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Construction of a psychological intervention model for artificial intelligence-driven learning motivation enhancement of higher vocational medical students

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SUMMARY: *The rapid development of artificial intelligence has broken the boundaries and modes of education, making the online education model increasingly mature and widely popular. The study is oriented to senior medical students, and the core lies in transforming the massive online learning behavior data into the understanding of students' learning motivation. Faced with numerous behavioral sequences, a Hidden Markov-based Bayesian model L²S is constructed to decipher students' stable learning styles from their click data. And self-determination theory was introduced as a scale to plan students into intrinsic motivation (IMS), extrinsic motivation (EMS), and no apparent motivation (UMS).The L²S model had an average classification accuracy of 78.03% in distinguishing learning styles such as practicing, planning, etc., which was significantly better than the comparative baseline models such as LSTM and KNN. Cluster analysis outlined the portraits of 64 intrinsically motivated students, 89 extrinsically motivated students, and 14 students with no apparent motivation, and IMS excelled in content exploration and video learning, with scores averaging 4.77 and 4.58 on a five-point scale, whereas all dimensions of the UMS were below 2, and the differences in the portraits were extremely sharp. The constructed psychological intervention model reached statistically significant levels of enhancement for all dimensions, both in the group and pre- and post-experiment interaction items, with p-values of <0.05. Its booster effects on intrinsic motivation (F=16.189) and self-efficacy (F=17.977) were particularly strong.*

KEYWORDS: *senior medical students; learning motivation; psychological intervention; Hidden Markov; learning style*

1 Introduction

In recent years, the rapid development of higher vocational education, annual enrollment accounts for “half of China's higher education” [1]. However, with the massive expansion of colleges and universities, the gradual increase in the number of students at the higher vocational level has also led to the uneven levels of students, and many problems have arisen in educational and teaching activities, which has also brought new challenges to university education and teaching [2, 3]. Among them, the problem of learning motivation is more prominent, which has become a key issue that seriously restricts the development of higher vocational colleges and universities and improves the quality of education and teaching.

As a specific group of university students, the university stage is a critical period for the formation of their outlook on life and values, and is an important stage of life development [4].

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As a future medical talent, “health is dependent on life” is not only the oath of every higher vocational medical school students entering the medical hall, but also the responsibility of every higher vocational medical school students cannot be shirked [5]. Therefore, active and effective learning of medical science, humanities knowledge and medical professional skills is the main focus of the life and activities of students in higher medical schools, and it is their main task during their school years [6, 7]. However, the lack of learning motivation of students in higher vocational medical schools, skipping classes, not listening to lectures, lack of positive initiative in learning, as well as the phenomenon of psychological problems occur from time to time, which will not only result in the lowering of the quality of learning and academic performance of students in higher vocational medical schools, but will also affect their physical and mental health development, and even ultimately affect the development of the entire higher medical vocational education, and affect the cultivation of adapting to the needs of the health care industry and medical science and technology development of the The goal of high-quality talents is realized [8-11].

Artificial intelligence technology has gradually emerged as the core driving force for the development of various industries, and the current research on artificial intelligence mainly discusses its application in the fields of energy, healthcare, and computer science, etc. It is found that the application of artificial intelligence in different industries can effectively improve the efficiency of the industry [12-14]. And the coexistence of opportunities and challenges in the era of artificial intelligence, which makes carrying out artificial intelligence + education, has become an inevitable trend [15]. The lack of new innovative talents is a new challenge facing the education sector, and cultivating intelligent talents with exploration and innovation and practical awareness is an indispensable condition for building an innovative country [16, 17]. This requires us to try to use the most advanced science and technology and teaching strategies in the AI classroom to ignite the intrinsic motivation of students' learning and cultivate a new generation of AI talents who will create the future [18, 19]. Artificial intelligence-driven instructional design, whether in terms of learning awareness, digital learning and innovation, creative thinking, and psychological quality, attaches great importance to the cultivation of students' core literacy, so that the content of the AI module becomes the highlight module of classroom teaching [20-22]. In addition, AI technology provides references and solutions to improve students' learning motivation, and AI drives the transformation of students' learning styles and improves their experimental operation, cooperative inquiry and independent learning abilities [23, 24]. Based on this, it is necessary to carry out the teaching of higher vocational medical students based on artificial intelligence technology, which is expected to solve the dilemmas faced by higher vocational education and stimulate the learning motivation of students.

Starting from a data-driven perspective, the study first analyzes the correlations between learners' multidimensional learning behavior characteristics and multiple types of learning effectiveness. Guided by the learning style theory in educational psychology, a learner's latent learning style model (L^2S) is proposed to characterize learning behaviors and learning state sequences, learning activeness, and learning behavior dynamics through a nonparametric Bayesian model, so as to identify and model the homogeneity of group learning behaviors. Based on this, we turn to collect raw clickstream data from the VLE platform, and through a series of feature engineering, quantify these data into such features as “average days of homework delay”, “learning resources access volatility”, etc., which can express the degree of effort, regularity and The data are quantified into motivational indicators that express students' effort, regularity and procrastination, such as “average days of delay in assignments” and “volatility of access to learning resources”. Finally, the previously identified learning styles were integrated with Self-Determination Theory (SDT). Instead of simply discussing which students belong to which data clusters, clear motivational connotations are assigned to these clusters. The mathematical definitions delineate the types of student motivation as (1) intrinsic motivation that is motivated by interest and self-growth, (2) extrinsic motivation that seeks out certificates and rewards, and (3) unmotivated states where motivation is scarce.

2 Modeling student profiles based on learning behaviors and motivations

2.1 Modeling Learning Styles of Potential Learner Cohorts Based on L²S Modeling

Firstly, the potential learning intentions embedded in the sequence of students' learning behaviors are observed, and in this section, the Hidden Markov Model and its extensions are introduced to model the dynamic dependencies between the sequence of learners' learning behaviors and the implied learning states.

2.1.1 Hidden Markov Models

A Hidden Markov Model (HMM) is used to model the dependencies between a learner's sequence of observed learning behaviors, the corresponding sequence of implicit learning intentions, and their learning intentions. Hidden Markov models are dynamic Bayesian nets with the simplest structure and are a probabilistic model of temporal sequences. The sequence of states randomly generated by a hidden Markov chain is called a sequence of states, and the random sequence of observations generated by generating one observation per state is called a sequence of observations.

