association between the transformative journey of learning preferences and cognitive advancement, holding far-reaching implications for educational practices. These revelations can capacitate educators to fine-tune their teaching approaches in line with student development, fostering personalized learning ecosystems. This research further holds significant merits for addressing complexities within finance education, aiding in the cultivation of adept professionals capable of navigating the fluid landscape of modern finance.

KEYWORDS

educational big data, cognitive progression, student learning preferences, learning preference evolution, association analysis

Li, M. (2023). A Model to Predict and Analyze Students' Learning Preferences and their Cognitive Development through Educational Big Data. *International Journal of Emerging Technologies in Learning (iJET)*, 18(16), pp. 182–197. https://doi.org/10.3991/ijet.v18i16.42701

Article submitted 2023-05-29. Resubmitted 2023-06-30. Final acceptance 2023-07-02. Final version published as submitted by the authors.

1 INTRODUCTION

The rapid advancement of information technology has led to an increasing prevalence of big data collection and analysis in the education field. This big data encompasses various aspects of students' performance, behavior, and interactions, providing educators and researchers with opportunities for a deeper understanding of the learning process [1, 2]. In recent years, big data in education has been recognized as an indispensable component for both educational research and practice [3–5]. Of particular interest is its application in finance, a field rooted in logic and analysis. By examining data on students' learning patterns and behavior, it is possible to more accurately identify students' needs and develop targeted teaching strategies [6–9].

However, the utilization of big data in education extends beyond conventional data analysis and monitoring of student performance [10–13]. Recent research has begun to focus on the progression of thought based on big data and the evolution of student learning preferences [14, 15]. For instance, in finance, where students are required to possess high levels of analytical and critical thinking abilities, researchers have started to observe how students' learning preferences evolve over time and attempt to identify potential correlations between these changes and students' progression of thought. A student learning financial analysis might gradually transition from a preference for memory-based learning to a deeper learning approach that emphasizes understanding and applying concepts.

Nonetheless, current research methods exhibit significant limitations in capturing and analyzing the relationship between the evolution of student learning preferences and the progression of thought [16–20]. On one hand, many methods are overly reliant on static data, neglecting the dynamic nature of student learning preferences. On the other hand, existing analytical tools and methods often fail to effectively handle the complex data structures and patterns in educational big data, a serious drawback in educational research in finance. Consequently, there is a need to develop new methods to more accurately capture the correlation between the evolution of student learning preferences and the progression of thought.

This study aims to construct a model for the evolution of student learning preferences and develop a correlation model, using the field of finance as an example to investigate how student learning preferences evolve over time. In addition, the complex relationships between these evolutions and cognitive advancement are analyzed. A dynamic trust-aware preference evolution model is proposed to more effectively understand and capture these dynamic processes. This model can not only accurately reveal changes in student learning preferences but also explore their intrinsic relationship with cognitive advancement.

2 CONSTRUCTION OF STUDENT LEARNING PREFERENCE EVOLUTION MODEL

The construction of the Student Learning Preference Evolution Model is a significant focus of this research. Traditional Bounded Confidence Models (BCM) generally assume, when dealing with the evolution of student preferences, that students unconditionally accept and entirely trust the preferences expressed by their peers during interactions. However, this assumption does not align with reality, as student acceptance and trust levels fluctuate in real-world scenarios. The proposed dynamic trust-aware preference evolution model is introduced to optimize shortcomings in the application of BCM to student preference evolution studies. The model takes into full consideration varying degrees of conservatism often present in students, as well as a certain level of adherence to their preferences. This implies that the model can more accurately reflect individual differences and choices among students when accepting new information or preferences. The model also considers that students' trust levels for other teachers or students are limited and may display varying degrees of trust for different individuals. This added dimension of trust enables the model to more accurately simulate the real behavior of students during interactions with others.

In reality, the level of communication and acceptance among students is influenced by various factors rather than a single standard. Each student's background, interests, learning methods, and experiences are unique, meaning their willingness to communicate and accept different preferences varies as well. By introducing a heterogeneous bounded confidence threshold, the model can more accurately simulate real-world student interactions, rather than simplifying them to a single standard. Viewing the bounded confidence threshold as heterogeneous allows the model to capture more complex interaction dynamics among students. This approach enhances the model's predictive accuracy of student learning preference evolution as it takes into account various factors rather than just a fixed threshold.

An important individual difference among students is their varying degrees of conservatism. Considering this difference can help more accurately capture the evolution of student learning preferences as it emphasizes each student's unique behavior and inclination when accepting new information or preferences. In reality, student learning preferences do not dramatically change due to a single interaction but gradually evolve through a series of interactions. By describing students' adherence levels to their preferences, the model can more realistically simulate the gradual evolution process of student preferences.

