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Design of Personalized Early Warning Feedback for Distance Learning from the Perspective of Participatory Design

Qixin Xu[1,a], Huanhuan Yuan[2,b], Ming Liu[3,c,*], Wei Liu[4,d]

[1]*Faculty of Education, Yibin University, Yibin, China*
[2]*College of Computer and Information Science, Chongqing Normal University, Chongqing, China*
[3]*The Faculty of Education, Southwest University, Chongqing, China*
[4]*Faculty of Education, Yibin University, Yibin, China*
[a]*923875621@qq.com,* [b]*2990443380@qq.com,* [c]*mingliu@swu.edu.cn,* [d]*29857604@qq.com*
[*]*Corresponding author*

Abstract: *Based on a participatory design perspective, the results of data analysis and constructed predictive models are applied to the design process of early warning feedback, which contributes to the selection of representative participants and early warning feedback elements. The participatory design process in this paper includes three stages of comprehending, creating and interacting, and includes participatory design methods such as teaching activity maps, persona profile, learner insight analysis maps and learning journey maps. The study selected 15 participants from different backgrounds to design and implement the learning early warning dashboard, and 38 learners were organized to evaluate the usability of the learning early warning dashboard in four dimensions: usefulness, cognitive load, user satisfaction, and self-direction, and the results indicated that 91.1% of the learners thought that the learning early warning dashboard would allow them to quickly and easily grasp their learning and would motivate them to learn and improve in a timely manner based on the learning strategies provided.*

Keywords: *Participatory Design; distance education; early warning feedback; learning early warning dashboard*

1. Introduction

Distance education is an important means to achieve equity in higher education in China, and has now entered a new stage of ubiquitous learning[1]. Most distance education learners are working people, and it is difficult to guarantee learning time and energy, so they are prone to encounter learning obstacles and frustrations; due to the teaching characteristics of time and space separation, there is a lack of real-time interaction between teachers and students, and learners encounter difficulties that cannot be solved in time, triggering problems such as declining learning motivation[2]. Therefore, how to identify learners with the risk of failing a course, provide them with personalized early warning feedback, stimulate learning motivation and reduce learning risks, so as to improve the efficiency of teaching and learning is an urgent problem for distance education. In recent years, learning analytics has become a cutting-edge technology-driven force in the development of modern distance education, but now relevant research generally focuses on the construction of risk prediction models, and lacks the design and provision of personalized feedback based on the results predicted by prediction models. Katerina et al. argue that the features of data analysis should be linked to visualization, and that visualization of data can improve the interpretability of data analysis results[3]. Pan Qingqing et al. argue that the results of learning analytics are not only key to teachers' decision-making interventions, but also to students' understanding of themselves[4]. Designing personalized feedback through participatory design methods is now a research direction in learning analytics, and effective personalized feedback cannot be achieved without the idea of participatory design, and it is crucial for learners, as recipients of personalized feedback, to understand their suggestions and ideas about the feedback[5]. Disalvo et al. point out that at this stage, there are still few successful cases of applying participatory design in the field of learning analytics[6], and participants The challenges of participatory design are the diversity of backgrounds, the different motivations for participation, and the "professional gap" between participants and personalized feedback design[7]. The different backgrounds and learning styles of participants not only affect their understanding and completion of tasks during the engagement process, but also the consistency in the selection of feedback

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elements. In this study, we analyze historical data from four online distance education courses to construct an online learning risk prediction model, then select representative participants based on demographic propensity characteristics associated with the risk of failure, and adopt participatory design methods such as teaching activity maps, persona profile, learner insight analysis maps and learning journey maps to design personalized early warning feedback- -Learning Early Warning Dashboard.

2. Literature review

On the construction and analysis of online learning risk prediction model, the online open course interrupt learning risk prediction model based on learning behavior by Zhang Yuan et al[8]. Research on predicting online learning performance or risk characteristics is divided into two main categories. One type of research only captures learners' online learning behavior data for research, e.g., Macfadyen et al. found that the number of forum discussions, emails sent, and quizzes completed effectively predicted learning performance[9]. Another type of research incorporates learners' demographic dispositional characteristics into the study data sample. For example, Hlosta et al. analyzed learners' background information such as age, sex, and geography in combination with online learning behavior data[10]; Zhao Lei et al. predicted learners' academic performance and group characteristics based on the MOOC learning behavior data, and timely implemented teaching intervention; explored the course data of Chinese University MOOC platform and found significant correlation between learning behavior and academic performance: interface interaction, content interaction, interpersonal interaction and participation assessment[11], Zhang Qi et al. used learners of a course in an "Internet+" blended learning scenario to construct prediction models, and compared the results of 28 classes of regression algorithms with 24 classes of classification algorithms, and found that the random Forest algorithm has the best performance in both numerical and classification prediction[12].

