

# Teaching Decision-Making Based on Online Learning Big Data of Tobacco Courses: The Perspective of Student Portraits

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**Abstract:**The high-quality development and technological upgrading of the tobacco industry put forward higher requirements for the overall quality of talents. In the context of the increasing popularity of blended teaching, in order to help teachers, major in tobacco, to make better teaching decisions in the teaching process, guide college students majoring in tobacco to better complete their studies and provide timely warnings for students' unhealthy conditions, this article proposes a method to assist teachers in teaching decision-making based on student portraits constructed based on online learning big data. First, collect basic student information and student learning information from the online learning platform. Secondly, preprocess of the data, delete data and normalize dense data. Then, collect and classify student information to form a portrait of basic student information, a portrait of learning achievements, a portrait of learning active level and a portrait of learning status. Analyze the portrait to guide and assist students in their learning and to give early warning of bad learning conditions. At last, analyze the student portraits according to different rules and put forward corresponding suggestions according to the characteristics of different groups of college students. According to the learning situation of learners majoring in tobacco, the article constructs the student portrait label system and portrait model. According to the constructed student portrait, it puts forward learning suggestions for individual students and student groups respectively. In the field of tobacco teaching, it has certain reference significance and application value in providing decision-making reference for differentiated and individualized teaching and assisting teaching decision-making.

**Key words:**blended teaching; teaching decision;tobacco courses; student portrait

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## INTRODUCTION

With the high-quality development and technology

ical upgrading of the tobacco industry<sup>1,2</sup> and the continuous development of information technology, massive diversified and ubiquitous

information makes it difficult for traditional classroom teaching to adapt to learners' personalized service needs who major in tobacco, which has led to continuous changes in learning models<sup>3</sup>. The learning model with "Internet plus" as its basic feature has caused a fundamental change in the way of acquiring knowledge. Teaching and learning are no longer restricted by time, place, personnel and other conditions. The education model is undergoing profound changes<sup>4</sup>. Tobacco courses are highly professional theoretical and practical courses. In the teaching of core courses, colleges and universities should focus on the organic combination of knowledge transfer, ability training and value guidance and pay attention to improving the professional ability and overall quality of tobacco students, and enhance their professional practical ability. The blended education model, which combines the advantages of online teaching and offline teaching has become the product of the new era in the education field. The blended education model is getting more and more attention. In the context of the large-scale development of blended teaching models, research on teaching decision-making is increasingly dependent on the support of big data and information technology<sup>5-7</sup>. Appropriately mining and using learners' learning data is the key to researching blended teaching models, improving the quality of education and enhancing the effectiveness of teaching. At the same time, the development of talent training with the help of user portraits is the research direction of future education<sup>8</sup>. Through the establishment of a multi-dimensional portrait system, a comprehensive and detailed analysis of learners' learning status and potential needs can provide teachers with help in teaching decision-making. The blended education model formed with the development of Internet technology combines online and offline teaching well<sup>9</sup>. In the context of the blended teaching model. Superstar learning platform used by many colleges and universities because of its complete functions and easy operation. Superstar learning platform is a smart teaching platform that integrates online course platform and interactive teaching platform<sup>10</sup>. Superstar learning APP includes three modules:

course interaction, learning resources, and learning management. The course interactive module includes activities such as answering questions, sign-in, topic discussions, online tests, homework, examinations and etc. The learning resource module includes course content, course materials and etc. The learning management module includes interactive course scores, number of course visits, video learning time and etc. Superstar learning platform records a large number of learners' learning behavior data in the above three modules. By analyzing these learning data, we can find out the data relationships hidden in the data resources. Extract the internal connections and external characteristics of students' behaviors and then use them to describe students' behavior patterns which can help teachers make teaching decisions and improve students' learning effects<sup>6,11</sup>.