A hidden Markov model consists of an initial state probability vector, a state transfer probability matrix, and an observation probability matrix. The study uses polynomial distributions to model the observation probability matrix and the hidden state transfer matrix separately.

Beta distribution is used to model the timestamp information corresponding to each learning behavior contained in the observation probability matrix in the hidden Markov model. It is assumed that different implied learning states are associated with different Beta distributions. For example, if the learning behavior $x_{w,t}^{u}$ corresponds to an implied learning state of $y_{w,t}^{u} = s_i$, then its corresponding timestamp $ts_{w,t}^{u}$ obeys the Beta distribution, i.e:

$$ts_{w,t}^{u} \sim Beta\left(\Omega_1^{s_i}, \Omega_2^{s_i}\right) \tag{1}$$

where $\Omega_1^{s_i}$ and $\Omega_2^{s_i}$ are two parameters of the Beta distribution. Due to the properties of the Beat distribution, we normalize the timestamp $ts_{w,t}^{u}$ corresponding to each learning behavior $x_{w,t}^{u}$ to the $[0,1]$ interval based on the length of the offering period of different courses.

The Poisson distribution is used to model the learning activity of learners. It is assumed that the learning activity of learner u within a weekly w, i.e., the length of the sequence of learning behaviors T_{w}^{u} obeys the Poisson distribution, i.e.:

$$T_{w}^{u} \sim Poisson\left(\mu^{k}\right) \tag{2}$$

2.1.2 Implicit Learning Style Model L²S

This paper presents a model for describing learners' learning behavior and their potential learning intentions in online courses. The model introduces a concept of potential learner clusters, i.e., learners with similar potential learning intentions are assumed to belong to the same potential learner group, and learners belonging to the same group share a set of model parameters. At the learner group level, the set of learners in a course is clustered into different potential learner groups. In particular, in a Hidden Markov Model, its observation probability matrix characterizes the clusters consisting of learning behaviors resulting from the same learning intentions, and the implied learning state transfer probability matrix describes the learners' preferences on how to manifest the different learning intentions in a sequential manner.

The set of potential learner group identifiers is denoted as $c=\{1,\ldots,k,\ldots,K\}$, where $c^u=k$ denotes the membership of the potential learner group to which learner u belongs. In each potential learner cluster k, α^k is a $(N+1)\times N$ matrix of state transfer probabilities, where N is the number of implied states, and β^k is a $N\times M$ matrix of observation probabilities, where M is the number of learning behavior events. It is assumed that the state transfer probability matrix α^k and the observation probability matrix β^k in the Hidden Markov Model obey polynomial distributions. Correspondingly, in the potential learner cohort k, if the implied state $y_{w,t}^u=s_i$, then the timestamp corresponding to the implied state s_i obeys the distribution $ts_{w,t}^u \sim Beta\left(\Omega_1^{k,s_i},\Omega_2^{k,s_i}\right)$, and the learner's learning behavior activity in week w obeys a Poisson distribution, i.e., $T_w^u \sim Poisson\left(\mu^k\right)$.

A cluster of potential learners k is represented by a set of model parameters $\theta^k=\left(\alpha^k,\beta^k,\mu^k,\Omega_1^k,\Omega_2^k\right)$. The probability of observing a sequence of learning behaviors x^u, a sequence of implied learning states y^u, information about the dynamics of learning behaviors ts^u, and behavioral activity T^u of a learner u in a potential learner cohort k is calculated as follows:

$$\begin{aligned} & p\left(x^u,y^u,ts^u,T^u \middle| c^u=k,\theta^{c^u}\right) \\ & = p\left(x^u,y^u \middle| \alpha^k,\beta^k\right) p\left(ts^u \middle| \Omega_1^k,\Omega_2^k\right) \prod_{w=1}^{W} p\left(T_w^u \middle| \mu^k\right) \end{aligned} \tag{3}$$

A corresponding conjugate prior distribution is introduced for each parameter. Assume that the corresponding state transfer probability matrices α^k and observation probability matrices β^k of the observed learned behavior sequence x^u and the implied learned state sequence y^u have a Dirichlet distribution as:

$$\begin{aligned} & \alpha^k \sim Dir(\eta) \\ & \beta^k \sim Dir(\lambda) \end{aligned} \tag{4}$$

where η and λ are parameters of the Dirichlet distribution.

And the parameter μ^k of the Poisson distribution describing the learning behavior activity T^u has a Gamma distribution as its prior distribution, i.e.:

$$\mu^k \sim Gamma(\xi, \varphi) \tag{5}$$

where ξ and φ are two parameters of the Gamma distribution.

For the Beta distribution describing the dynamics of the learning behavior ts^u, we use the exponential distribution as its prior probability since it does not have a conjugate prior distribution:

$$\begin{aligned} \Omega_1^k &\sim Exp(\delta_1) \\ \Omega_2^k &\sim Exp(\delta_2) \end{aligned} \tag{6}$$

where Ω_1^k and Ω_2^k are two parameters of the Beta distribution, and δ_1 and δ_2 are two parameters of the exponential distribution.

The model can express the potential learning intentions of learners and how learners produce corresponding learning behaviors according to different learning intentions. The model is named as the implied learning style model, which is referred to as the L^2S model. Figure 1 demonstrates a concrete representation of the L^2S model.

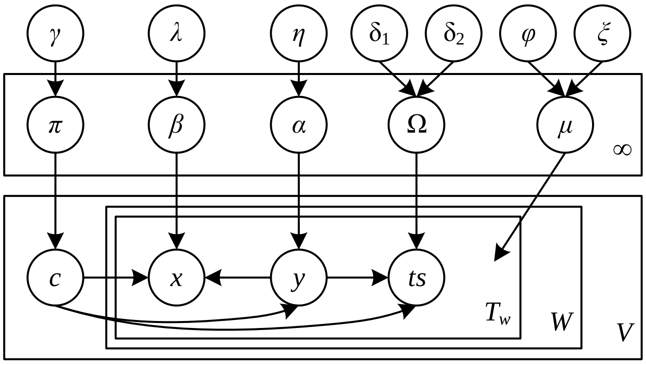

Figure 1: The specific representation of the model L^2S

where x and ts denote observed variables and the remaining circles denote implied random variables. The lower outer box indexed by V denotes the set of learners, the inner box indexed by T_w denotes the sequence of learners' learning behaviors in week w, and the different weeks are denoted by the middle box indexed by W. Where x denotes the sequence of learners' observable learning behaviors, y denotes the sequence of implied learning states, ts denotes the time sequence corresponding to the learning behaviors, and c denotes the identification of the group of potential learners that the learner belongs to. The upper boxes in Figure 1 represent the possible potential learner groups and their corresponding parameters. Where α and β denote the implied state transfer probability matrix and the learning behavior observation probability matrix, respectively, Ω denotes the parameter of the Beta distribution, μ denotes the parameter of the Poisson distribution, and π denotes the Dirichlet distribution that generates the group of potential learners. The top part of Figure 1 represents the parameters of the prior distributions corresponding to the different model parameters in the middle part.