In terms of personalized early warning feedback design research, it mainly contains learning dashboard design based on theories and feedback design principles related to self-regulated learning, and teacher- or student-centered learning feedback design. Early learning early warning systems present a relatively simple form of feedback, for example, Purdue University's signal light system uses red, yellow, and green colored lights to present overall academic warning information[13].Sedrakeyan et al. proposed a conceptual framework for learning analytics dashboard feedback based on theories related to learning science, and designed personalized learning resource recommendation feedback based on learning goals. Based on the learners' current mastery of domain knowledge capabilities, this feedback not only recommends the next learning topic and the required learning time, but also allows learners to monitor their learning progress and make learning suggestions[14]. Domestic scholars, Huang Changqin et al, based on feedback design principles, proposed a strategy for visualization implementation in four aspects: spatial visualization element change, knowledge point organization, visualization way conversion and group visualization content presentation content, and designed and implemented a learning behavior big data visualization subsystem based on this strategy[15]; however, such feedback design methods ignore the actual needs of learners for feedback. Professor Pardo et al. in Australia combined learning analytics and teacher-developed feedback templates to build the On-Task system, which gives interventions by email push according to different learners' learning situations, achieving effective personalized feedback for a large number of learners, and the study pointed out that personalized feedback is an important factor in supporting learners' success[16].

Comprehensive domestic and foreign research found that the existing relevant research has the following two deficiencies: first, learning risk prediction model performance evaluation in distance education multi-disciplinary comparative research is relatively small, at present mainly focused on learning risk prediction model performance evaluation research based on the learning behavior of a single catechism course. Second, there is less research on early warning feedback, and the existing feedback designs are mainly designed by researchers based on their own experiences and relevant theories, lacking user participation. This study will be based on participatory design perspective to design personalized early warning feedback suitable for distance education. Based on this, the following two research questions are proposed: First, can a cross-course online learning risk prediction model be constructed based on big data of distance education? Which characteristics of distance learners are more strongly correlated with learning performance? Second, how to apply learning analytics to participatory design, select representative participants, and reduce the "professional gap" to design personalized early warning feedback for distance learning?

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3. Online learner characteristic analysis and risk prediction model construction

3.1. Data collection and pre-processing

The 14,448 learners of four courses offered in 2017 in the College of Online and Continuing Education of a university in Chongqing were used as the research sample, including two science courses on hydraulics and engineering geology, and two liberal arts courses on pre-school health and history of pre-school education. Their personal background information and online learning behavior data were collected as the study sample, and private information such as learners' names were anonymized and normalized for characteristics such as the length of online learning and the average time to submit assignments from the due date that differed too much in value. Referring to the study of Chen Zijian et al. the learners' learning performance was divided into risk categories of failure with a cut-off of 70[17], less than or equal to 70 was classified as risky and greater than 70 was classified as no risk.

3.2. Selection and analysis of predictive features

For the selection of features related to predicting academic performance, based on the study of related literature and with reference to Fan Yizhou et al.'s review of the literature on predictive features in the field of learning analytics[18], this study classified the 12 original predictive feature indicators used into three dimensions. Among them, demographic propensity features include sex, education (high school, college, undergraduate, other), ethnicity (Han, minority), age, and prior study major; human-computer interaction features include total hours of online learning, total number of assignment submissions, total number of online study sessions, usual assignment grades, and average time from submission date to deadline; and interpersonal interaction features include total number of online discussions and total number of online questions.

Step 1: The data from the liberal arts and science courses were combined and called integrated courses, and the cardinality test in SPSS software was used to explore the relationship between demographic propensity characteristics in integrated courses and whether learners were at risk of failing the course, i.e., learners' sex, education, ethnicity, age, and major were cardinality tested and cardinality post hoc analysis was done with the presence of risk of failing the course, and the results are shown in Tables 1 and 2, respectively.