## RELATED RESEARCH

User Profile was first proposed by interaction designer Cooper in 1999<sup>12</sup>. He believes that user portraits are virtual representations of real users and a target user model based on a series of real data such as marketing data and usability data<sup>13</sup>. In the era of big data, new progress has been made in the understanding and application of user portraits in various fields. User portraits have become a research hotspot in countries all over the world and are attracting widespread attention in various fields<sup>14-16</sup>. More importantly, it is also one of the key technologies for many applications<sup>17</sup>. In the field of education, Sun et al<sup>18</sup> focuses on the modeling process of learning style. Through case analysis of online learners, they elaborated on the application of learner portraits in learning resource recommendation, assessing learners' academic failure or exit risk, etc. By studying the Field-Silverman learning style model, ElBishouty et al<sup>19</sup> helped teachers improve curriculum design and increase the degree of support for different learning styles in the curriculum. Baumann. B<sup>20</sup> constructs user portraits as a teaching agent to apply to teaching design, which can not only promote students' learning but also provide students with a summary description<sup>21</sup>. In the field of libraries, Based on the cold start and user

reading learning process, Li B<sup>22</sup> introduced user portrait technology to provide solutions for personalized reading resource recommendation services in the field of university libraries. In the field of intelligence, Xiang Set al<sup>23</sup> introduced user portrait technology into academic journal knowledge services and constructed user portraits in academic journals to better serve users.

Teaching decision-making is a process in which teachers perceive and process information and make decisions based on existing information and their own knowledge and skill reserves in a specific teaching environment<sup>24</sup>. Marsh et al proposed that the ability of teachers to digitize information largely determines the teaching effect<sup>25</sup>. In the context of big data, Wu<sup>26</sup> introduced a decision tree mining algorithm based on the actual situation and designed a teaching decision support system with evaluation function to assist teachers in teaching decision-making. Jorge<sup>27</sup> proposed a method based on multi-attribute decision-making by classifying user portraits and determined the most effective use standard according to a specific combination aiming to maximize the effectiveness and efficiency of the teaching process.

In summary, user portrait technology is widely used in many fields but the research on college

student portrait and its application in teaching decision-making is still rare. Most of them are research on learners' learning behaviors and learning styles. There is less research on constructing comprehensive student portraits and helping teachers make decisions.

This article collects the learning data from the Superstar learning platform and offline course test scores of students majoring in tobacco engineering and modern tobacco industry from the School of Food Science and Engineering, Hebei University of Science and Technology in 2020. From the four aspects of learner basic information, learner learning achievements, learner activity level and learner learning state, the individual and group portraits of learners are established respectively and the application of learner portraits in teaching decision-making and learning early warning are discussed.

### RESEARCH PROCESS AND METHODS

As shown in Figure 1, this article mainly consists of three parts: data acquisition and processing, portrait construction, and portrait display and analysis.