In the L^2S model, the cluster identity c^u is considered as a random variable and its corresponding model parameter θ^k is assumed to come from a Dirichlet process (DP) prior.

A Dirichlet process $DP(G_0,\gamma)$ is a distribution based on the base distribution G_0 and the scaling parameter γ. The L^2S model can automatically classify learners into their appropriate groups of potential learners through a Dirichlet process.

Assuming that the distribution of the population of potential learners in the set of learners of a course obeys a Dirichlet process, the joint probability of learner u's sequence of learning behaviors x^u, sequence of implied learning states y^u, learning activity T^u, and time-domain distribution of learning behaviors ts^u can be described as follows:

$$p\left(x^u, y^u, ts^u, T^u \middle| \gamma, G_0\right) = \sum_{k=1}^{\infty} \pi_k \delta_{\theta k} \tag{7}$$

where the model parameters corresponding to the population of potential learners obey $\theta^k \sim G_0$, G_0 is the base distribution, which describes the generation of θ^k, and $\delta_{\theta k}$ is the distribution that focuses on θ^k and is defined in Eqn. (3), with $\pi_k = \pi'_k \prod_{t=1}^{k-1}\left(1-\pi'_t\right)$, and $\pi'_k \sim Beta\left(a,\gamma\right)$.

2.2 Learning Motivation Modeling Based on Clickstream Data

Having built a L^2S model of learning styles, we now turn to the data level, acquiring clickstream data in a Virtual Learning Environment (VLE) and constructing behavioral metrics that reflect learning motivation through feature engineering.

2.2.1 Analytical Model of Learning Motivation

The construction process of the data-driven learning motivation analysis model mainly includes three main processes: online learning data acquisition, data processing and learning motivation analysis. Its specific process is shown in Figure 2. First acquire the clickstream data, and then extract the features related to learning motivation. Conduct feature transformation and construct the feature vectors needed for subsequent analysis. After constructing the feature data, cluster analysis and statistical analysis are performed on them. Descriptive statistics are used to describe the potential relationship between learning behaviors and different learning. The constructed features are used to further analyze the motivation of different student groups using the deep clustering model proposed in this paper.

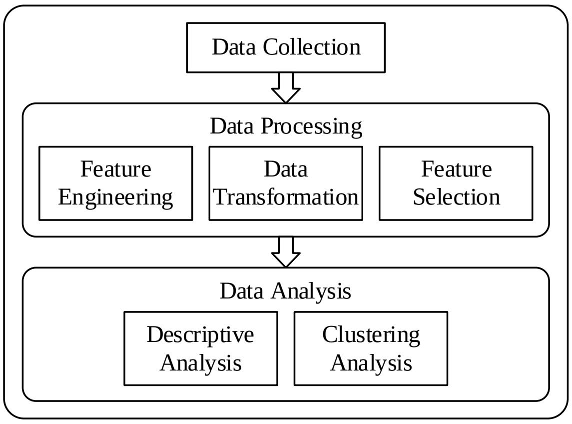

Figure 2: General flow chart

The dataset used in this research is sourced from the "Xuexitong" teaching platform, which includes content and materials related to the course. This platform has collected some demographic information of the students and the clickstream interaction data recorded on the online learning platform. Currently, there are approximately 20,000 students on this platform studying different courses. Data regarding course materials and other contents (such as exercises) will be provided to the students through this platform. The interactions between users and the course materials or other users on the platform will be recorded and stored in the university's data warehouse.

Figure 3 depicts the typical structure of a course representation, and as can be seen from the figure, the length of each course is typically 4 months. In the first few weeks before the course starts, the online learning service of the platform is first turned on by the backend administrator of the learning platform, and the relevant course resources are uploaded to the online education platform. Students can enroll a few weeks before the start of the course, and the relevant online users can then choose a certain number of courses to register and log in according to their own preferences until enrollment closes two weeks after the start of the official course. Students can no longer register and course work begins. The inclusion of several in-class quizzes in the middle of a regular course flow can be used as an indicator to evaluate the user's mastery of the course. After the final exam is taken, the course is closed.

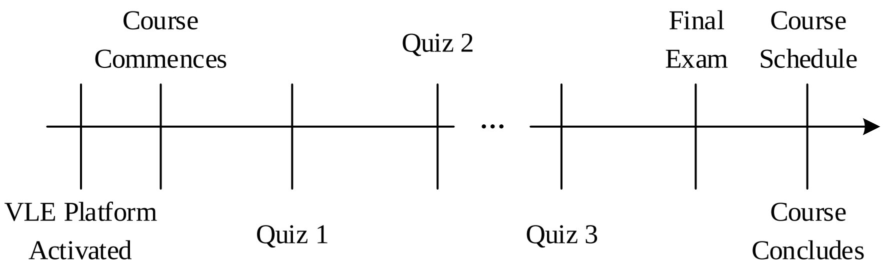

Figure 3: Architectural graph of a module

2.2.2 Modeling and Analysis of Learning Motivation Data

The study was conducted by extracting medical related courses from the VLE for senior students. The courses lasted for about 16 weeks. All the study resources for the course were released a few days before the start of the course. There were 26 accompanying assignments in the course as well as a midterm and a final exam. Students' final grades are measured based on their combined performance on the accompanying assignments and exams. In general, final grades can be a good indicator of a student's motivation to learn, but for enrollees who did not pass the course or dropped out of the course early, we cannot judge their motivation solely from their final grades. Therefore, we categorized students based on a combination of features in the dataset of learning activities, assignment scores, days of delay in submission of assignments, and final grades. The symbols of the features used in the study are as follows:

S represents the students as a whole and the number of students is $|S| = N$.

$$g_i\left(1,2,\cdots N\right) \quad (8)$$

As shown in equation (8) g_i represents the score of a student submitting a particular assignment.

$$d_{i,j}\left(i=1,2,\cdots,N;\ j=1,2,3\right) \quad (9)$$

The $d_{i,j}$ in Equation (9) denotes the number of days delayed for the j th assignment of student i.

varClicks is the variance of the clickstream of a specific student over a specific time period. It represents the frequency with which online learning behavior varies across learning resources.

avgDelay is the average number of days students delayed in submitting their assignments, where a negative number indicates the number of days students submitted their assignments well in advance of the deadline, and a positive number indicates the number of days delayed. As shown in equation (10).

$$avgDelay = \frac{\sum_{i,j=1}^{3} d_{i,j}}{3} \tag{10}$$

In this paper, students are categorized into intrinsic motivation, extrinsic motivation and no apparent motivation based on Self-Determination Theory (SDT). The criteria and steps for categorizing students based on different motivations are described below.

Intrinsically motivated students (IMS) are those students who are interested in the course content. The goal of these students is not necessarily to pass the course because their goals are primarily focused on what interests them. Therefore, intrinsically motivated students can be categorized into students who pass the course (IMPS) and students who do not pass the course (IMFS). The meanings of each are shown below:

$$\begin{gathered} IMPS = \Big\{ \forall s \in S \Big| \big[(g \geq 60) \& (g \leq 80) \& (avgDelay \leq 8) \big] \Big| \\ \big[(\mathrm{var}Clicks \geq 150) \& (\mathrm{var}Clicks \leq 300) \big] \Big\} \end{gathered} \tag{11}$$

$$\begin{gathered} IMFS = \Big\{ \forall s \in S \Big| \big[(g \geq 40) \& (g \leq 59) \big] \Big| \big[(avgDelay \geq 3) \\ \& (avgDelay \leq 14) \& (\mathrm{var}Clicks \leq 200) \big] \Big\} \end{gathered} \tag{12}$$

Extrinsically motivated students (EMS) are students who have a strong desire to master an area of relevant knowledge with the goal of receiving a final award or certificate. Most of the students in this group want to get a certificate at the end of the program to prove their academic achievement. Students in this group can be categorized according to Equation (13), which shows that extrinsically motivated students tend to have higher homework scores and rarely experience delays in handing in assignments.

$$EMS = \Big\{ \forall s \in S \Big| \big[(g \geq 75) \big| (avgDelay < 3) \& (\mathrm{var}Clicks \geq 20) \big] \Big\} \tag{13}$$

Students with no apparent motivation (UMS) are those who drop out of the course or have few learning behaviors. It is expressed as follows, from equation (14), students with no apparent motivation have low scores on their assignments while they delay handing in their assignments for a long time.

$$UMS = \Big\{ \forall s \in S \Big| \big[(g \leq 30) \big| (avgDelay \geq 14) \& (avgClicks \leq 250) \big] \Big\} \tag{14}$$

3 Model validation and empirical analysis of learning styles and motivational profiling

Based on the construction of the implicit learning style model and the learning motivation analysis model in Chapter 2, the design of the mapping path from raw behavioral data to underlying psychological traits (learning style, learning motivation) was completed. In order to explore the actual efficacy of the models and the behavioral characteristics presented by different student groups identified by them. In this chapter, after comparative experiments and cluster analysis, the two dimensions of learning style and learning motivation are integrated to finally output a vivid learner portrait.

3.1 Learning behavior and style association rule mining and correlation analysis

Taking the 2023 pharmacy major students of a higher vocational college as the research object, 10944 sets of behavioral data of 167 students of this major in VLE online courses were obtained, including course searching and course browsing. Then based on the Learning Style Categorization Scale, the 167 test subjects were tested for their learning styles. The study categorized learning styles into four major styles: practical, planning, logical and sensory.

Twelve learner behaviors were categorized as S1 course retrieval, S2 browsing course recommendations, S3 browsing course details, S4 browsing course evaluation, S5 browsing course materials, S6 asking questions, S7 video playback, S8 video pause, S9 video setup, S10 completing post-tests, S11 evaluating the course, and S12 participating in course discussions.

3.1.1 Inference rules between behavioral events and learning styles

Now the subjective Bayesian method of uncertainty inference in L^2S model is utilized to describe students' learning styles.

Firstly, we analyze the relationship between learners' learning behavioral events and learning styles in the learning process, give the inference rules from behavioral events to learning styles, and calculate the updated probability values of style types in each dimension of the learning style model by the subjective Bayesian method.

For the inference rule A→B, the subjective Bayesian method introduces two values of LS and LN. LS indicates the degree of influence on B being true when A is true, indicating the sufficiency of rule A→B. LN indicates the degree of influence on B being true when A is false, indicating the necessity of rule A→B.

Table 1 gives the inference rules and their probability values for each behavioral event to the corresponding learning style. The numbers in the behavioral events indicate frequency thresholds, e.g., S4>20 indicates that the number of times the course evaluation was viewed was greater than 20.

Table 1: Behavior event to the corresponding reasoning rules for the learning style

	Behavioral events	The triggered learning style type		LS	LN
Rule1	S4>20	Practical style	Proactive type	1.63	1.00
Rule2	S5>50		Reactive type	1.74	1.00
Rule3	S6>100		Proactive type	1.85	1.00
Rule4	S7>100		Reactive type	1.89	1.00
Rule5	S10>20		Proactive type	1.93	1.00
Rule6	S1>10	Planning style	Global type	1.45	1.00
Rule7	S2>15		Detail-oriented type	1.27	1.00
Rule8	S3>20	Logical style	Rational type	1.23	1.00
Rule9	S11>15		Emotional type	1.58	1.00
Rule10	S12>50		Emotional type	1.64	1.00
Rule11	S8>30	Sensory Style	Visual type	1.51	1.00
Rule12	S9>15		Auditory type	1.41	1.00

The LN values indicate the effect of the necessity of a behavioral event not occurring on the type of learning style, and here they are all 1.00, indicating a neutral effect. In other words, even if a behavior did not occur, it is not a basis for ruling out a particular learning style. For example, a student may rarely perform the action of S6 questioning, but this does not mean that he is not an active practice style.

