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Retraction

Retracted: Construction and Empirical Study of Learner Portrait in Online General Education Course

Discrete Dynamics in Nature and Society

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Z. Zhang, "Construction and Empirical Study of Learner Portrait in Online General Education Course," *Discrete Dynamics in Nature and Society*, vol. 2022, Article ID 9952300, 9 pages, 2022.

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Research Article

Construction and Empirical Study of Learner Portrait in Online General Education Course

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The problems of high course selection rate, low completion rate, and insufficient pertinence of learning support services in online general education courses are the focus of current general education researchers. Based on 3P (presage, process, and product) learning theory, we put forward a "three-stage, four-level" framework for learners' portrait process of online general education course, including three learning stages of "presage process product" and four levels of "portrait goal, data collection, label analysis, and portrait service." Then, taking the learners of the online general education course of Zhejiang Shuren College as an example, we make a case analysis based on the portrait framework, evaluate the learning effect from different stages, and put forward targeted teaching strategies and measures. Research results show that the proposed framework can reflect the characteristics of online learning experience, online learning investment, and online learning results of high-risk learners and can provide data support for the design of online learning support services and optimizing learning effects.

1. Introduction

General education is an important part of higher education in China. Its purpose is to cultivate "complete people" and enable students to have a more reasonable knowledge structure, ability structure, and elegant interest [1]. Throughout history, all previous important general education reforms have taken curriculum reform as the core. Whether in the research of general education or its specific development, the curriculum system has always been the focus and core [2, 3]. With the advent of the era of "intelligent education," especially the deep integration of online open course and artificial intelligence, it has accelerated the development and reform of online general education course [4]. According to statistics, at present, more than 2000 colleges and universities in China have more than 10 million students using online general education courses, and online general education courses have become one of the important carriers of general education. Taking our college as an example, since 2019, a total of 400 online general courses in five modules of open science and technology, the foundation of traditional Chinese studies, human thought, literature and art, and historical civilization have been selected by all students of the college, with a total of 101524 person-times. Although the online general education course has been widely accepted, there are still many problems in the implementation process, such as high course selection rate, low completion rate, unclear characteristics of learners, lack of teaching process evaluation, and inability to accurately provide personalized learning support services, which have triggered people's reflection on the teaching quality of online courses.

User portrait is the labeling of user information. It uses the virtualization representative to identify the real users. It is a user model established from a series of actually generated data. The research results of user portraits at home and abroad involve the fields of e-commerce, library and information, healthcare, and tourism, showing obvious interdisciplinary characteristics [5]. Learner portrait is the core content of personalized teaching at this stage, that is, to establish learner portrait by collecting learners' static and dynamic data information in an all-round way and deeply mining data resources. Finally, based on the portrait, learners' learning ability, learning level, and learning style are carefully analyzed in a multiangle way comprehensively, and then personalized learning schemes are provided according to these typical characteristics [6].

Based on the above analysis, this paper combines theoretical research with practical research. Firstly, using visual learning analytics and portrait construction technology, combined with Biggs's 3P (presage, process, and product) model and characteristics, this paper designs a "three-stage, four-level" online learner portrait construction process framework of online general education course, which are used for clarifying learner characteristics and digital modeling. Then, taking the online learners of the online general education course of Zhejiang Shuren College as an example, based on the big data of learners' basic situation, learning process, and learning results, the portraits of high-risk learners are output from the three stages of learning premise, process, and product, help learners find out the problems and deficiencies in the learning process in time, and promote more effective learning and finally carry out accurate teaching analysis through the portrait results, put forward targeted teaching strategies and measures, optimize the online teaching effect, and improve the teaching quality of general courses.

The next part of this paper is constructed as follows. The relevant theoretical research is shown in Section 2. In Section 3, the online learner portrait process framework of online general education course based on the 3P learning model is proposed. In Section 4, taking the learners of the online general education course of Zhejiang Shuren College as an example, we make a case analysis. The discussion and suggestions based on case data are in Section 5. Finally, Section 6 presents the conclusions.