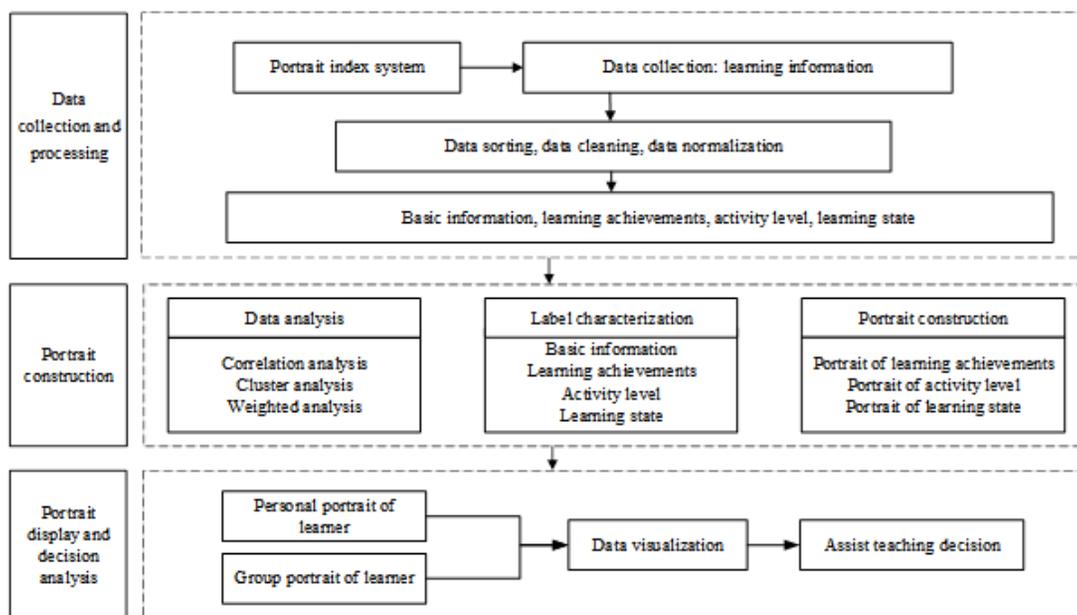


Figure 1 Research flow

### Data Collection and Processing

(1) Data collection. The research data in this paper comes from the Superstar learning APP and the educational administration management system of the College of Food Science and Engineering, Hebei University of Science and Technology. Contains the online learning data of the Superstar learning platform and the offline test score data of the educational administration system in 2020 for students in the three grades majored in tobacco engineering and modern tobacco industry.

(2) Data processing. The collected data covers various information of learners, including chapter access rates, discussions, quizzes, assignments, etc. In order to facilitate statistical data and reduce calculation errors, the data must be cleaned up before calculation. Use the Sigmoid function to map the dense data of the learner to the interval  $[0, 1]$ <sup>28</sup>. Assign weights to calculate label values to more accurately describe the learning situation of learners. Finally, we get the data describing the use of each label.

The function formula of Sigmoid is:

$$S = \frac{1}{1 + \frac{1}{S_a} e^{-(S_a - \overline{S_a})}} \quad (1)$$

In formula (1),  $S_a$  represents the frequency of learners' participation in activity a,  $\overline{S_a}$  indicates the average frequency of all learners participating in the activity.

The weight formula is:

$$I_t = \sum a_t * \omega_{at} \quad (2)$$

In formula (2),  $I_t$  indicates the value of the calculated label t,  $a_t$  is the data value used when calculating the value of the label t,  $\omega_{at}$  is the weight value of the data value  $a_t$  when calculating the label t.

### Portrait Construction

The portrait construction includes three parts: data analysis, label characterization and portrait construction. Data analysis mainly performs cluster analysis, correlation analysis and weighted analysis

on the acquired data. The portrait label characterization mainly includes two parts: static label characterization and dynamic label characterization. The static label mainly contains the basic information of the learner, such as name, major, etc. The dynamic label description includes three parts: learning achievements, activity level, learning state. The portrait construction is completed on the basis of the first two parts.

### Portrait Realization and Analysis

This part is to use the experimental data to realize the established portrait model and use the tools of data visualization to display and analyze. Finally, discuss the application of the model in the field of performance warning and personalized service for the realized user portrait model, further enhance the intuitiveness of the display of educational resources, increase the utilization rate of educational resources and provide learners with scientific and efficient services<sup>29</sup>.

### PORTRAIT LABEL CONSTRUCTION

In order to accurately profile learners from multiple dimensions, comprehensively considering the requirements for profile construction and the availability of data, this study constructs learner profiles from four aspects: learner basic information, learner learning achievements, learner activity level, and learner learning state.

#### Learner Basic Information

The learner basic information label mainly reflects the learner's basic information, including data items such as name, school, professional, class, number, contact, etc. The data comes from the educational administration management system and the backstage system of Superstar learning platform.

#### Learning Achievements

The learning achievement label mainly reflects the learner's performance after learning. Reflected by data such as grades, course points, course grade points and average grade points (GPA) calculated from course grades and course grade points. The assignment rules of Hebei University of Science and Technology course grade points are shown in

Table 1. The grade point calculation formula is as shown in formula (3). Divide the sum of the student's grade points by the sum of course credit to get the student's grade point average (GPA). The calculation formula is shown in formula (4).

$$\begin{aligned} &\text{Grade points} \\ &= \text{course credits} \\ &* \text{course points} \end{aligned} \quad (3)$$

$$\text{GPA} = \frac{\sum \text{course grade points}}{\sum \text{course credits}} \quad (4)$$

Table1 The Assignment Rules of Course Grade Points					
Hundred-mark system	90-100	80-89	70-79	60-69	<60
Five level system	Excellent	Good	Medium	Pass	Fail
Course points	4.0	3.7	3.0	2.0	0

Under the learning achievement label, there are four sub-tabs: excellent, good, pass and fail. The classification is based on the ranking of learners' performance. On the other hand, consider judging its performance from the GPA. The assignment

rules of course grade of Hebei University of Science and Technology are shown in Table 2. In Table 2, the maximum GPA published by the Hebei University of Science and Technology academic affairs management system is 4.0.