Student conservatism varies over time and across different interaction scenarios. By introducing dynamic heterogeneity in conservatism and constructing equations to dynamically update conservatism, the model can better replicate real-world student behaviors, i.e., more accurately portray changes in student preferences when facing different interaction partners and over time.

It is assumed that a set of bounded confidence thresholds corresponding to a student is represented by the vector $\gamma = \{\gamma_1, \gamma_2, \gamma_3, \ldots, \gamma_b\}$, satisfying $\gamma \in 0{,}1(1 \leq u \leq l)$. A set of dynamic heterogeneity conservatism at moment y for a student is represented by the vector $Sv(y) = \{Sv_1(y), Sv_2(y), Sv_3(y), \ldots, Sv_b(y)\}$. The conservatism of student S_u at moment y is represented by $Sv_u(y) \in [0,1]$. Conservatism $Sv_u(y)$ is proportional to time y, and the measurement formula is given as follows:

$$Sv_u(y+1) = \left(1 - \frac{1}{1 + PA_u y}\right) Sv_u(0) \tag{1}$$

In the aforementioned formulation, a parameter $PA_u \in (0, m]$ is set to control the speed at which a student's learning conservatism value increases. The faster the conservatism increases, the higher the PA_u value. Initial conservatism values for each student are given as parameters in $Sv(0) = \{Sv_1(0), Sv_2(0), Sv_3(0), \ldots, Sv_b(0)\}$.

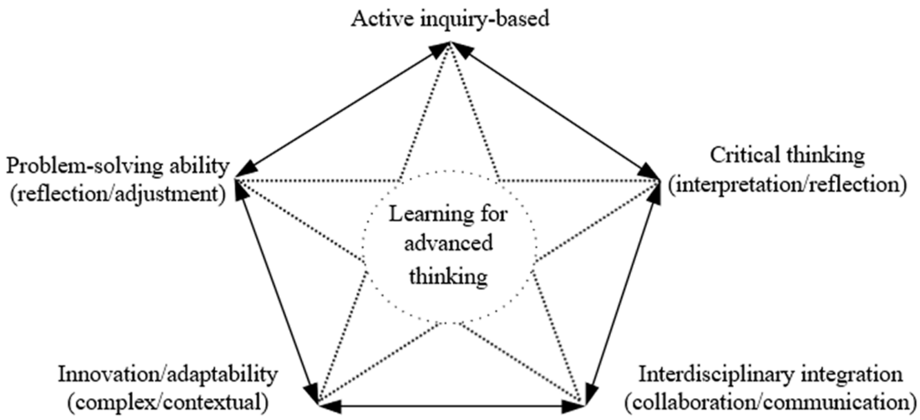

Fig. 1. Learning characteristics oriented towards cognitive advancement

In real life, the degree of a student's need for cognitive advancement to some extent determines the trust in teachers, which significantly influences their learning preferences. Figure 1 illustrates the learning characteristics oriented towards cognitive advancement. When the trust between students and teachers is high, the student's learning preferences are greatly influenced by the teacher. Conversely, they are less influenced by the other's preferences. The current study proposes that the difference in learning preferences of a student at the current time is the primary factor influencing the trust between the student and the teacher at the next moment. The difference in actual learning preferences of student S_u and the estimated preferences of S_k is represented by $f_{uk}(y)$, and the following equation provides its formulation:

$$f_{uk}(y) = \left| z_u(y) - d_{uk}(y) \right| \tag{2}$$

The construction formula for the trust degree $s_{uk}(y+1)$ is given in the following equation:

$$\alpha_{ij}(t+1) = \begin{cases} \beta_{uk}(y) - \beta_{uk}(y)(f_{uk}(y) - CR_{uk}(1-\gamma_u))^{os}, f_{uk}(y) > CR_{uk}(1-\gamma_u) \\ \beta_{uk}(y), (1-\gamma_u)\gamma_{uk} \le f_{uk}(y) \le CR_{uk}(1-\gamma_u) \\ \beta_{uk}(y) + (1-\beta_{uk}(y))((1-CR_{uk})\gamma_{uk} - f_{uk}(y))^{os}, f_{uk} \le (1-CR_{uk})\gamma_{uk} \end{cases} \tag{3}$$

To adjust the speed at which S_u trust in S_k changes, a parameter $os \in (1,+\infty)$ is set in the above formula. The rate of change in trust between the student and teacher is inversely proportional to os. The critical value parameter is represented by the matrix CR, with the critical value parameter for calculating the trust between student S_u and teacher S_k represented by $CR_{uk} \in [0,1]$. If S_u bounded confidence threshold is represented by γ_u, then the combination of CR_{uk} and γ_u can serve as the critical condition value for changes in trust between the student and teacher. That is, when $f_{uk}(y) > CR_{uk}(1-\gamma_u)$, $s_{uk}(y+1)$ decreases, and the rate of change is directly proportional to $f_{uk}(y) - CR_{uk}(1-\gamma_u)$. When $f_{uk}(y) < (1-CR_{uk})\gamma_u$, $s_{uk}(y+1)$ remains unchanged, which aligns with the tolerance observed in the interactions between students and teachers. Differences in student learning preferences within this tolerance do not cause fluctuations in trust between the student and teacher.