The LS value indicates the sufficient influence of the occurrence of a behavioral event on the type of learning style, and the larger the value, the stronger the influence. So we determine the contribution of different behaviors to the style by looking at the LS values of different rules. The rule "S10>20→Active" has an LS as high as 1.93, i.e., if a student completes the post-test more than 20 times, the higher the probability that he belongs to the active type of the practice style. Similarly, the LS for the behavior "S7 video played > 100 times" attributed to the reactive type was 1.89, indicating that students who consistently watched instructional videos were more inclined to the reactive practice style.

3.1.2 Correlation analysis of learning behaviors and learning styles

Then Pearson correlation analysis was used to verify the correlation between different learning behaviors and different dimensions of learning styles. The correlation analysis between students' behaviors and different dimensions of learning styles was obtained as shown in Figure 4.

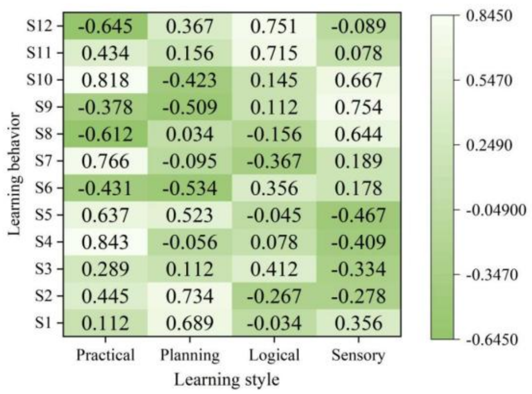

Figure 4: Correlation between Student Behaviors and Dimensions of Learning Styles

It can be found that each learning behavior is significantly correlated with a certain dimension of learning style, which verifies the idea that there is a correlation between learners' learning styles and their behavioral sequences in section 2.1. Specifically, the correlation coefficient between S4 navigating course evaluations and practice style is 0.843, which shows a very strong positive correlation, and S10 completing the post-course test is also strongly correlated with practice style, with a correlation coefficient of 0.818, which is in line with the rule of inference between learning behaviors and styles derived in the previous subsection.

There are also some significant negative correlations, for example, the Person coefficient = -0.645 between S12 participation in course discussion and practical style shows a strong positive correlation with logical style, with a coefficient of 0.751. i.e., the higher the degree of course discussion, the more students tend to become logical critical thinkers, and the less their learning styles will be skewed towards the practical style.

3.2 Comparative Experiments on Learning Style Classification Models

Section 3.1 establishes an association between learning behaviors and learning styles through subjective Bayes rule and correlation analysis. In order to explore whether this association can be applied by the model in classification, this section launches a comparative experiment on learning style classification models, choosing three commonly used machine learning classification models, namely, LSTM long- and short-term memory network model, KNN model by K-nearest neighbor method, and decision tree model, to compare with them. The classification recognition accuracy of the four models for each learning style dimension is shown in Figure 5.

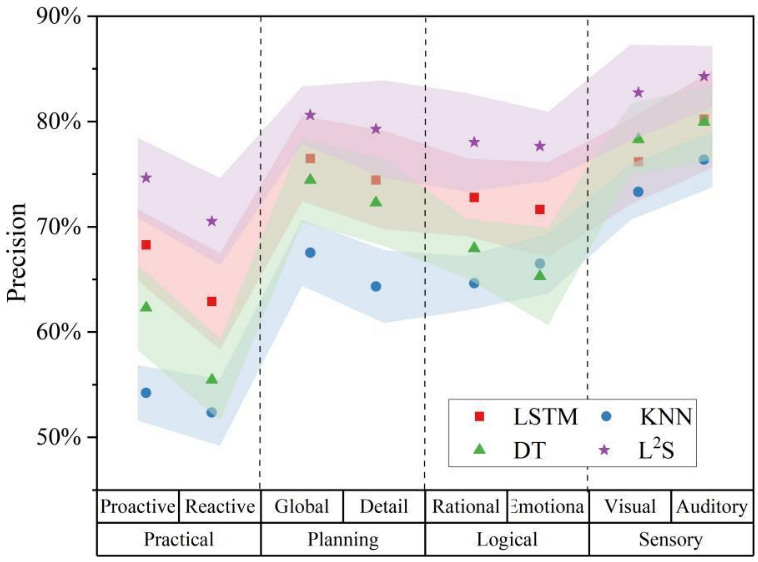

Figure 5: The classification precision of 4 models for each learning style dimension

The L²S model designed in this paper averaged 72.58%, 79.94%, 77.85%, and 83.53% correct rates among the four learning style classification dimensions, namely, practical, planning, logical, and sensory, respectively, which are higher than other machine learning classification models. Specifically, in practice style recognition, the L²S model's classification accuracies for proactive and reactive styles are 74.65% and 70.51%, respectively, which is more than 20% gap compared with the weakest performing KNN model. It is well illustrated that portraying the implicit temporal states and intentions behind students' behaviors through Hidden Markov Bayesian Models can capture their intrinsic learning style preferences more accurately than using conventional classification models directly.

3.3 Learner Portrait Construction Based on Learning Motivation Analysis

Identifying learning styles alone is not sufficient for a comprehensive understanding of student learning drive mechanisms. This chapter starts from the motivation dimension, clusters students' motivation, and integrates both learning styles and motivation to construct a more comprehensive and three-dimensional learner portrait.

3.3.1 Cluster analysis of learners' motivation to learn

Based on the analytical model of learning motivation in section 2.2 and the Self-Determination Theory (SDT), the 12 categories of behavioral data of 167 students were integrated and the students were clustered into three groups of Intrinsic Motivation (IMS), Extrinsic Motivation (EMS), and No Apparent Motivation (UMS). The mean values of the 12 behavioral indicators for the three clustered students are shown in Table 2.