2. Related Works

2.1. 3P Model. The 3P model proposed by Biggs focuses on the main line of student learning, integrates learning subjects (teachers and students), objects (teaching process, teaching environment, and learning results), and other factors, and constructs spiraling learning closed loop composed of "presage," "process," and "product" [7]. In this model, the learning results of a previous period constitute the learning presage of the next stage, and the three interact to form a dynamic system, which provides assessment, diagnosis, feedback, and improvement measures for students to modify the learning process and improve the learning quality [8, 9]. Wang applied the 3P teaching model to analyze the path evolution of teaching evaluation and formed different evaluation objectives and evaluation cores [10]. Chun analyzed the theoretical connotation, educational concept, and contemporary significance of the 3P teaching model and proposed measures to promote China's undergraduate education reform under the background of "double first class" construction through analysis and reference [11]. Based on the 3P model, Rui et al. reconstructed the case teaching path and described the classroom teaching process from the three aspects of perfecting the presage, standardizing the teaching process, and strengthening the evaluation and feedback [12]. Based on the 3P analysis framework, Hu et al. constructed a relationship model of influencing factors in online learning to explore the correlation and influence relationship among learners' information literacy, learning engagement, and learning performance [13]. 3P model not only is applied in foreign MOOCs (Massive Open Online Courses) [14] but also supports sustainability in management education [15]. Kember proposes the refocusing of the 3P model by incorporating a learning and teaching environment and graduate attributes [16]. Deng uses the 3P model as an organizing framework to analyze the key learning and teaching aspects of MOOCs [17].

Based on the existing research, this paper uses 3P learning model to evaluate the teaching of online general education course, based on data deep mining and labeling processing, and combined with these teaching links establishes an interconnected and integrated information panorama, promotes the spiral rise of learning cycle system, and improves learning quality through scientific feedback evaluation.

2.2. Learner Portrait. Learner portrait is derived from user portraits, which describe characteristics comprehensively, establish label system, and draw behavior model to meet personalized service demands. Learner portrait can accurately assess students' learning ability and also help teachers reflect on teaching and dynamically correct the process of teaching and learning [18, 19]. For example, Minghua et al. systematically discussed the construction process, implementation path and method, presentation content, and form of student portrait based on visual learning analysis technology so as to effectively serve personalized teaching [20]. Xiao et al. designed the construction process of learner portrait from the four perspectives of target, data, analysis, and service, providing methods for the application and evaluation of learner portrait teaching [21]. In addition, some studies have applied user portraits as teaching agents in teaching design to provide interaction and promote learning [22]. Other studies are carried out from the aspects of learning style and learning path. For example, Samarakou et al. developed a digital learning system based on a multigranularity neural network for feature extraction of text features [23]. Through clustering and tracking of learners, appropriate learning paths are finally given. Nigenda designed the learning path planning and evaluation algorithm model, which can provide diversified learning according to students' learning process and learning ability [24].

According to the literature analysis, most studies pay action to the construction, analysis, and visualization of learner portraits. Existing studies rely on personal experience or data-driven data analysis, lack the guidance and regulation of educational theory on the whole construction process, and have not carried out detailed and in-depth research on learner portraits under the background of general education. Therefore, based on the characteristics of diversity, foundation, and integration of general education, this paper puts forward a learner portrait model suitable for different learning stages of an online general education curriculum. The model focuses on the description of learners' learning experience, emotion and ability objectives, and general literacy, highlighting the characteristics of general education.

3. Online Learner Portrait Process Framework Based on 3P Model

Based on the 3P model, this paper puts forward the online learner portrait process framework of "three stages and four levels" of online general education course, as shown in Figure 1. In the framework, learners' learning ability rises spirally through the 3P model of "prediction," "process," and "product." In each stage, it accurately analyzes the learning experience, learning behavior, and general literacy level through four levels: building goals, learning big data, designing labeling system, and outputting portrait services. Finally, determine whether the goal is achieved in teaching application and evaluation. If not, enter the next round of portrait analysis application to form a closed loop.