In the constructed model of student learning preference evolution, the students are represented by the vector $S = \{S_1, S_2, \ldots, S_B\}$, discrete time is represented by y, and the preference values of each student at time y are represented by $z(y) = (z_1(y), z_2(y), \ldots, z_b(y))$, where the preference of student S_u at time y is represented by $z_u(y) \in [0, 1]$. Let $U(S_u, Z(y)) = \{S_k \| x_u(y) - d_{uk}(y)| \le \gamma_{uk}(y)\}$ represent all students with a preference difference less than the bounded confidence threshold between time y and the next. The following evolution formulas are provided for the real student learning preference, student-teacher communication preference, public student preference, and future estimated student learning preference when there is dynamic trust perception between students and teachers.

(1) Evolution equation of real student learning preference

It is postulated that the real learning preference of student S_u at moment y is represented by $z_u(y) \in [0,1]$, and that only S_u is aware of the existence of $z_u(y)$. S_u conservatism at time y is denoted by $Sv_u(y)$, and the total preference of teachers who interact with S_u at time y is represented by $OTz_u(y)$. The evolution formula for $z_u(y + 1)$ is given as follows:

$$z_u(y+1) = Sv_u(y)z_u(y) + (1 - Sv_u(y))OTz_u(y) \tag{4}$$

Furthermore, it is assumed that the trust level of student S_u in teacher S_k at time y is represented by $s_{uk}(y)$, and that the estimated preference of student S_u for teacher S_k at time y is represented by $d_{uk}(y)$. All students for whom the preference difference with S_u at time y is less than the bounded confidence threshold γ are represented by $U(S_u,Z(y))$, and the number of teachers in $U(S_u,Z(y))$ is represented by $\#U(S_u,Z(y))$. The calculation formula for $OTz_u(y)$ is provided as follows:

$$OTz_u(y) = \begin{cases} \displaystyle\sum_{k=1,S_k \in U(S_u,Z(y))}^{B} \frac{\beta_{uk}(y)}{\displaystyle\sum_{k=1,S_k \in U(S_u,Z(y))}^{B} \beta_{uk}(y)} d_{uk}(y), \#U(S_u,Z(y)) \neq 0 \\ z_u(y), \#U(S_u,Z(y)) = 0 \end{cases} \tag{5}$$

As can be inferred from the above, the weight of $d_{uk}(y)$ in $OTz_u(y)$ is directly proportional to $s_{uk}(y)$; the greater $s_{uk}(y)$ is, the larger the weight of $d_{uk}(y)$. This suggests that student S_u is more inclined to accept the influence of teacher S_k on their preference expression.

(2) Evolution equation of student-teacher communication preference

The communication preference expressed by student S_u to teacher S_k at time y is represented by $x_{uk}(y) \in [0,1]$, where $u,k = 1, 2, \ldots, B$ and $u \neq k$. It is also assumed that only S_u and S_k are aware of $s_{uk}(y)$. If the trust of student S_u in teacher S_k at time y is represented by $s_{uk}(y)$, and all students for whom the difference in preference with teacher S_u at time y meets the threshold requirement γ_u are represented by $(S_u,Z(y))$, the evolution formula for $x_{uk}(y + m)$ is given as follows:

$$x_{uk}(y+1) = \begin{cases} \beta_{uk}(y)z_u(y) + (1 - \beta_{uk}(y))x_{uk}(y), S_k \in U(S_u,Z(y)) \\ \dfrac{z_u(y+1)}{z_u(y)} x_{uk}(y) \end{cases}, u \neq k \tag{6}$$

(3) Evolution equation of public student preference

If the communication preference of student S_u for teacher S_k at time $y + 1$ is represented by $x_{uk}(y + 1)$, then the evolution formula for public student preference $t_u(y + 1)$ is provided as follows:

$$t_u(y+1) = \frac{1}{B-1} \sum_{k=1,k \neq u}^{B} x_{uk}(t+1) \tag{7}$$

(4) Evolution equation of estimated future student learning preference

Assuming that the dynamic trust of student S_u in teacher S_k at time y+1 is represented by $s_{uk}(y+1)$, and that the communication preference of student S_u for teacher S_k at time y+1 is represented by $x_{uk}(y+1)$, and that the public preference of student S_u at time y+1 is represented by $t_k(y+1)$, then the evolution formula for the estimated future student learning preference $d_{uk}(y+1)$ is given as follows:

$$d_{uk}\left(y+1\right) = \beta_{uk}(y+1)x_{ku}(y+1) + (1-\beta_{uk}(y+1))t_k(y+1), u, k = 1,2,3\ldots B, u \neq k \quad (8)$$