Table 1: Results of chi-square test analysis

Predictive features \ Coefficient	X^2	df	p
sex	133.9	1	0.000
education background	217.5	3	0.000
nationality	59.779	1	0.000
age	131.3	5	0.000
specialty	41.322	1	0.000

*X^2 is the chi-square value, df is the degree of freedom, and P is the significance

Table 2: Results of chi-square posterior significant risk category analysis

Features type \ Risk category	non-risk	risky
female	5297 (-13.0)	2526 (13.0)
Other qualifications (ex-servicemen)	538 (-11.9)	430 (11.9)
High school diploma	6485 (-5.0)	2679 (5.0)
national minority	774 (-6.2)	426 (6.2)
Under 20 years of age	669 (-5.0)	354 (5.0)
20-24 years old	2086 (-8.5)	1066 (8.5)

*Standardized residuals are in parentheses, and the sample frequency for that category is on the left

Table 1 shows that learner sex, education, ethnicity, age and major in the integrated course are significantly correlated with the risk of learning to fail, and Table 2 shows that the adjusted standard residuals for the presence of risk are greater than or equal to 5 for female, other education (veteran), high school education, minority, under 20 years old, and 20-24 years old, indicating that this group of learners is at high risk of learning to fail. Therefore, we will focus on selecting representatives of minority female learners with high school degrees or other degrees and aged 24 years and younger to participate in designing personalized early warning feedback.

Step 2: Correlation and multiple linear regression analysis in SPSS software was used to investigate the relationship between predictive features and academic performance in different course properties and the results are shown in Table 3.

Table 3: Results of Pearson correlation analysis of characteristics and academic performance

Predictive features \ Coefficient \ Course nature	Science courses		Liberal arts courses	
	r	p	r	p
age	0.021*	0.019	0.079**	0.000
Total hours of online learning	0.007	0.444	0.027*	0.014
Total number of online studies	0.035**	0.000	-0.029**	0.008
Homework grades during the day	0.069**	0.000	0.031**	0.005
Total number of online discussions	0.008	0.024	0.017	0.124
Total number of online questions	-0.027**	0.002	0.008	0.476
Total number of assignments submitted	0.042**	0.000	-0.074**	0.000
Average time to deadline for submission of assignments	0.062**	0.000	-0.004	0.749

*r is Pearson correlation, P is significant, **. Significantly correlated at the 0.1 level (bilateral)*. Significantly correlated at the 0.05 level (two-sided)

As can be seen from Table 3, science courses have more predictive features that are correlated with academic performance than liberal arts courses; in science courses, there is no correlation between only one human-computer interaction feature (total number of hours spent studying online) and academic performance, while in liberal arts courses, there is no correlation between learners' human interaction features (total number of online discussions and total number of online questions) and academic performance, and neither human-computer interaction feature (average time to submit assignments from the due date) did not correlate with academic performance either. In order to further explore the influence relationship between characteristics and learning performance, all characteristics that had correlation with learning performance in different course natures were selected and multiple linear regression analysis was conducted, and the results are shown in Table 4.

Table 4: Results of multiple linear regression analysis of characteristics and academic performance

Predictive features \ Coefficient \ Course nature	Science courses		Liberal arts courses	
	B	P	B	P
age	0.034	0.024	0.074	0.000
Total number of online studies	0.181	0.000		
Homework grades during the day	0.106	0.000	0.072	0.000
Total number of online questions	-0.575	0.000		
Total number of assignments submitted			-0.046	0.000
N	12802		8068	
R^2	0.30		0.18	

*N is the number of learners, R^2 is the linear correlation, B is the coefficient, and P is the significance

3.3. Online learning risk prediction model construction and evaluation

The pre-processed dataset was imported into Weka for training, and five classification algorithms, decision tree (Part), random forest (RF), logistic regression (LG), neural network (BP) and decision tree (J48), were applied to construct learning risk prediction models using a 10-fold cross-validation method[19]. In this study, Smote sampling was used to solve the problem of uneven distribution of learner risk category data samples, and two indicators, Kappa value and F-score, were used for model evaluation, and then the performance of learning risk prediction models constructed for integrated courses and different course properties were compared, and the results are shown in Table 5.