3.1. Portrait Target Layer. The portrait target layer is the core of the whole frame. Based on the 3P learning theory, learners' portrait objectives are constructed from the perspective of general education, and they are divided into presage objectives, process objectives, and product objectives. Through group identification, feature analysis, and learning evaluation, learners' learning experience, learning engagement, learning style, and general literacy level are focused on. "Presage" is at the front of the learning sequence. The presage variables include students' individual characteristics and learning experience, so the target of this stage's portrait focuses on identifying learners' basic characteristics, such as basic information and online learning experience. "Process" is the core of the learning sequence, which will be affected by presage variables and result variables. Therefore, this stage focuses on identifying learners' behavioral characteristics and paying attention to online learning engagement and online learning style. "Product" is at the end of learning, but it is not a simple summative evaluation. It is the beginning of a new cycle, focusing on identifying learners' performance and gains, including learning evaluation and general literacy level.

3.2. Data Collection Layer. The data collection layer is the basis of the whole framework, which collects big data through a learning platform database, educational administration system database, and mobile access platform for different learning stages and portrait targets. Among them, basic attributes come from the big data of learners' basic situation, learning experience comes from the questionnaire data of the platform, learning engagement and learning style in behavioral characteristics come from the big data of learning process, and learning evaluation and general literacy level in learning results come from the big data of learning results. Then, unstructured and semistructured data are transformed into recognizable structured data through data preprocessing. After data specification and cleaning to ensure the accuracy of data mining results, the learner's portrait accurately approximates the real situation of learners.

3.3. Label Analysis Layer. The label analysis layer is the key to the framework. Data analysis of labels in different learning stages was carried out by cluster analysis, regression analysis, factor analysis, and correlation analysis. The "presage" stage displays static labels and dynamic labels, including basic personal information, such as number, name, gender, major, and grade. The process of online learning experience includes course content perception, self-efficacy, and social interaction. The "process" stage displays the dynamic label. It uses learning analysis technology to construct personalized learning behavior and supports the dynamic presentation of students' online learning investment, such as learning participation, concentration, interaction, and online learning style, such as information processing, information perception, information type, and information acceptance. The "product" stage displays the prediction label. It evaluates the periodic learning results of learners, such as knowledge mastery, learning satisfaction, and general literacy level. The level of general literacy covers five dimensions of science and technology, the basis of sinology, human thought, literature and art, and history and civilization. A comparative analysis is made with the stage of "presage" in the next round to present the development trajectory of learners' general literacy level.

3.4. Portrait Service Layer. The portrait service layer is the focus of the entire framework. By means of data association, synchronous processing, and data visualization, the learner's portrait is processed to the abstract internal structure in a graphical way, and the results are applied to the related fields of personalized learning. For example, personalized learning partner matching and path recommendation services are provided according to learners' basic information and learning experience. Personalized learning resources are provided according to the differences in learning styles. Personalized learning behavior supervision services are provided according to online learning input to improve knowledge precipitation rate and conversion rate. Individualized evaluation and early warning are provided according to the learning results of each stage, so as to understand the weak links of the general literacy and measure one's level in different modules of the general education curriculum system.

4. Construction of Online Learner Portrait in Online General Course

Taking the learners of the online general education course of Zhejiang Shuren College as an example, we make a case analysis based on the portrait framework, evaluate the learning effect from different stages, and put forward targeted teaching strategies and measures.