3 MODEL CONSTRUCTION FOR THE ASSOCIATION BETWEEN COGNITIVE DEVELOPMENT AND EVOLUTION OF STUDENT LEARNING PREFERENCES

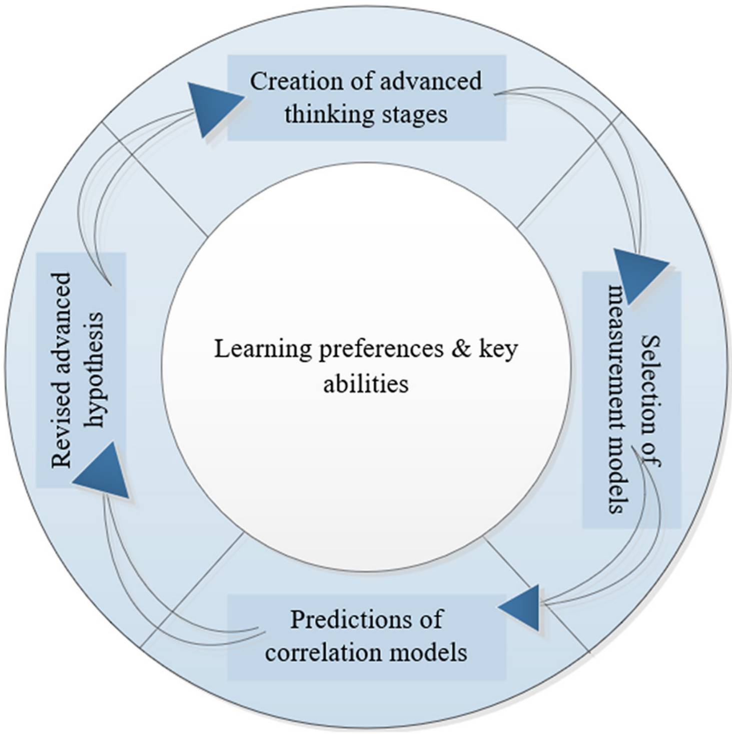

Fig. 2. The cycle of research on the association between cognitive development and the evolution of student learning preferences

In the research of the association between cognitive development and the evolution of student learning preferences, based on educational big data, constructing a regression model is of paramount importance. A regression model is not only capable of revealing the relationships between variables, but it can also quantify the intensity of these relationships. It aids researchers in identifying the correlation between educational variables (such as teaching methods, learning resources, student participation, etc.) and students' learning preferences as well as cognitive development. This is crucial for understanding the factors that influence the student learning process. Moreover, the regression model, by processing multidimensional and highly complex data in the environment of educational big data, enables predictions about how students' learning preferences and cognitive development may vary under specific educational environments or conditions. Figure 2 illustrates the cycle of research on the association between cognitive development and the evolution of student learning preferences.

The purpose of constructing a regression model is to test the association between cognitive development and the evolution of student learning preferences, based on educational big data. This model has the following characteristics:

(1) Dependent Variable: Student learning preferences. This is the primary outcome of interest in this study, and the model aims to analyze how other variables affect student learning preferences.

(2) Independent Variables: The model includes two independent variables directly related to cognitive development. These are the variables that the study aims to examine in terms of their impact on student learning preferences.
- Innovative Thinking Score (LE): Quantifies the student's ability to use new methods or ways of thinking when solving problems.
- Critical Thinking Score (BA): Quantifies the student's ability to analyze and evaluate information to form judgments.

(3) Control Variables: The model also contains 11 control variables. Control variables are those that might also impact student learning preferences, but are not the primary focus of our study. Including these variables helps to eliminate interference from other potential factors, allowing for a clearer view of the impact of the independent variables on the dependent variable. These control variables include:
- Teacher-Student Trust Level (PL): Quantifies the student's trust level for a specific teacher.
- Conservatism (CO): Measures the student's degree of adherence to their current learning preferences.
- Bounded Confidence Threshold (YSYP): In a bounded confidence model, this measures the threshold of a student's acceptance of other students' preferences.
- Teaching Method of the Teacher (DI): Such as teaching style, textbooks used, and teaching strategies.
- Feedback and Evaluation Method of the Teacher (SI): Such as homework evaluation, tests, etc. The feedback from the teacher may influence the student's learning preferences.
- Course Content (DU): Emphasizes whether the course encourages students to develop innovative and critical thinking.
- Student Participation (OW): The level of student engagement in class discussions and activities.
- Student Motivation (YE): The intrinsic or extrinsic motivation of the student to learn.
- Learning Resources (IN): Such as learning materials provided by the teacher, library resources, etc.
- Classroom Environment (GE): Includes class size, interactions among students, etc.
- Course Difficulty (VD): The difficulty of the learning materials and the course can affect the student's learning preferences.