Table 2: The average values of 12 behavioral indicators for three groups of students

	Cluster 1 (N=64) IMS	Cluster 2 (N=89) EMS	Cluster 3 (N=14) UMS
S1 Course Search	18.75	12.33	5.21
S2 Browse Course Recommendations	15.62	22.45	8.67
S3 Browse Course Details	35.41	28.91	10.35
S4 Browse Course Evaluations	25.88	18.67	3.79
S5 Browse Course Materials	42.36	35.82	15.43
S6 Ask Question	8.94	4.12	0.85
S7 Video Playback	105.27	98.51	32.66
S8 Pause Video	35.82	18.45	6.39
S9 Set Video Settings	12.57	8.93	2.17
S10 Complete Post-Class Test	23.15	25.78	6.42
S11 Evaluate Course	6.48	9.25	1.33
S12 Participate in Course Discussion	15.73	7.16	0.91

Sixty-four students belonged to the category of IMS intrinsically motivated students (38.32%). This group of students is characterized by self-driven motivation and active control of the pace of learning. The highest frequency data was achieved in almost all indicators data. On average, they browsed the course materials 42.36 times, viewed the course details 35.41 times, and even paused the video with high frequency (S8=35.82). It shows that this group of students is good at thinking and will even press the pause button at any time in order to digest knowledge, focusing their goals mainly on what interests them.

For extrinsically motivated students, their share is predominant at 53.29%. They have externally motivated goals such as clear rewards or certificates to push themselves to study. This group of students would focus more on completing the post-tests, S10 = 25.78, and also show high interest in the system recommended courses, browsing the recommended courses a number of times, S2 = 22.45. Behind this combination of behaviors refracts their learning strategies: completing the assessment tasks efficiently and actively looking for resources that may be helpful for the certification. Their learning path is more direct and everything revolves around a clear external reward.

As for the 15 students with no apparent motivation, all of their behavioral indicators are running low. In particular, the interaction type behaviors, such as the number of questions asked in S6 and the participation in discussion in S12 were only 0.85 and 0.91, which means that there existed some students who didn't even have any questioning or discussion behaviors occurring.

No apparent motivation causes students to show a low state, and this clustering outlines an image of a learner who hovers on the edge of the course and lacks motivation to participate.

3.3.2 Learner Profile Outputs

The 12 metrics were categorized under the information retrieval, content exploration, active interaction, video learning, and task feedback dimensions. The five dimensions contain S1,S2; S3,S4,S5; S6,S12; S7,S8,S9; S10,S11 specific indicators respectively. Based on this, 3 types of learning motivation learner portraits are constructed as shown in Fig. 6, Fig. 7 and Fig. 8.

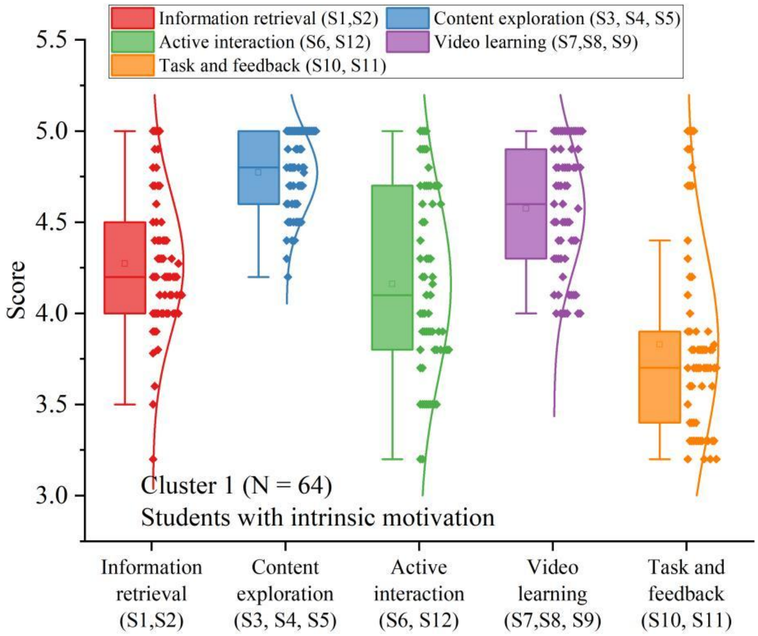

Figure 6: The profile of students with intrinsic motivation in Cluster 1

For the 64 intrinsically motivated students in Cluster 1, they have near perfect scores on the dimensions of content exploration and video learning, 4.77 and 4.58 respectively, with no shortage of perfect scorers. This means that they not only watch the course video repeatedly and strive to master each knowledge point, but also actively browse the course details and expansion materials to build their knowledge system. They are also active in information retrieval and active interaction, with scores of 4.27±0.38 and 4.16±0.35, respectively. These students take the initiative to ask questions and participate in discussions, and the whole learning process is full of autonomy. In contrast, the task and feedback dimension scored a lower score of 3.83±0.52, and the distribution of students was mainly clustered in the band between 3-4 points, with only six students achieving a high score of 4.5 points or more. This indicates that completing assignments and obtaining marks are not the ultimate goal of learning for this group of students.

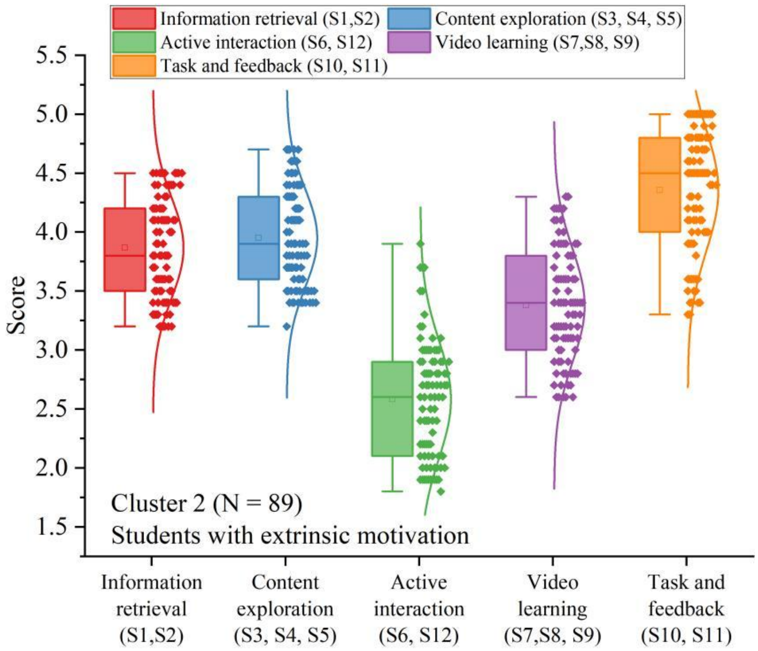

Figure 7: The profile of students with extrinsic motivation in Cluster 2

Cluster 2 externally motivated students have a very prominent spike in their behavioral portrait with a high score of 4.35 on the task and feedback dimension. This is because completing post-tests and giving course evaluations are closely related to the final grade, and therefore externally motivated students will invest the most effort here. Compared to intrinsically motivated students, this group of students' behavioral patterns only achieved a score of 2.58 ± 0.51 on the active interaction dimension, indicating that they rarely speak or ask questions in the discussion forum. Similarly, they invested less in video learning and content exploration, scoring 3.38 and 3.95, respectively. The learning path for this group of students is a straight line leading to rewards or certificates, with few stops for interest exploration.