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Table 5: Indicators of learning risk prediction models constructed for different course natures

Classification algorithm	Science courses		Liberal arts courses		Integrated courses	
	Kappa value	F-score	Kappa value	F-score	Kappa value	F-score
Part	0.5502	0.739	0.3339	0.584	0.4760	0.733
RF	0.6816	0.833	0.4447	0.705	0.5863	0.782
LG	0.2236	0.672	0.0897	0.511	0.1522	0.572
BP	0.3168	0.652	0.1800	0.573	0.2574	0.629
J48	0.5491	0.762	0.3468	0.623	0.4723	0.735

The results show that the integrated course learning risk prediction model constructed by applying the random forest algorithm has a significant improvement in Kappa value and F-score, and although there is a slight decrease in prediction performance compared to the science course model, its F-score is 0.782 and Kappa value is 0.5863, which is still close to high consistency, so the online learning risk prediction model constructed by the integrated course is applicable across courses.

4. Design and evaluation of personalized early warning feedback

Through the preliminary analysis of predictive features and the construction and evaluation of the online learning risk prediction model, this section focuses on how to use the results of the preliminary data analysis and the constructed learning risk prediction model to design personalized early warning feedback ------the learning early warning dashboard and collect learners' evaluation results and feedback on the effectiveness of the learning early warning dashboard comments.

4.1. Selection of participants

Participants in the personalized early warning feedback design included 10 distance education learners, one learning center administrator, two university faculty members, and one researcher and user interface designer. Based on the results of the predictive features analysis (see Tables 3 and 4), the 10 distance education learners selected were all under the age of 24, 8 of whom were female and 2 male, and included 4 ethnic minorities and 5 learners who had completed high school or less. One of the selected learning center administrators had been engaged in distance education management for 15 years and was familiar with distance education teaching, management, and evaluation methods, and two university faculty members were from the College of Liberal Arts and the College of Computer Science at a university in Southwest China, both with more than 10 years of teaching experience. Figure 1 depicts the overall idea of applying participatory design methods to design personalized early warning feedback based on a participatory design perspective.

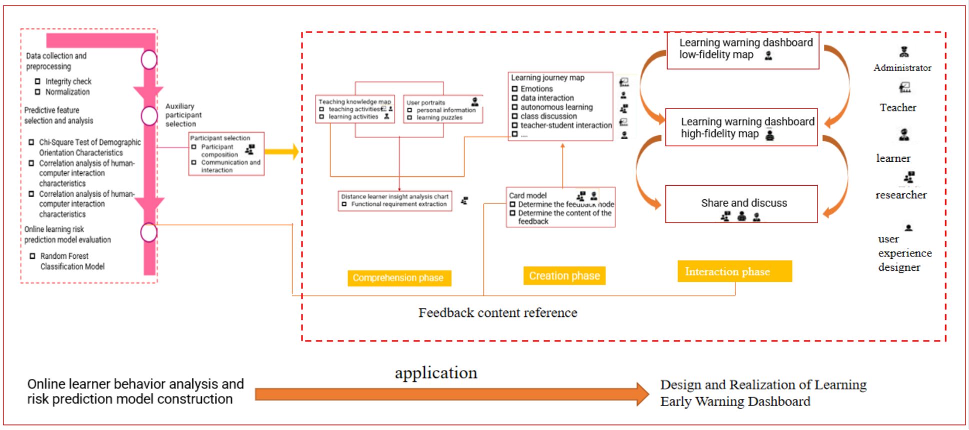

Figure 1: Flow chart of early warning feedback design based on participatory design perspective

4.2. Personalized early warning feedback design process

The core of participatory design theory is user-centeredness, and this study incorporates learner-centered design thinking throughout the design process of the learning early warning dashboard,

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modifying the design thinking framework proposed by Ellingsen, with the entire process consisting of three design phases: the understanding phase, the creation phase, and the interaction phase[20].

4.2.1. Comprehension stage

The comprehension phase is the first stage of the design process and consists of three sessions: teaching activity maps, persona profile, distance learner insight analysis maps. First, the teaching activity maps and persona profile sessions provide the researcher with an in-depth understanding of the main teaching and learning activities and learners' background information, learning experiences, and learning goals in distance education. Finally, the learner insight analysis session distills online learning problems and needs and suggests system feedback features.