To validate Hypothesis 1, which posits a positive correlation between innovative thinking ability and students' learning preferences, the following model (1) is constructed to reflect this association:

$$PE = \alpha_0 + \alpha_1 PL + \alpha_2 CO + \alpha_3 BA + \alpha_4 DI + \alpha_5 SI + \alpha_6 DU + \alpha_7 OW + \sum_{u=8}^{12} \alpha_u YE_u + \sum_{k=13}^{38} \alpha_k IN_K + \sigma \tag{9}$$

To validate Hypothesis 2, which proposes a positive correlation between critical thinking ability and students' learning preferences, the following model (2) is established to reflect this relationship:

$$\begin{aligned} PE = \alpha_0 + \alpha_1 OW + \alpha_2 GR + \alpha_3 VD + \alpha_4 LE + \alpha_5 YSYP \\ + \alpha_6 DI + \sum_{u=7}^{11} \alpha_u YE_u + \sum_{k=12}^{37} \alpha_k IN_k + \sigma \end{aligned} \tag{10}$$

To validate Hypothesis 3, suggesting that both innovative thinking ability and critical thinking ability jointly exert a positive influence on students' learning preferences, the following model (3) is created:

$$\begin{aligned} PE = \alpha_0 + \alpha_1 PL + \alpha_2 CO + \alpha_3 BA + \alpha_4 DI + \alpha_5 SI + \alpha_6 DU \\ + \sum_{u=7}^{11} \alpha_u YE_u + \sum_{k=12}^{37} \alpha_k IN_k + \sigma \end{aligned} \tag{11}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1 presents a comparative analysis of performance metrics across four distinct models: the Markov Decision Process, the Mixed-Utility Model, the Agent-Based Simulation Model, and the Model developed in this study. These performance metrics comprise the Minimal Preference Deviation and the Evolution Steps (measured in step numbers).

The Minimal Preference Deviation metric represents the difference between the predicted and actual learning preferences, with a smaller value suggesting a closer alignment with the actual scenario. The Evolution Steps metric denotes the number of steps required for the model to reach a steady state, with fewer steps indicating a more rapid stabilization.

Table 1. Comparison of performance metrics for different models

Data Item	Minimum Preference Difference			
	Markov Decision Process	Mixed Utility Model	Agent-Based Simulation Model	The Model in this Study
1	0.341	0.365	0.398	0.289
2	0.367	0.321	0.376	0.278
3	0.467	0.312	0.423	0.298
4	0.388	0.352	0.362	0.299
5	0.391	0.582	0.341	0.269
6	0.411	0.329	0.421	0.301
7	0.321	0.243	0.324	0.291
8	0.323	0.254	0.355	0.283
9	0.354	0.327	0.372	0.279
10	0.376	0.347	0.345	0.268

(Continued)

Table 1. Comparison of performance metrics for different models *(Continued)*

Data Item	Evolution Steps (Unit: Number of Steps)			
	Markov Decision Process	Mixed Utility Model	Agent-Based Simulation Model	The Model in this Study
1	6	149	8	639
2	2	148	11	119
3	4	141	91	120
4	2	144	198	458
5	6	127	10	157
6	4	121	12	288
7	2	129	13	149
8	8	149	8	95
9	8	130	9	181
10	3	121	19	118

From the data in the table, it can be inferred that the Model developed in this study generally exhibits lower values for Minimal Preference Deviation, suggesting a higher degree of precision in predicting learning preferences compared to the other models. In terms of Evolution Steps, the developed model appears to accommodate a greater evolution of student preferences.

As per the analysis of Figure 3, significant insights can be drawn from the changing curve. The model proposed in this research surpasses Markov decision processes, hybrid utility models, and Agent-based simulation models when the bounded confidence is greater than 0.22. This superiority indicates a more precise or detailed simulation of the evolution of student preferences. The evolution steps of this model peak when the bounded confidence is approximately 0.05, and then gradually decrease, nearing the level of 30. This might suggest that increasing bounded confidence within a certain range could make the model more sensitive or detailed, but an excessively high bounded confidence might slow down the model's convergence speed. In comparison to the other three models, this model exhibits a higher number of evolution steps in most circumstances, which might indicate the capture of more details during the simulation, thereby being more reflective of actual scenarios. Overall, this model has superior performance in simulating the evolution of student preferences. This advantage could potentially be attributed to the consideration of heterogeneity in bounded confidence thresholds in this model. By allowing each individual to use different bounded confidence thresholds, this model is capable of capturing more individual differences and complexities. On the contrary, in the other three models used for comparison, all individuals employ the same bounded confidence threshold, possibly leading to the loss of certain details during the simulation. Thus, the introduction of more complex bounded confidence thresholds in this model enables a more accurate simulation of the evolution of student preferences, even if it might be at the expense of the convergence speed.