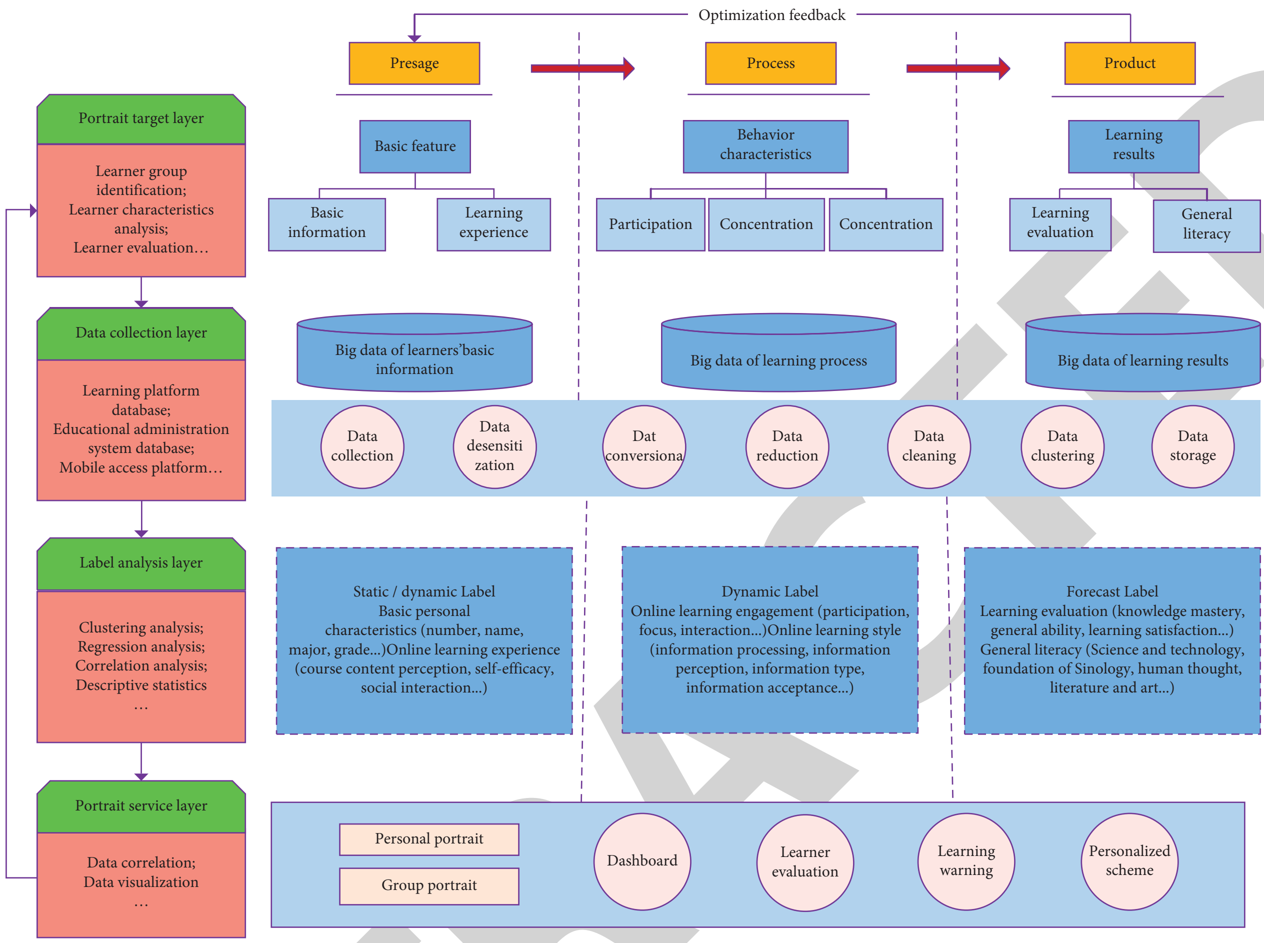

FIGURE 1: Online learner portrait process framework of online general education course.

4.1. Data Collection

4.1.1. Data Collection in the "Presage" Stage. The data in this stage come from the basic information of learners in our school's educational administration system and the questionnaire data of the "Online Learning Experience Survey" issued by the learning platform of online general courses. There were 25 items in the questionnaire, and each item was designed using a five-point Likert formula (1 = completely disagree; 5 = completely agree). Factor 1 is "quality of course content," which mainly investigates students' perception of the relevance, thinking, interest, and advance of the course content. Factor 2 is "self-efficacy," which mainly investigates the status of students in course learning. Factor 3 is "social interaction," which mainly investigates students' perception of teacher-student interaction, student-student interaction, and platform interaction. Factor 4 is "learning support services," which mainly investigates students' satisfaction with learning support services of online general education. The results of confirmatory factor analysis for this scale were $X^2/DF = 9.859$, RMSEA = 0.066, NNFI = 0.938, CFI = 0.903, IFI = 0.904, and TLI = 0.952. If NNFI and CFI values are greater than 0.9 and RM-ESA values are less than 0.8, it is considered that the hypothesis model has a good degree of fitting with the research data and has good validity [25].

A total of 1628 valid questionnaires were collected. Male and female students accounted for 47.6% and 52.4% of the sample. In terms of grade distribution, freshmen accounted for 26.2%, sophomores 37.8%, juniors 24.2%, and seniors 11.8%. In terms of major distribution, science and technology accounted for 33.1 percent, arts and management 38.4 percent, medicine 14.4 percent, and art 14.1 percent. In terms of the learning experience of online general education courses, those who have participated in one course account for 13.5%, those who have participated in 2-3 courses account for 22.1%, those who have participated in 4–5 courses account for 42%, and those who have participated in more than 5 courses account for 22.4%.