The teaching activity maps and learning activities in the first session can be used in different conference discussions to provide a more diverse reference for researchers and learners to express their views and information about their views[21]. The map of teaching and learning activities jointly developed by the researcher, the learner, the instructor, and the learning administrator can further capture the main teaching and learning interventions online and offline in distance education, and provide a reference for the development of a learning journey map for the creation phase.

The persona profile drawn in the second session required learners to review their personal learning experience in terms of their personal learning experience, while also once again facilitating reflection on the learning process. The researcher looked at the learner's persona profile, including basic personal information, devices used for learning, usual habits and preferences when studying, whether they had any past experiences with distance learning, learning goals for participating in distance education, learning expectations for participating in distance learning, and bad experiences and confusions encountered during the learning process, to gain a deeper understanding of the learner's individual needs. Figure 2 shows the persona profile drawn by 1 learner who participated in the feedback design.

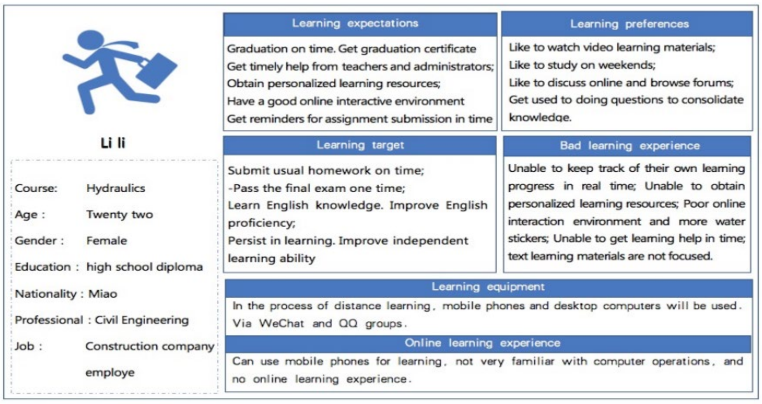

Figure 2: User profile of risky learners

The third session is the distance learner insight analysis maps, where the researcher, after participating in the process of mapping the teaching and learning activities and person profile of the learners and gaining an in-depth understanding of the distance education process, teaching and learning styles, and the students' experiences in distance learning, distills the phenomena of students' learning behaviors and needs into a summary of the system functional requirements, which provides a reference for the subsequent design of the learning early warning dashboard. Figure 3 shows the distance learner insight analysis map jointly drawn by the researcher, learner, instructor, and learning center administrator groups. In the design of the early warning dashboard session in the interaction phase, we used the functional requirements of the insight analysis diagram as a reference, combined with the results of the feature analysis closely related to the risk of failure in the previous phase (see Chapter 3), to design and implement the main feedback modules of the early warning dashboard.

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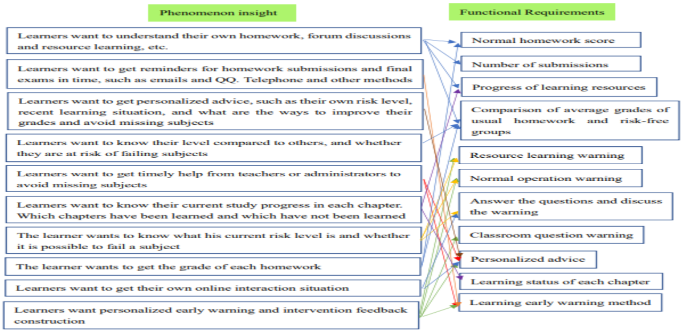

Figure 3: Distance learner insight analysis chart

4.2.2. Creation phase

The creation phase is the second stage of the design process and is a discussion between learners, learning center administrators, and teachers around what kind of feedback and intervention content is needed from the learning center during the learning process with the goal of promoting learners' academic success.Mears states that the learning journey is the activity of all participants and interactions in the learning process that together generate a complete learning journey map, with a general learning journey map includes elements such as learning activities, sequence of learning activities, learning emotions, learning devices, and data interactions[22]. The learning journey allows the researcher to understand the key learning activities that learners need to complete or experience during the learning process, and to gain a deeper understanding of learning behaviors and how learners interact with the learning platform. The researcher organizes learners, learning center administrators and teachers to complete a distance learning journey map to explore what kind of feedback needs to be given to learners and the time point for giving feedback in the actual learning process of distance education by combining the needs collated from the comprehension phase and the characteristics that influence learners' learning performance through correlation analysis.