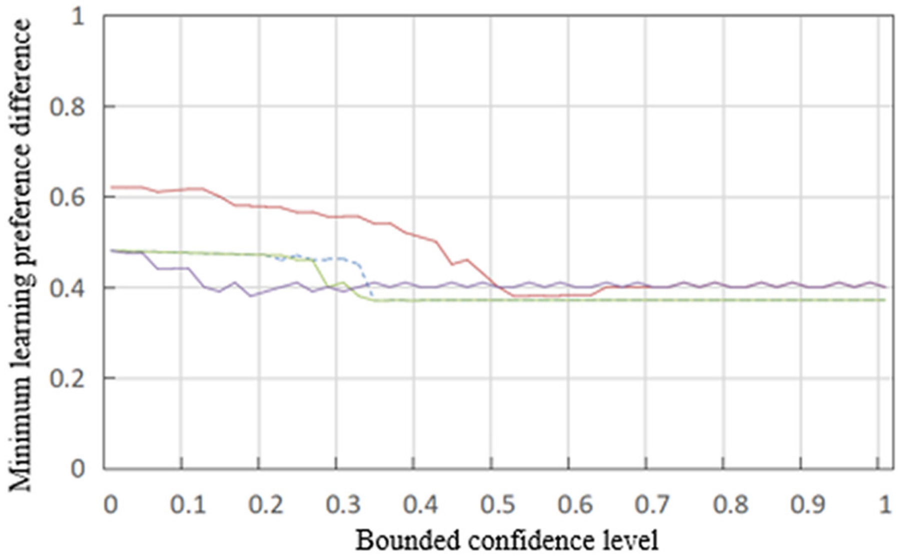

Fig. 3. The impact of the bounded confidence threshold on the minimal preference deviation

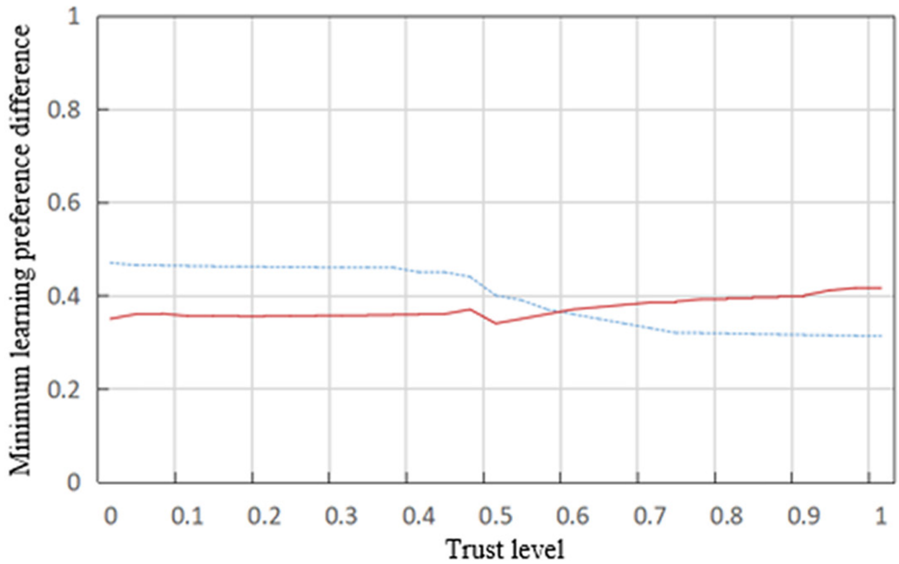

Fig. 4. Impact of trust level on minimum preference difference

Turning attention to Figure 4, the impact of trust on the minimum preference difference is evaluated. The proposed model, in accordance with increasing trust values, displays a slight decrease initially followed by a slight increase, but the overall change is minuscule. This demonstrates the good stability of this model under various trust values. The model's minimum preference difference is generally lower than that of the Agent-based simulation model, indicating the model's superiority in terms of accuracy. Although both models use matrices reflecting heterogeneity to represent trust, the model proposed here has more parameters and a more complex formula. This might enable this model to capture more details and complexities, thereby improving accuracy. However, the potential of this model might not be fully exploited simply by adjusting trust, which explains why the influence of trust changes on this model is relatively small. Therefore, it can be concluded that this model surpasses the Agent-based simulation model in terms of accuracy. This advantage may stem from the more parameters and more complex formulas in this model, enabling it to better capture the details and complexity of the data. Although the adjustment of trust has limited impact on this model, it still exhibits high accuracy under consistent data structure.