4.1.2. Data Collection in the "Process" Stage. The data in this stage comes from the big data of the learning process, and the learning analysis technology is mainly used to construct the personalized learning behavior. In order to accurately analyze the characteristics of learners' learning behaviors, the author formulated an online learning engagement scale from three dimensions of participation, concentration, and interaction and constructed an online learning engagement model as shown in Table 1. "Participation" in the model refers to the time and energy learners invest in online

Table 1: Online learning engagement model.

Dimension	Secondary dimension	Measurements
Participation	Video learning time Resource accessing quantity	Video regurgitation ratio Number of resource views
Concentration	Task completion Quality of work Chapter test Answer situation	Task completion percentage Operation module usage frequency Number of completed jobs Average number of questions
Interaction	Interaction with teachers Interaction with students	Number of topics discussed Response times

learning, including the rumination ratio of watching videos and the number of resource visits. "Focus" refers to the depth of learners' involvement in online learning, including task completion, homework quality, and answer performance. "Interaction" refers to learners' enthusiasm for online learning, including the frequency and quality of teacher-student and student-student interactions.

Based on the online learning investment model, this study collected the learning behavior data of 11,372 learners on the learning platform of our college's online general education course in the spring semester of 2021 and obtained 71,103 records of completing task points, 36,792 records of completing exams, 89,638 records of comments, and 387,522 records of data related to resource access. There were 112,145 records of activity-related behavior data and 237,854 records of activity-related behavior data. Due to different data types, the value range varies greatly. Therefore, raw data cannot be directly processed. Therefore, this study uses a z-score normalization algorithm to normalize the data.

4.1.3. Data Collection in the "Product" Stage. In this study, the general ability scale and general literacy assessment were distributed on the Erya General Education learning platform of our college to collect data in the "product" stage. The general ability scale includes 15 questions and is scored by a five-point scale (1 = completely inconsistent; 5 = completely consistent) to investigate the completion of the knowledge goal, the completion of the ability goal, and the completion of the emotional goal. The scale had good validity, $X^2/DF = 20.859$, $RMSEA = 0.069$, $NNFI = 0.941$, $CFI = 0.937$, and $TLI = 0.952$. The general literacy assessment randomly selects 50 questions from the background massive question bank for students to answer. The selected questions include five dimensions of science and technology, foundation of sinology, human thought, literature and art, and history and civilization, with 10 questions for each dimension. The answer time is 20 minutes, and the total score is 100 points.

This data collection requires students to complete a questionnaire on general ability before the general literacy assessment. A total of 4346 students have been collected. The overall participation rate of the whole school reached 74.88%, indicating that the data can basically accurately reflect the actual general literacy level of the school. From the perspective of each grade, the number of senior students is small, only 14%, while the number of freshmen, sophomores, and juniors is basically the same, about 85%, which shows a good representation.

4.2. High-Risk Learner Portrait Label

4.2.1. Portrait Labels of High-Risk Learners in the "Presage" Stage. In this study, four factors of "course content perception, self-efficacy, social interaction, and learning support services" obtained from the online learning experience survey were selected as the evaluation basis for the "early" stage of learning. The test results of the measurement model are shown in Table 2. From an average point of view, all factors are 3 points higher than the theoretical median value, indicating that the evaluation tends to be positive and there is room for further improvement in social interaction. In terms of standard deviation, social interaction fluctuates greatly. Cronbach's a were all greater than 0.7, indicating good data reliability and high reliability. The average variance extracted (AVE) and combined reliability (CR) were both greater than 0.5 and 0.8, indicating that the intrinsic quality of the factors was good and the convergence validity was ideal.

In order to identify high-risk learners in the "presage" stage of learning, this study took course content perception, self-efficacy, social interaction, and learning support services as indicators and conducted k-means clustering analysis using SPSS25.0. Sig values of the four indicators are all less than 0.01, indicating that the clustering effect is effective. Table 3 describes the number of learners of the four types after clustering and the mean values of each characteristic. The number o-f high-risk learners accounts for 0.98%, indicating that they have poor perception of course content, are not confident in learning, have a negative attitude, rarely participate in interactive activities, and find it difficult to obtain learning support services.