Table2 The Assignment Rules of Course Grade		
Grade	GPA	Label
>=90	>=3.7	Excellent
<80&>=70	<3.7&>=3.0	Good
<70&>=60	<3.0&>=2.0	Medium
<60	<2.0	Pass

From the perspective of the learner's personal portrait, the change of the learner's performance ranking within one year can observe the change of their learning achievement. By observing changes in learning achievement, suggestions are made for teachers to make personalized teaching decisions. From the perspective of learner group portraits, a visual analysis of the distribution of the number of sub-labels of students in different grades can show that the performance changes with the change of grades, so as to better arrange targeted teaching modes for different grades.

### Activity Level

Activity level mainly reflects the learner's activity in the course, which is reflected by chapter, discuss, task, sign, answer, absence, late. Learner activity level contains three sub-tags: highly active, relatively active and inactive. The activity level label is calculated from the above seven data items and the statistical format of the seven data items is frequency

statistics. Since activity level has no comparative effect in different courses, the label value of learner activity level is calculated and compared in each teaching class. In order to facilitate statistics and improve calculation accuracy, use formula (1) to normalize the data value and then use formula (2) to perform weighting calculation to obtain the value of activity level<sup>30,31</sup>. The weight of each data item is shown in Table 3.

Table 3 Weight Table of Learner Activity Label Data Item	
Item	Weights
Chapter	0.20
Discuss	0.40
Task	0.40
Sign	0.20
Answer	0.40
Absence	-0.40
Late	-0.20

These seven data items require the initiative of the learner to complete. The more active the learner is in the learning process, the more often these activities are completed. According to the level of initiative required to complete the task,

weights are assigned to different data items. The sum of the weights of each data item is 1. Absence and lateness are reverse indicators. The higher the frequency of absenteeism and lateness, the lower the learner's activeness in the course. And compared with being late, the impact of absenteeism is higher. Among the other five data items, discuss, task and answer have a greater positive influence on learner activity label than chapter and sign. This is because chapter and sign are mostly mandatory tasks in the actual learning process, so they are given lower weights.

**Learning State**

The learning state mainly reflects the comprehensive performance of learners in the learning process, which is reflected by chapter, task, work, test, exam. The learning state contains three sub-tabs: autonomous learning, semi-autonomous learning, and passive learning. Since learning state has no comparative effect in different courses, the label value of learner state is calculated and compared in each teaching class. The learning state label is calculated from the above five data items and the statistical format of the five data items is frequency statistics. When calculating the learning state label, it is converted into the completion rate of each activity and calculated according to the maximum value of the completion frequency of each activity.

The calculation formula for the completion rate is:

$$R_a = \frac{F_{ai}}{F_a} \quad (5)$$

$F_{ai}$  is the frequency that learner 'i' completes in activity 'a',  $F_a$  is the maximum frequency of activity completed in the teaching class.

$$I_t = \sum t_i * \omega_{ti} \quad (6)$$

Assign different weights to the calculated completion rate of each activity and calculate the learning state label value by formula (6). The weight value distribution of each data item is shown in Table 4.

Item	Weights
Chapter	0.3
Task	0.3
Homework	0.1
Test	0.2
Exam	0.1

Chapter and task are dependent on active data items, so it is given the highest weight. The test requirements are different depending on the course. In the actual learning process, because the test in some courses is not included in the final grade, some learners do not complete the homework, so medium weight is given. Homework and exams are mostly mandatory completion projects, so they are given a lower weight.

**PORTRAIT REALIZATION AND DECISION ANALYSIS**

The data for the realization of the portrait model in this paper comes from the Superstar learning platform and the educational administration management system of the College of Food Science and Engineering, Hebei University of Science and Technology. Contains three grades of 211 students majoring in tobacco engineering and modern tobacco industry online learning data on the Superstar learning platform and offline test results from the educational administration system in 2020. The data of the Superstar learning platform is provided by Superstar company. The data content mainly includes basic student data and online course learning data. The basic student data includes the learner's name, number, school, major, etc. Online course learning data includes participation and completion results of in-class activities such as discussions, chapter, answers, coursework, quizzes, exams, etc. The data provided by the educational administration management system includes basic course information, basic learner information and grade data. Basic course information includes course number, course name, course credits and whether it is an optional course or a compulsory course. Grade data includes grades for each course, total grades of all courses, total credits and grade point, etc.