First, the researcher introduces the meaning and role of the learning journey map to the learners so that the learners are clear about the tasks and the presentation of the tasks at this stage and motivate participation. Second, the teacher divides the learning stages and learning scenarios to facilitate learners, administrators and teachers to review and summarize the distance education process from the dimensions of time and learning scenarios, to help the researcher to be familiar with the teaching and learning process of distance education, and to develop horizontal and vertical coordinates key nodes in conjunction with the map of teaching and learning activities. Again, learners, teachers and administrators populate the learning activities and teaching activities to the corresponding coordinate positions to form a distance education process map. Finally, learners use the card model to comment around the feedback content and write the feedback content they need (e.g. learning risk prediction map/learning progress note) on sticky notes to be posted at the corresponding time nodes according to their ideas.

4.2.3. Interaction phase

The interaction phase is the last phase of the design process, which applies the findings of the understanding and creation phases. Those involved in the design include user experience designers in addition to researchers, learners, teachers and learning center administrators. The researcher will introduce educational pedagogical theories such as: educational data storytelling, formative assessment theory and cognitive load theory, and guide learners to integrate these theories into the design process of early warning feedback in easy-to-understand language. Visualization software such as E-charts will be used to generate online interactable diagrams, which will be modified through multiple iterations to obtain the final online interactable high-fidelity learning early warning dashboard prototype.

Firstly, the researcher introduces the learners to the task of this phase, the meaning, role and application areas of the learning early warning dashboard, so that the learners can have a preliminary knowledge and understanding of the learning early warning dashboard. Secondly, the UX designer introduces the learners to various presentation forms and cases of learning dashboards from the design perspective, and analyzes the advantages and disadvantages of each presentation formation, so that the learners can have a deeper understanding and intuitive feelings. Again, the feedback content is determined by filtering and analyzing the content of the sticky notes. In this session is where the researcher, the learner sketches for each feedback content in turn, the UX designer provides consultation, and the design includes the form of presentation, the content of the diagram, etc.

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Finally, the user interface designer combined with visualization tools such as E-charts to write code to create an interactive learning early warning dashboard version 1.0 based on a low-fidelity prototype diagram. The researcher introduced educational data storytelling (Storytelling), cognitive load theory, and other relevant educational teaching theories into the iterative design process of early warning feedback, highlighted the important content of the visual analysis diagram, and invited two teachers to participate in the designation of the learning strategy template, and then the learning early warning dashboard version 2.0 was implemented by the user designer, as shown in Figure 4.