4.2.2. Portrait Labels of High-Risk Learners in the "Process" Stage. According to the data collected by the online learning engagement model in this study, combined with the elbow method and contour coefficient analysis, the k-means ++ algorithm was used to group the learning engagement data. After repeated tests, the error square and SSE values were selected as the local minimum. The clustering results are shown in Table 4.

In order to better identify high-risk learners and understand groups with different learning engagement performance, this study compares the average value of each variable of learning engagement in different clusters with the overall average value in the data of the final cluster center, as

Table 2: Measure the test value of the model.

Factor	Average	Standard deviation	Cronbach's a	AVE	CR
Course content perception	3.798	0.663	0.854	0.8326	0.8704
Self-efficacy	3.808	0.762	0.902	0.7674	0.8525
Social interaction	3.607	0.809	0.815	0.7657	0.9047
Learning support services	3.878	0.695	0.863	0.8713	0.8699

Table 3: *K*-means clustering results.

	High-risk learner ($N = 16$)	Mediate-risk learner ($N = 302$)	Low-risk learner ($N = 732$)	Excellent learner ($N = 578$)
Course content perception	1.09	1.97	2.69	3.92
Self-efficacy	1.24	2.06	2.77	3.44
Social interaction	1.18	1.85	2.56	3.82
Learning support services	1.24	2.13	2.81	3.91

Table 4: Clustering results data.

Type	Type 1	Type 2	Type 3	Type 4
Video regurgitation ratio	0.55	1.04	1.87	0.95
Average number of resource views	11.62	8.56	23.32	15.62
Average number of tasks completed	0.68	1.25	2.19	0.57
Mean operation usage frequency	11.95	14.39	17.27	11.53
Average number of jobs completed	0.79	0.94	2.23	0.37
Mean of total number of questions	0.34	0.81	2.21	0.33
Average number of topic discussions	0.27	1.64	1.11	0.55
Average number of comment replies	4.46	22.28	18.19	5.97

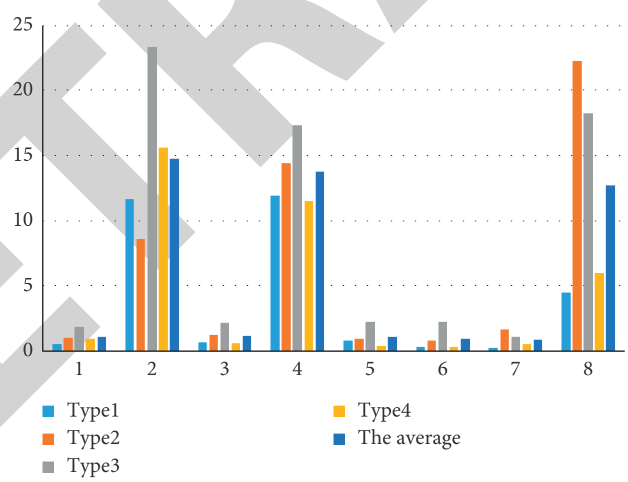

Figure 2: Comparison of learning engagement among different clusters.

shown in Figure 2. Class 1 learners are the weakest in terms of learning engagement performance, which is basically lower than the overall average level. They are high-risk learners in the "process" stage. This type of learner presents the following characteristics: they spend less time and energy on online resource browsing and learning, the quality of homework is average, their performance in chapter tests is not ideal, and their online activity is not high. The overall level of type 2 learners is basically the same as the average, but they are lower than the average in resource browsing and exceed all learners of other categories in interaction, belonging to the group of low-risk learners. The three types of learners have the best performance in terms of learning engagement, all of which are higher than the overall average level and belong to excellent learners. The four types of learners are basically equal to the average in terms of learning engagement but lower than the average in terms of concentration and interaction, belonging to medium-risk learners. This type of learner presents the following characteristics: they are able to watch videos and browse resources instantly, but their homework quality is average and their online activity is not high.