**Portrait of Learner Basic Information**

The basic student data includes the learner's name, number, school, major, etc. The specific content is shown in Table 5.

No.	School	Major	Class	Number
1	Food science and engineering	Tobacco Engineering	171	170007101
2	Food science and engineering	Tobacco Engineering	171	170007102
3	Food science and engineering	Modern tobacco industry	181	180001107
4	Food science and engineering	Tobacco Engineering	191	190007121
5	Food science and engineering	Tobacco Engineering	191	190007122

**Portrait of Learning Achievements**

The learning achievement label is reflected by data such as grades, course points, course grade

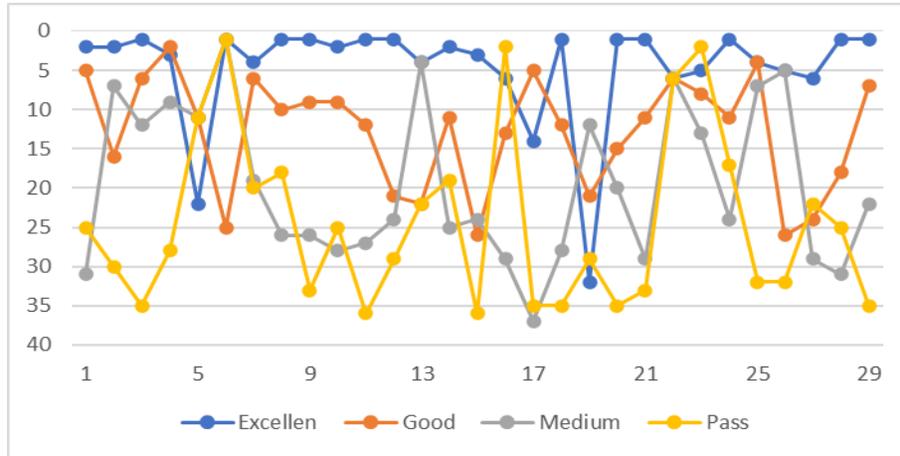
points and GPA, mainly reflects the learner's performance after learning. The calculation process of the learning achievement label is shown in Table 6 and the results are shown in Table 7.



No.	School	Major	Class	Number	GPA	Label
1	Food science and engineering	Tobacco Engineering	191	19000107	2.47	Medium
2	Food science and engineering	Tobacco Engineering	191	190007108	3.22	Good
3	Food science and engineering	Tobacco Engineering	191	190007109	3.62	Good
4	Food science and engineering	Tobacco Engineering	191	190007110	2.45	Medium
5	Food science and engineering	Tobacco Engineering	191	190007112	3.72	Excellent

The analysis of learners' learning achievements changes is mainly based on the changes of learners' course rankings in 2020. When selecting the analysis object, randomly select the data of a learner from the four sub-tabs for analysis. The

four learners are from the same class. When processing the data, the elective courses with a small number of classes were deleted, and finally 29 courses studied by four learners were obtained. The analysis results are shown in Figure 2.