Based on Figure 5, the following analytical results and conclusions can be derived from the change curve. As dynamic conservatism increases, the minimum preference difference in the model under study ascends at an extremely slow pace. However, the overall change is very minimal, indicating a high level of stability (minimum preference difference) in the model when dynamic conservatism changes. The minute variation in the minimum preference difference in the model as dynamic conservatism changes suggests that dynamic conservatism has a negligible impact on the model's accuracy. This could indicate a higher sensitivity of the model to other factors, or the model's design may have already taken into account the changes in dynamic conservatism, making the appropriate optimizations. Therefore, the conclusion is that the model under study exhibits high stability when dynamic conservatism changes, and its accuracy (minimum preference difference) is not greatly affected by dynamic conservatism. Such stability could be due to the model's design considering changes in dynamic conservatism and maintaining a higher accuracy under different levels of dynamic conservatism through parameter adjustments or algorithm optimization. This also suggests that the model under study has robustness when dealing with changing environments or factors.

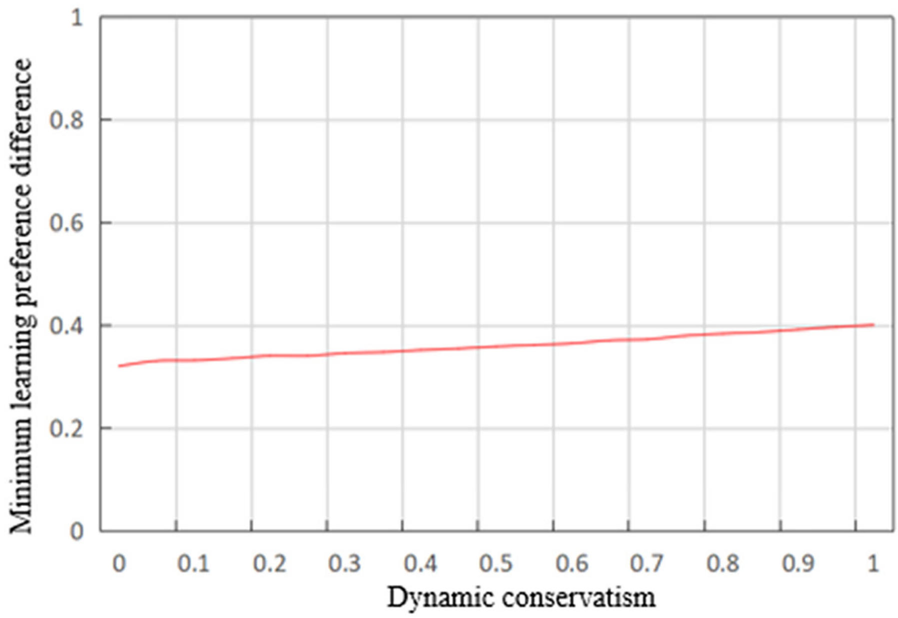

Fig. 5. Influence of dynamic conservatism on minimum preference difference

Table 2 displays the results of correlation tests of core control variables. The significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively.

Table 2. Correlation test results of core control variables

	Teacher-Student Trust Level	Conservatism	Bounded Confidence Threshold	Teacher's Teaching Methods	Teacher's Feedback And Assessment Methods	Course Content	Student Engagement
Teacher-Student Trust Level	1						
Conservatism	0.881***	1					
Bounded Confidence Threshold	0.636***	0.569***	1				
Teacher's Teaching Methods	–0.069***	–0.047**	–0.099***	1			
Teacher's Feedback and Assessment Methods	0.086***	0.072**	0.093***	–0.071***	1		
Course Content	–0.052*	–0.074***	–0.047**	0.28	0.135***	1	
Student Engagement	0.214***	0.212***	0.205***	–0.271***	–0.088***	–0.060	1