Next, this study continues to explore the relationship between learners' learning engagement and their daily performance. First of all, the collected chapter test scores and homework scores are averaged to generate the average score of ordinary times. Then, the correlation analysis was conducted between the average score of ordinary times and the participation, concentration, and interaction of online learning input. The results showed that the significant correlation between score and participation ($R = 0.257$, $P < 0.01$), concentration ($R = 0.678$, $P < 0.01$), and interaction ($r = 0.066$, $P < 0.01$) was within 0.01. There is a strong correlation between concentration and performance, while interaction shows a weak correlation. Therefore, we should pay more attention to the high-risk learners with low concentration.

4.2.3. Portrait Labels of High-Risk Learners in the "Product" Stage. In this study, the three labels of "knowledge goal, ability goal, and emotion goal" obtained from the general ability survey and the mean score of the five-point system obtained from the general literacy evaluation were selected as the evaluation basis in the "product" stage. Cronbach's a coefficient of general ability scale was 0.908, the mean variance variation (AVE) was 0.855, the combined reliability (CR) was 0.867, and the convergence validity was ideal, which could be used for data analysis of this measurement model. In order to identify high-risk learners in the "product" stage, SPSS25.0 was used for k-means clustering analysis. Sig values of the four indicators were all less than 0.01, indicating that the clustering effect was effective. The number of high-risk learners after clustering accounted for 3.78%. The data results show that the completion of knowledge and conceptual and procedural knowledge objectives is low, the ability of critical thinking, analysis, and problem-solving is weak, and the improvement of scientific literacy and multiperspective is low. At the same time, their literacy foundation is weak and needs to be focused.

In order to further explore the performance of learners in each module of general literacy, a picture of learners' general literacy is obtained by combining the average level of this major, our school, and previous data, as shown in Figure 3. The portrait dynamically shows my performance in each module and also presents the average performance of students of this major and the whole school in different modules, so as to help students intuitively understand and compare, so as to adjust the learning direction, tend to courses with weaker literacy, and comprehensively improve their general ability.

5. Discussion and Suggestions

5.1. Learning Experience of High-Risk Learners in the "Presage" Stage. In the portrait analysis of the "premise" stage of learning, the number of high-risk learners accounts for 0.98%. It can be seen from the data results that their perception of curriculum content, self-efficacy, and social interaction are poor. This also reflects that these kinds of learners are not interested in the content of the course, are not satisfied with the appropriateness, scientificity, and thinking of the content, are not confident in learning, have a negative learning attitude, and have a poor experience of the platform. In order to avoid affecting the next stage of learning and reduce the loss of learners, we should strengthen the construction of curriculum quality, open more high-quality general education courses according to the needs and abilities of students, and provide timely learning support services. Specific strategies include the following: (1) to carry out separate and specialized regular and accurate content quality evaluation of online general education courses, comprehensively evaluate the compatibility and effectiveness of existing courses with the general literacy cultivation of our school, classify and rank existing courses based on survival of the fittest, build high-quality general education courses, and improve the teaching quality of general education courses [26]. (2) Do well in introductory courses of general education so that students can understand the training objectives of general education of our school, and set relevant questionnaires on the platform to evaluate students' general literacy so that students can effectively understand the advantages and disadvantages of their general literacy level, so as to guide the selection of courses and choose courses appropriate to their learning objectives. (3) Provide multichannel, timely, and effective learning support services to improve students' enthusiasm and initiative. Through stage comparison with other learners, students can learn from others, gain indirect experience, enhance their confidence in achieving the same goal, improve the learning experience, increase learning input, and reduce the possibility of students giving up learning.

5.2. Learning Experience of High-Risk Learners in the "Process" Stage. In the portrait analysis of the learning "process" stage, the number of high-risk learners accounted for 4.98%, and their learning engagement performance was the least ideal, with participation, concentration, and interaction ranking the last. Through correlation analysis, it is found that the correlation between concentration and average score is the highest. In order to avoid affecting the next stage of learning and obtain satisfactory learning results, we should actively guide students to devote themselves to learning, help them develop good habits of continuous learning and lifelong learning, and then realize the concept of whole-person education in general education. Specific strategies include the following: (1) pay attention to the situational creation of learning tasks and promote deep learning. Virtual simulation and big data technology are used to create a strong experiential learning situation based on problems according to the teaching content, learners' characteristics, learning behavior, and "presage" learning experience. By clarifying task objectives, learners can stimulate learning motivation and solve situational problems so that learners can make use of the knowledge they have learned and have their own internal understanding. (2) Pay attention to teachers' participation and guidance to build a learning community. The efficient development of online learning is inseparable from teachers' organization, management, monitoring, and emotional motivation, timely feedback of homework,