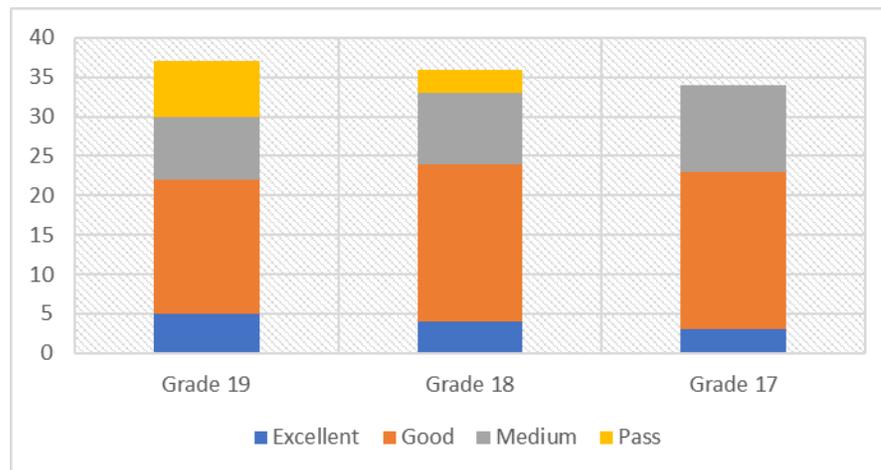


**Figure 2** Changes in learning achievement under different labels

It can be seen from Figure 2 that the ranking of learners under the excellent label is basically stable in the range of 1-5 and there are only a few cases where the performance fluctuates greatly. Most of the learners' rankings under the good label are in the range of 5-20, and a small part of the course rankings fluctuate greatly. The ranking of learners under the medium label fluctuates greatly but there are still some courses whose score ranking is stable in the range of 20-30. For learners under the pass label, most of the course grades fluctuate greatly and only a few are stable in the range of 35-40. It can be seen that the learning status of the learners under the excellent label is relatively stable. Judging from the results of the course grades, there is no obvious likes or dislikes for most courses. Among the students with the pass label, the academic performance ranking

fluctuates greatly. It may be due to the learners' likes and dislikes of the course or the different teaching methods of the instructor that affect the learner's degree of learning in the course. It can be seen that learners under different labels are likely to achieve better results in the course, the learning results are different because of the degree of influence of the influencing factors in the learning.

After discussing the learning achievements of individual learners, discuss whether the label distribution of learning achievements changes as the grade increases. In order to reduce the research error, mainly discuss the changes in the label distribution of the modern tobacco industry in the three grades. Learners of the same grade come from the same class, and the analysis results are shown in Figure 3.



**Figure 3** Distribution of learning achievement labels of different grades

As can be seen in Figure 3, the number of learners with passing labels and excellent labels decreases as the grade increases. Most learners are concentrated in the good and medium range. It can be seen that with the growth of grades, learners' investment in learning has decreased, and they tend to only pass exams. According to this situation, teachers can adjust the teaching method according to the actual situation, instead of just focusing on the final exam results.

### Portrait of Activity Level

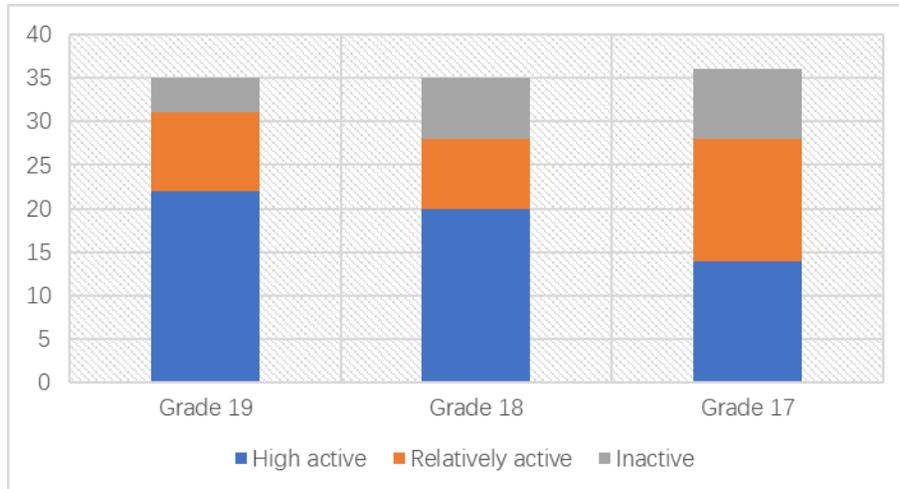
The activity level label is calculated from the seven data items: chapter, discuss, task, sign, answer, absence, late which reflects the learner's

activity in the course. According to the result level, it is divided into several sub-tags: high active, relatively active, and inactive. The calculation process of learner activity label is shown in Table 8 and the calculation result is shown in Table 9. The learner whose activity value is lower than 0.191836 is marked as inactive, the learner whose activity value is higher than 1.099999 is marked as highly active and the learner whose activity value is between the two values is marked as relatively active. In order to reduce the error, the two cut-off values are obtained by calculating the quarter point of the activity value of 211 learners.