The table shows the relationships among several core control variables previously discussed. It's evident that teacher-student trust is positively correlated with conservatism and very significant (0.881***), indicating that when students' trust in teachers increases, their conservatism often increases as well. This could be due to students being more likely to stick to their learning preferences when they trust their teachers. Teacher-student trust is also positively correlated with bounded confidence threshold, and very significant (0.636***), implying that students with higher trust levels are more likely to accept the influence of teachers and classmates, but with certain limits. Conservatism and bounded confidence threshold show a significant positive correlation (0.569***), suggesting that while maintaining their preferences, students may also accept other influences to some degree. The teacher's teaching methods show a negative correlation with other variables, but the correlation is weak, suggesting that the changes in teaching methods may not directly relate to students' trust and conservatism. The teacher's feedback and evaluation methods show a weak positive correlation with teacher-student trust and the bounded confidence threshold, and a weak negative correlation with the teacher's teaching methods. This indicates that feedback and evaluation methods may have some impact on students' trust and acceptance. The course content shows a positive correlation with the teacher's teaching methods, but a weak negative correlation with teacher-student trust and conservatism, suggesting that course content might be more closely related to teaching methods. Student engagement shows a positive correlation with teacher-student trust, conservatism, and the bounded confidence threshold, but a negative correlation with the teacher's teaching methods and the teacher's feedback and evaluation methods. This might indicate that students' active participation is related to their trust in the teacher and their conservatism, but it might be inconsistent with the teacher's teaching methods and feedback methods.

Table 3. Regression results

Control Variables	Student Learning Preferences
Conservatism	3.587**
	(1.637)
Bounded confidence threshold	2.132*
	(1.213)
Teacher's teaching methods	–32.98***
	(9.637)
Teacher's feedback and assessment methods	0.231***
	(0.0377)
Course content	–4.879***
	(1.049)
Student engagement	–11.32***
	(2.764)
Student's learning motivation	27.93***
	(5.548)
Learning resources	2.158
Classroom environment excellence	*YES*
Course difficulty appropriateness	*YES*

Table 3 presents the regression results of several core control variables on students' learning preferences. The significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively. The table shows that the regression coefficient of conservatism is 3.587, and its significance is **, indicating that conservatism is positively correlated with students' learning preferences and the correlation is significant. As students become more insistent on their learning preferences, their learning preference scores are often higher. The regression coefficient of the bounded confidence threshold is 2.132, with significance at *, implying that the bounded confidence threshold is positively correlated with students' learning preferences, but the correlation is weaker. This could mean that students may accept other influences to some degree, which might increase their learning preference scores. The regression coefficient of the teacher's teaching methods is –32.98, and the significance is ***, showing that the teacher's teaching methods are significantly negatively correlated with students' learning preferences. This might be due to certain teaching methods not aligning with students' learning preferences. The regression coefficient of the teacher's feedback and evaluation methods is 0.231, and the significance is ***, indicating a weak positive correlation between the teacher's feedback and evaluation methods and students' learning preferences. The regression coefficient of the course content is –4.879, and the significance is **, suggesting a negative correlation between course content and students' learning preferences, possibly because the course content does not align with students' interests or preferences. The regression coefficient of student participation is –11.32, and the significance is ***, implying a significant negative correlation between student participation and learning preferences. This could be due to excessive participation having a negative impact on learning preferences. The regression coefficient of students' learning motivation is 27.93, and the significance is **, indicating a significant positive correlation between students' learning motivation and learning preferences. Students with higher learning motivation often have higher learning preference scores. The regression coefficient of learning resources is 2.158, with no significance indication. This might suggest that the relationship between learning resources and students' learning preferences is not clear.

5 CONCLUSION

This study focuses on constructing a student learning preference evolution model and an associated model, using finance education as an example to explore in-depth how students' learning preferences evolve over time and analyze the complex relationship between these changes and cognitive advancement. Based on the experimental results, the following summary conclusions can be drawn:

(1) From the perspective of minimum preference difference, the model presented in this study typically performs better than Markov decision processes, mixed utility models, and agent-based simulation models. This indicates that it is more accurate in predicting the evolution of student learning preferences.
(2) Regarding the influence of bounded confidence, the evolution step count of the proposed model is higher than the other three comparison models when the bounded confidence is greater than 0.22. This is because the model adopts a heterogeneous bounded confidence threshold, increasing the model's complexity while enhancing its precision to a certain extent.
(3) By considering multiple control variables (such as conservatism, teacher's teaching methods, and course content), a deeper understanding of the factors affecting student learning preferences can be achieved. This provides data support for designing teaching strategies tailored to different student characteristics.
(4) Through the correlation and regression analysis of core control variables, the relationships between different variables and their impact on student learning preferences are understood. For example, the teacher's teaching methods, course content, and student's learning motivation have a significant influence on student learning preferences.
(5) When dynamic conservatism changes, the proposed model demonstrates high stability, and its accuracy is not significantly affected by dynamic conservatism. This indicates that the model has strong robustness in handling changing environments or factors.

In summary, the model presented in this study has high accuracy and stability in predicting and analyzing the evolution of student learning preferences. By considering multiple factors and control variables, it can provide in-depth insights, helping educators develop more effective teaching strategies based on students' different characteristics and preferences.

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