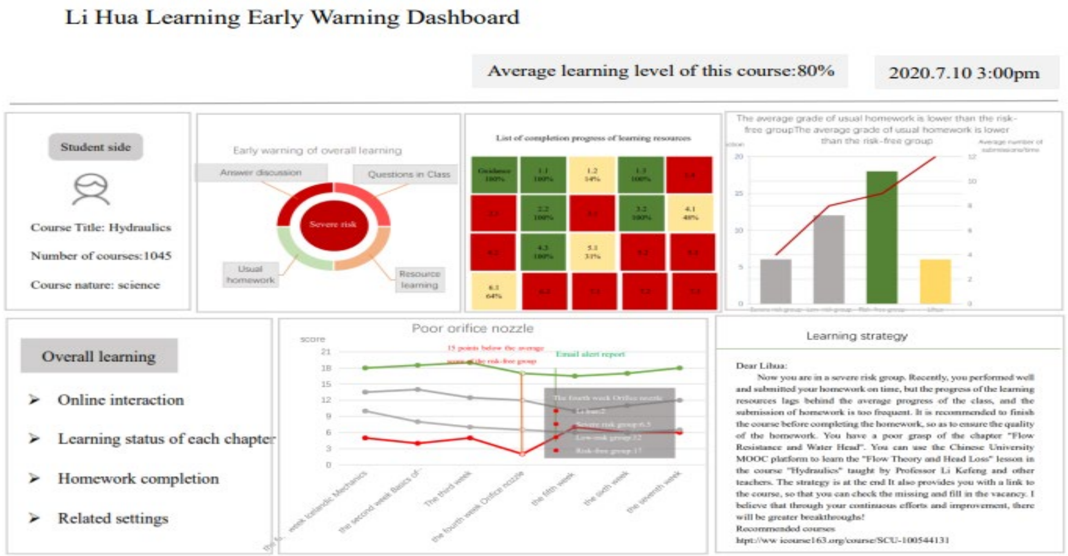

Figure 4: Learning early warning dashboard high fidelity prototype diagram

4.3. Evaluation of the effectiveness of the prototype learning early warning dashboard

After implementing a prototype high-fidelity learning early warning dashboard, 38 non-participating learners from the liberal arts and sciences in distance education were invited to evaluate its effectiveness. The questionnaire was based on a 5-point Likert scale from 1 to 5, corresponding to "disagree" to "fully agree", and contained 14 single-choice questions in four areas: perceived effectiveness, cognitive load, user satisfaction and self-direction, as shown in Table 6.

Table 6: Learning early warning dashboard prototype usability questionnaire

Factors	Summary	Quantities
Perceived usefulness	Accurate grasp of learning status, insight into online learning behavior performance, and easy to check knowledge mastery, clarify learning strategies and plans	4
Cognitive load	Appropriate number of data indicators, ease of understanding of graphs, quick grasp of learning	3
User satisfaction	Value of prototype information, authenticity of early warning feedback, comfort of interface design	3
Self-direction	Knowledge acquisition, online learning behavior, usual assignments, learning risk status	4

The total number of questionnaires distributed was 38 and the total number of questionnaires returned was 38, after careful screening, 2 questionnaires were invalid and 36 questionnaires were valid with an effective rate of 95%. This study used SPSS software to analyze the reliability of the questionnaire, and the Cronbach Alpha coefficient was used for the reliability analysis, and the Cronbach Alpha coefficients of the overall reliability, usefulness, cognitive load, user satisfaction and self-direction of the questionnaire were obtained as 0.951, 0.832, 0.866, 0.813 and 0.911, respectively. The results showed that subscale reliabilities were all greater than 0.8, and the overall reliability of the questionnaire was above 0.9; therefore, the questionnaire passed the reliability test. Validity analysis used KMO value and Bartlett's sphericity test and obtained KMO=0.814>0.8, Bartlett's sphericity test approximate chi-square value of 396.057, probability value Sig.=0.000<0.05 at degree of freedom (df) of 91, indicating that there is significant correlation between each variable, and the questionnaire design passed the validity test. The results of the usability evaluation are shown in Table 7 below.

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Table 7: Usability evaluation results of the learning early warning dashboard prototype

variable	Mean	Standard Deviation (SD)
Perceived usefulness	4.403	0.12
Cognitive load	4.287	0.24
User satisfaction	4.194	0.17
self-direction	4.319	0.14
population (statistics)	4.307	0.15

As can be seen from Table 7, the high mean (mean=4.307) and small standard deviation (SD=0.15) of the overall ratings indicate that all learners have a high acceptance and uniform opinion of the designed learning early warning dashboard prototype. The highest perceived usefulness of the learning early warning dashboard (mean=4.403 standard deviation=0.12) indicates that the vast majority of learners found the learning early warning dashboard easy to use and 91.1% of learners felt that the alert prototype would allow them to quickly and easily keep track of their learning without spending too much time and effort. This is followed by the self-directedness factor (mean = 4.307 standard deviation = 0.15), indicating that the warning prototype motivates them to learn, with 88.9% of learners indicating that the learning early warning dashboard prototype allows them to learn about their online interactions and make targeted changes, with the middle and lowest levels being cognitive load (mean = 4.287 standard deviation = 0.24) and user satisfaction (mean = 4.194 standard deviation = 0.17).

5. Discussion

Predictive feature analysis and learning risk prediction model construction are important components of designing personalized early warning feedback. Studies have found that learner sex, education, and ethnicity are closely related to learning risk status. Zhao Hong et al. pointed out that there were significant differences in learning toughness among learners of different sexes, and there were also significant differences in positive and negative emotions between male and female learners, and the emotional states of male and female learners showed opposite trajectories as learning proceeded. In addition, Shapiro et al. noted that low-education learners are more likely to suffer from learning disabilities[23], and Zhao Hong et al. noted that there are significant differences in the emotional states of learners at different levels of education[24]. It is evident that learners with different educational levels have different cognitive abilities and knowledge bases, and learners of different ethnicities are located in different geographical areas and are exposed to significantly different educational approaches and resources, leading to different learning preferences or learning styles and different online learning efficiency. Applying the participatory design approach to the early warning feedback design process, the learning early warning dashboard designed by representative participants was selected through an in-depth understanding and adoption of users' suggestions and needs, and combined with the results of predictive modeling and other relevant feature analysis, which improved student satisfaction with the learning early warning dashboard as well as student self-direction. Compared to studies in the field of learning analytics, the learning early warning dashboard designed using a combination of participatory design and the results of feature analysis has the following two main characteristics.