In Table8, all activities are expressed as activity\_i.

<b>Table 8</b>	
<b>Calculation Process of Learning Activity</b>	
<b>Algorithm 1</b>	
Input: Participation in course activities	
<pre> # Define activities def activity(a,w):     ''' 'a' is the list '''     return sum(a*w) # Define the Sigmoid function def sigmoid(x,xaverage):     t=x-xaverage     return 1/(1+1/xaverage*np.exp(-t)) # Define the weight activity_i['weight']=w # Normalization of calculated values activity_i [' frequency ']=task.groupby(' activity_i ').size() activity_i ['a']= activity_i [' frequency '].apply(sigmoid) # Calculate activity resfin['activity']=resfin['a']*resfin['weight'] # Assign label based on activity df['label'] = df.activity. apply(lambda x: 'Inactive' if x&lt;=0.191836 else 'Relatively active'if x&lt;=1.099999 else 'High active') Output:Learner activity level label                     </pre>	

<b>Table9</b>						
<b>Calculated Results of Learning Activity Level</b>						
No.	School	Major	Class	Number	Activity	Label
1	Food science and engineering	Tobacco Engineering	171	170207117	0.099961	Inactive
2	Food science and engineering	Tobacco Engineering	171	170207118	0.389420	Relatively active
3	Food science and engineering	Tobacco Engineering	181	180207123	1.247681	High active
4	Food science and engineering	Tobacco Engineering	181	180207136	0.800000	Relatively active
5	Food science and engineering	Tobacco Engineering	191	190207112	1.599988	High active



**Figure 4** Distribution of activity level labels of different grades

In order to reduce the research error, mainly discuss the changes in the label distribution of the modern tobacco industry in the three grades. Learners of the same grade come from the same class, and the analysis results are shown in Figure 4.

As can be seen in Figure 4, with the growth of grades, the number of highly active people is decreasing, the number of inactive people is increasing and the number of more active people is increasing volatility. It can be seen that learners are more active when they first enter the school, and their enthusiasm for intraclass interaction has declined as the grade increases. Based on such problems, different teaching modes should be arranged according to the actual situation of the grade. For example, an autonomous classroom model can be added to grades with lower levels of activity.

### Portrait of Learning State

The learning state label is calculated from five data items: chapter, task, work, test, exam which mainly reflects the comprehensive performance of learners in the learning process. The learning state contains three sub-tabs: autonomous learning, semi-autonomous learning, and passive learning. The learner whose learning state value is lower than 1.394407 is marked as passive learning, the learner whose learning state value is higher than 2.759995 is marked as autonomous learning and

the learner whose learning state value is between the two values is marked as semi-autonomous learning. Since grades are largely affected by the learning status of learners, the upper cut-off value is calculated based on the proportion of school scholarships of Hebei University of Science and Technology. The proportion of Hebei University of Science and Technology's school scholarships is 18% for the third prize, 10% for the second prize, and 3% for the first prize. Therefore, the first 30% of the 211 learners' learning state values are recorded as autonomous learning and the calculated cut-off point is 2.759995. The last 30% is passive learning and the calculated cut-off point is 1.394407. The calculation process of learning state label is shown in Table 10 and the calculation result is shown in Table 11.

In Table 10, the activities are all expressed as state<sub>i</sub>.