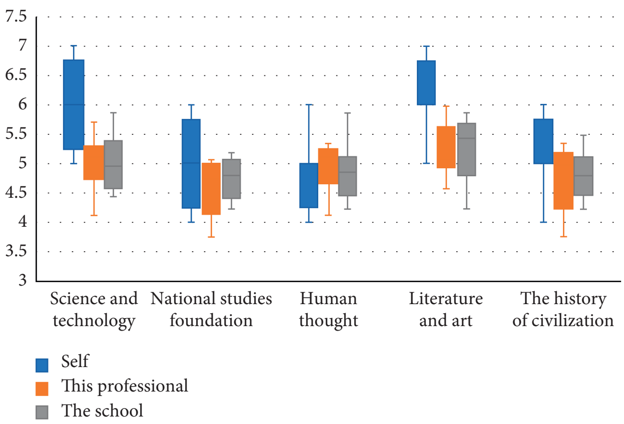

Figure 3: General literacy portrait presentation for students.

tracking and guiding task completion progress, and helping learners to perceive destination and collective existence. Create a learning community for general education, break the limitations of majors, enhance cross-disciplinary exchanges, and form a good learning atmosphere and tradition. Good learning community cultivation is of great significance to the promotion of general education and the all-round development of students. (3) Strengthen the construction of group dynamic mechanism to promote in-depth interaction. It is found that the current online discussion is mainly structured, the quality of the interactive text is not high, and there is “formal interaction.” Therefore, it is necessary for teachers to carry out macrocontrol and flexible dynamic adjustment of learning interaction and topic discussion, such as “recognition homework based on peer evaluation and peer recommendation” and “cross review of problem matching,” so as to improve learning participation and deepen learning.

5.3. Learning Experience of High-Risk Learners in the “Product” Stage. In the portrait analysis of the learning “product” stage, the number of high-risk learners accounted for 6.63%, and their knowledge goal, ability goal, emotional goal completion, and general literacy test level were all low. This reflects that such learners have problems in their attitude towards answering questions in the evaluation process, or their general literacy foundation is extremely weak. In order to improve the learning in the next “presage” stage and promote the generation of oriented learners, we should guide students to effectively choose their deficient areas of learning according to the evaluation results. Specific strategies may include the following: (1) clarify course objectives and adjust course structure. Analyze the general literacy situation of the whole school, optimize the proportion of courses in each section and the theme of a single course in the curriculum system, and build the internal connection between knowledge for students. Students choose courses of different levels according to their own portraits and the reference levels of each module to accurately improve the general literacy of corresponding modules. (2) Construct supporting general resources. According to the differences in the score changes of each section in the general literacy data, the needs, preferences, and expectations of learners for general resources are analyzed, and the main resource builds the ability of students towards their weak links so as to improve the teaching effect. (3) Improve the course assessment system. Make clear the course assessment target, reform the assessment content, and establish a diversified, multilevel, and multitype dynamic assessment model. It can be seen that we can better achieve the goal of general education only by paying attention to the assessment of the ability to analyze and solve problems, paying attention to identifying, judging, and analyzing some social events with correct views and ideas, and paying attention to the use of communication means for effective activities.

6. Conclusion

In view of the problems existing in the current online general education, we first analyzed the characteristics of general education and proposed a learner portrait framework of “three stages and four levels” based on the 3P learning theory. At the same time, taking the online learners of the online general education course of Zhejiang Shuren College as the research object, this paper analyzed the modeling and portrait output, discussed the relevant characteristics of high-risk learners in different learning stages, and put forward targeted teaching strategies and measures. The results show that learner portraits can reflect the characteristics of learners’ online learning experience, online learning investment, and online learning results and can provide data support for the design of online learning support services and the optimization of learning effects. In future research, we will further improve the accuracy of the premise, process, and outcome stages from the aspects of data collection and processing, learners’ emotional experience, and general ability evaluation.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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