First, formative feedback early warning. When mapping the learning journey during the participatory design creation phase, most learners raised the need for more detailed early warning feedback, prompting us to design a formative feedback early warning model that contains both an overall early warning light and relevant early warning information such as the progress of learning resource completion and the usual homework grade score. In the presentation of learning resource completion progress, the color blocks allow learners to perceive their learning progress macroscopically, and quantify their learning progress through specific percentages. In the presentation of learners' usual homework grades, the number of homework assignments submitted by learners is added, which can show whether learners are brushing up on their work. In presenting the learner's completion of each unit of work, the table header presents the conclusions of the learning that the chart is intended to present, and to highlight the contrasting effect of the line graph, the unimportant information is discounted and darkened to increase interpretability and reduce the cognitive load on the learner[24]. In contrast to Purdue University's summative academic risk warning system, the early warning feedback designed in this study contains both an overall warning and the ability to view the status of related elements that affect the final outcome, which can help learners understand their weaknesses.

The second is actionable textual feedback. Compared to Purdue University's academic early warning signal system, the early warning feedback designed in this study includes textual learning tips feedback in addition to pictorial feedback on specific elements that affect student performance displayed in line graphs and bar charts. On the textual learning tips, based on self-learning regulation theory, the instructor provides learners with textual feedback templates for general learning, learning behavior status, and learning strategies to make the early warning feedback more meaningful for implementation.

6. Conclusions

This paper focuses on the construction of online learning risk prediction models in distance education, the analysis of predictive features, and the design of personalized early warning feedback based on participatory design ideas using data from 14,448 learners in four distance education courses. To address research question one, it was found that the selection of Smote sampling method to balance data samples can improve the performance of the prediction model; the constructed online learning risk prediction model for comprehensive courses with F-score of 0.782 and Kappa value of 0.5863 has good portability and can be used across courses; secondly, the characteristics that affect learners' learning performance vary across courses, with female learners, other and high school-educated learners, minority learners, and learners under the age of 24 have a higher risk of failing a course, and learners' regular homework grades have the strongest correlation with academic performance. For research question two: In the design of personalized early warning feedback, participatory design methods such as teaching activity maps, person profile, learner insight analysis maps and learning journey maps are used to fully realize the human-centered design idea and maximize the actual needs of users, while the results of predictive feature analysis and the constructed predictive models are applied to the process of participatory design, including the representative participant selection, and the presentation of early warning feedback content. In addition, relevant educational teaching theories are introduced to make the design of the learning early warning dashboard more scientific. The results of the study can provide theoretical and methodological guidance and practical basis for distance education teaching researchers in improving the quality of distance education and designing effective personalized early warning feedback based on the participatory design perspective.

However, there are some shortcomings: first, the personalized early warning feedback design has fewer participants, and the surface of the feedback content requirements extraction is still slightly inadequate, although the designed learning early warning dashboard applies the real historical data of distance learners, but in terms of learning early warning dashboard evaluation, the learners involved in the evaluation browse not their own real-time data, resulting in possible discrepancies in the evaluation results of the dashboard. Second, the designed early warning feedback has not been studied deeply enough in terms of application and has not been studied empirically in actual distance education teaching courses. Second, the participatory design process requires a lot of time to mitigate the "professional gap" because participants do not understand the early warning feedback design. This caused problems with task completion, such as mapping the learning journey, which required repeated presentations and demonstrations by the researcher. In addition, the researcher needed to spend a lot of time training participants on the connections and implications between the different design stages. In the next step of the study, the focus will be on the effectiveness and continuous improvement of the online learning risk prediction model and the early warning feedback designed using participatory design methods in distance education teaching. For example, whether the designed feedback can influence students' cognitive, affective, and self-regulated learning abilities. In the process of participatory design, we can consider the introduction of VR/AR and other advanced technologies to assist participants in understanding the whole participatory process, realizing the meaning structure and reducing the "professional gap".

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