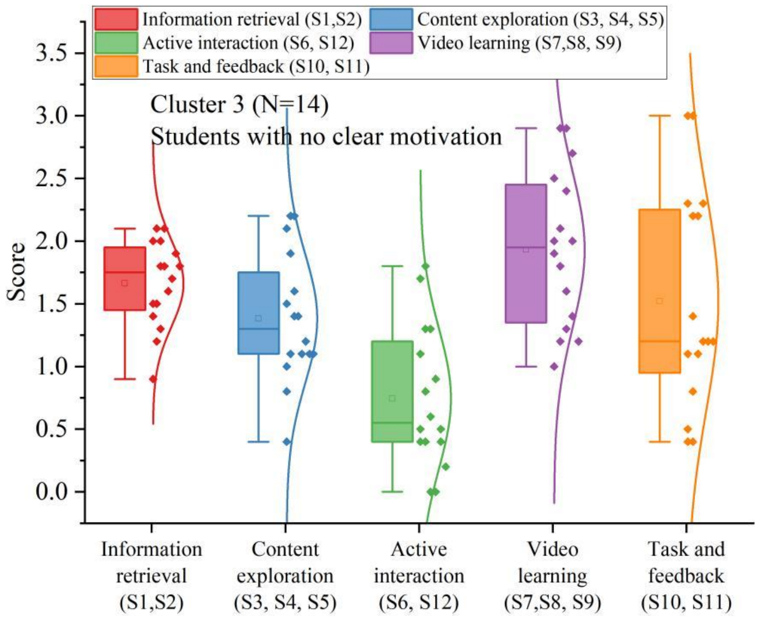

Figure 8: The profile of students without obvious motivation in Cluster 3

Cluster 3 students with no apparent motivation have a maximum score of only 1.93 ± 0.62

on the video learning dimension, implying that they tend to watch videos, if at all, in a brief and sporadic manner. And its scores of 1.38 and 1.66 on content exploration and information retrieval indicate that such students have little willingness to actively seek learning. In the dimension of active interaction, it even reaches an ultra-low score of 0.74±0.56, with two students directly obtaining a score of 0, which almost means that this kind of senior medical students are completely silent in the classroom and do not have any interactions with their teachers and classmates. There is a need to focus on strengthening the support and supervision of such students.

4 Construction and efficacy analysis of a psychological intervention model for senior medical students

The behavioral portraits of students with different learning motivations successfully outlined in the previous paper provide precise targets for the construction of the psychological intervention model. The study constructs a psychological intervention model for higher vocational medical students based on the four aspects of cognition, thinking, identity and emotion, and at the same time, in order to test its specific effect on enhancing students' learning motivation, the CMQ-II Learning Motivation Scale is introduced in the empirical test to analyze the efficacy of the students who apply the psychological intervention model.

4.1 A psychological intervention model to enhance learning motivation

For the problems of insufficient learning motivation and academic burnout among senior medical students, based on the psychological foundations of self-determination theory and expected value theory, the study proposes a multidimensional psychological intervention model for this. The four psychological dimensions of task value, growth mindset, value affirmation and social belonging are synergized.

4.1.1 Mission value interventions

The central dilemma for students with low motivation, like those in Cluster 3, is often that they do not know why they are learning. The task-value intervention model is based on the expected value theory, which stimulates motivation by enhancing students' perceptions of the value of the course. For specific implementation, teachers can carefully design intervention activities. For example, when teaching basic medical theory, they can organize students to read and discuss real-life cases of helping people, such as “The Contribution of Primary Healthcare Workers in the New Crown Epidemic”, so that students can deeply perceive the great social value of what they have learned. At the same time, outstanding alumni can be invited to share their experiences of how they successfully solved patients' problems in primary care by applying their knowledge of anatomy and pharmacology learned in school, so as to closely link the abstract course content with their future career achievements and personal goals. This kind of intervention can effectively help students discover the meaning of learning and move from the passive state of “I want to learn” to the active exploration of “I want to learn”.

4.1.2 Thinking interventions

Medical students have a heavy academic load and are prone to setbacks. Some students tend to attribute their failure in an exam to fixed, negative internal factors such as “I'm not good at thinking”, resulting in a sudden drop in motivation. The Thinking Frames intervention aims to reshape students' attributional styles and cultivate their growth mindset.

Specifically, it can be implemented universally during the orientation period for new students. The key belief that challenges are part of the growth process can be conveyed by having upperclassmen tell the story of how they overcame academic difficulties during their freshman year. Further, we can design special “Growth Mindset Training Workshops” where students watch videos about brain plasticity and engage in the cognitive exercise of “Intelligence is like a muscle, the more you train, the stronger you get”, leading them to believe that their abilities can be enhanced through hard work. When students perceive difficulties as challenges rather than as a dead end, their resilience and motivation to learn are significantly enhanced.

4.1.3 Personal Values Affirmation Intervention

Higher education medical students may experience self-doubt due to the level of their education or the difficulty of their specialty. Personal value affirmation interventions are based on self-affirmation theory to preserve students' self-integrity against the threat of negative evaluations by directing them to focus on their core values.

At the operational level, it can be seamlessly embedded into course instruction. For example, in a Medical Ethics or Nursing Humanities course, written writing tasks on topics such as “Why I chose medicine” or “Qualities I value most in a healthcare worker” can be set. This reflective process effectively reminds students of their inner core values of altruism and caring, and strengthens their identity as “future health care providers”. When students' sense of self-worth is strengthened, they are more confident in coping with academic pressures and transform their personal values into lasting motivation for learning.