**Table 10**  
**Calculation Process of Learning State**

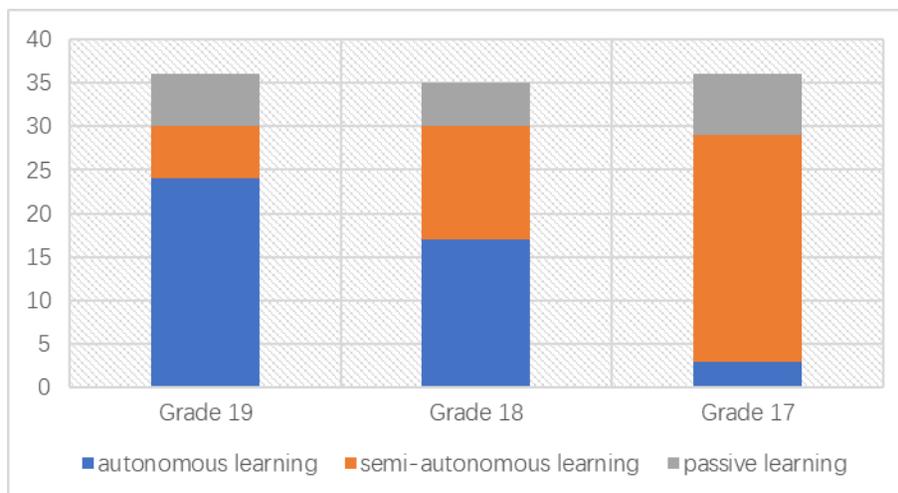
**Algorithm 2**

```

Input: Participation in course activities
# Define learning state
def state (a,w):
    "'a' is the list '"
    return sum(a*w)
# Define the weight
state_i['weight']=w
# Calculate the completion rate of each activity
state_i ['total'] = []
for c in w_li:
    xl=a[a['class']=='%s'%(c)][['a']].max()
a.append(xl)
state_i [' frequency ']= state_i [' frequency ']/ state_i ['total']
# Calculate final value
resfin['state']=resfin['a']*resfin['weight']
# Assign label results
df['label'] = df.state.apply(lambda x: ' passive learning ' if x<=1.394407else ' semi-autonomous learning ' if x<=2.759995 else ' autonomous
learning ')
Output:Learner learning state label
    
```

**Table 11**  
**Calculation Result of Learning State**

No.	School	Major	Class	Number	Activity	Label
1	Food science and engineering	Tobacco Engineering	191	190207101	2.855976825	autonomous learning
2	Food science and engineering	Tobacco Engineering	191	190201135	2.412771218	semi-autonomous learning
3	Food science and engineering	Tobacco Engineering	181	180207124	2.640878786	semi-autonomous learning
4	Food science and engineering	Tobacco Engineering	181	180207112	0.836627907	passive learning
5	Food science and engineering	Tobacco Engineering	171	170207121	1.750297146	semi-autonomous learning



**Figure 5** Distribution of learning state labels of different grades

In order to reduce the research error, mainly discuss the changes in the label distribution of the modern tobacco industry in the three grades. Learners of the same grade come from the same class, and the analysis results are shown in Figure 5.

As can be seen in Figure 5, as the grade increases, the number of self-learning students decreases. The number of passive learners fluctuates to a certain extent but not much. The number of semi-autonomous students has increased significantly. It can be seen that learners

have a high degree of autonomy in learning when they first enter the school and their enthusiasm for courses has declined as the grade increases.

### Comprehensive Application of Portrait

After displaying the realization of the four labels of learner basic information, learning achievement, activity level and learning state, integrating the four parts to get the overall situation of the student portrait as shown in Figure 6. Analysis of the results of the learner label, in addition to the basic information of the learner, the learning achievement label contains four sub-labels of excellent, good, medium and pass. The learning activity level contains three sub-labels of high activity, relatively active and inactive. The learning state includes three labels: autonomous

learning, semi-autonomous learning and passive learning. There are 36 possible outcomes for student portraits. Considering the actual situation, only partial results can be achieved, such as excellent of learning achievement, inactive of activity label and passive learning of learning state at the same time have almost no chance to appear. This article takes the learner in Figure 6 as an example to analyze. The learner's learning achievement is excellent, the activity level is relatively active and the learning state is semi-autonomous. The teacher should remind the learner to strengthen online self-learning and take the initiative to learn the knowledge content that is not taught in class but needs to be supplemented independently.



Figure 6 Student portrait

### CONCLUSION

This paper uses the learner data of the tobacco engineering major and the modern tobacco industry major of Hebei University of Science and Technology to construct the student portrait of online learning big data for tobacco majors from the four aspects of learner basic information, learner learning achievements, learner activity level and learner learning state. It also shows the application of student portraits in teacher decision-making and proposes suggestions and opinions from different angles which improves the learning efficiency of learners and enhances the teaching effect of teachers. There are still many shortcomings in this article. First, due to data limitations, it is

impossible to analyze the content of the tobacco professional courses in more detail. Second, the actual teaching situation should be considered, not just from the perspective of results. Third, the program failed to completely realize the construction and application of student portraits.

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## Author Declaration

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