4.1.4 Social belonging interventions

Medical studies are a long way to go, and loneliness is a major factor in sapping motivation. Creating a sense of collective belonging is crucial. The implementation path includes building a learning community that combines online and offline. Offline, stable cooperative learning groups are formed to work together on complex clinical case study tasks. Online, teachers and tutors should actively create a supportive communication atmosphere, respond to student questions in a timely manner, and encourage students to share their learning experiences in discussion forums. When students feel that they are respected and supported members of the group, their sense of academic security and willingness to persist in learning will be strongly enhanced.

4.2 Validation of the efficacy of the psychological intervention model in enhancing students' motivation to learn

In order to verify whether the psychological intervention model proposed above can effectively enhance the learning motivation of higher vocational medical students. A higher vocational college was sampled and 2023 pharmacy major students were selected as the research subjects and the experiment was conducted on a class basis.

4.2.1 Experimental design

Class 1 (54 students) was the experimental group, which was taught using the psychological intervention model constructed in the article; Class 2 (55 students) was the control group, which was taught using the traditional teaching model. A semester-long teaching was carried out for the two classes of students, and CMQ-II questionnaires were administered before and after the experiment, and the pre and post-test data of the students in class 2 were analyzed by ANOVA with SPSS26.0. To verify whether the psychological intervention model is helpful in enhancing the learning motivation of senior medical students.

The CMQ-II scale is a scale of students' motivation to learn, with 25 entries attributed to five factors, namely intrinsic motivation, career motivation, self-determination, self-efficacy, and academic performance. The number of entries for each factor was equal. The Likert 5-point scoring system is adopted. The test-takers range from 1 point for "strongly disagree", 2 points for "disagree", 3 points for "neutral (neither agree nor oppose)", 4 points for "agree", and 5 points for "strongly agree". To prevent students from not understanding the content of the items, an additional option "Do not understand the meaning of the question and cannot answer" is added. If students choose this option, Then handle it as a missing value. Calculate the scores of each dimension and the overall average. The higher the score, the stronger the learning motivation of the tested students.

4.2.2 Analysis of covariance across dimensions

The analysis of covariance for each CMQ-II dimension is shown in Table 3.

Table 3: Covariance analysis of each dimension of CMQ-II

Motivation category	Source of variation	SS	df	MS	F	P
Intrinsic motivation	Group	22.584	1	22.584	19.327	0.000
	Before and after the experiment	15.237	1	15.237	13.041	0.001
	Group × Before and after the experiment	18.915	1	18.915	16.189	0.000
	Residual	121.365	104	1.167		
	Total	178.101	107			
Career Motivation	Group	20.147	1	20.147	18.256	0.000
	Before and after the experiment	12.885	1	12.885	11.678	0.001
	Group × Before and after the experiment	16.332	1	16.332	14.801	0.000
	Residual	114.758	104	1.103		
	Total	164.122	107			
Self-decision-making	Group	7.451	1	7.451	7.122	0.009
	Before and after the experiment	5.223	1	5.223	4.992	0.028
	Group × Before and after the experiment	6.884	1	6.884	6.58	0.012
	Residual	108.795	104	1.046		
	Total	128.353	107			
Self-efficacy	Group	25.893	1	25.893	20.987	0.000
	Before and after the experiment	18.446	1	18.446	14.954	0.000
	Group × Before and after the experiment	22.174	1	22.174	17.977	0.000
	Residual	128.284	104	1.234		
	Total	194.797	107			
Academic performance	Group	14.225	1	14.225	13.233	0.000
	Before and after the experiment	9.871	1	9.871	9.183	0.003
	Group × Before and after the experiment	11.638	1	11.638	10.827	0.001
	Residual	111.782	104	1.075		
	Total	147.516	107			
Score motivation	Group	28.415	1	28.415	20.271	0.000
	Before and after the experiment	19.637	1	19.637	14.009	0.000
	Group × Before and after the experiment	24.886	1	24.886	17.752	0.000
	Residual	145.802	104	1.402		
	Total	218.74	107			

The results of this two-way ANOVA based on group and pre- and post-experimental classes clearly reveal the positive changes brought about by the psychological intervention model. The "group x pre- and post-experiment" interactions were significant on all motivation dimensions, with p-values <0.05. In intrinsic motivation and self-efficacy, the test statistics F for the two dimensions were 16.189 and 17.977, respectively, which indicates that the students in the experimental group experienced a great increase in intrinsic interest and self-efficacy as a result of the one-semester psychological intervention model. Meanwhile, F=14.801, p<0.001 for career motivation indicated that students were more motivated to become healthcare professionals based on psychological interventions. The interaction was equally significant even for the self-decision-making dimension with a lower enhancement, F=6.580, p=0.012<0.05. This corroborates that the intervention empowers students to take more ownership of their learning.

5 Conclusion

This study is based on the implicit learning style model and the learning motivation analysis model, and the research path is behavioral data collection→learning style identification→ motivational portrait construction→psychological intervention construction→comparative efficacy validation.

(1) The 12 inference rules obtained from the subjective Bayesian approach indicate that the behavior of completing the post-course test has the highest adequacy for identifying practice styles, with LS = 1.93; browsing course evaluations and video playback are also strong evidence for proactive and reactive practice styles, with LS values of 1.63 and 1.89, respectively.

(2) Based on the L^2S model in identifying sensory styles, an accuracy of 84.29% was achieved for auditory learners, as well as an accuracy of 70.51% in categorizing students with the worst practice style-reactive.

(3) Significant differences in the behavior of the three groups of students obtained by cluster analysis. Extrinsically motivated students, who accounted for the largest proportion of students, included a high score of 4.35 on the task and feedback dimension of the indicators S10 Completion of post-tests and S11 Evaluating the course, which was the highest-scoring group among the three clusters.

(4) A two-way ANOVA showed that the experimental group showed significantly greater gains in key motivation dimensions than the control group, especially in intrinsic motivation and self-efficacy, where the interaction effect was most prominent. The mean square residuals were 1.167 and 1.234.

The study integrates the principles of psychology with the characteristics of medical specialties, awakens students' enthusiasm for learning from the inside out, and lays a solid psychological and ability foundation for their career.

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