Pre-Recommend or Post-Recommend? A Study on the Design of the Recommender System for Aesthetic Education

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Abstract—This paper describes a user's feature found during the design of the aesthetic education recommendation system, namely, Changes in students' (N=873) needs for art education information after a short time (1 hour) in an online art appreciation course offered by the authors. The change indicates that an increase in user demand for the knowledge of the art being recommended. At the same time, the correlation between users' satisfaction with artworks and their demand for recommended art information increase, including art history (0.22), performance information (0.22), famous artists and artworks (0.2), and information about similar art disciplines (0.18). Based on this phenomenon, conclusion points out that the educational recommender system should take into account the rapid changes of students' demand for recommended content.

Keywords- ML, recommender system, ERS, aesthetic education, higher education, SOR

1 INTRODUCTION

Digital education methods are widely used in this epidemic, and more and more artificial intelligence tools are being applied to the digital education process in addition to conventional MOOCs [1,2]. As an important application area of machine learning, recommender systems are

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gradually gaining importance in digital education. The digital traces left by students in various school databases [3] provide sufficient user characteristics for educational recommendation systems. The current application results such as course recommender [4,5] and learning material recommender are increasing in the field of educational recommender system research [6, 7]. However, these are dependent on sufficient characteristics of user digital tags, and it is worthwhile to study in depth how to take advantage of recommendation systems for fields with fewer personal characteristics of students, such as aesthetic education.

Aesthetic education is a kind of education which is different from other disciplines. It emphasizes the immersion and experiential education methods, and it needs to stimulate people's aesthetic consciousness to improve the aesthetic level [8]. Moreover, aesthetic education is a kind of practical education, which is difficult to convey aesthetic ability through simple lectures. It requires students to gain artistic perception through appreciation and personal practice, so as to enhance their aesthetic taste. In the process of art learning, especially in the process of art appreciation education, necessary art information can enhance students' aesthetic experience [9, 10], which is also necessary. However, everyone's aesthetic level and artistic knowledge accumulation are different, and these are difficult to find in the existing school database, which also makes the design of aesthetic education recommendation system more difficult.

From January to February of 2022, in order to explore the practical learning method of aesthetic education, we organized 32 students to carry out independent distance art appreciation learning based on ICT in 8 different provinces [11]. The learning process was smooth and research results were achieved, such as the improvement of interest in art learning came from the satisfaction of art appreciation (correlation 0.78), and the influencing factors of satisfaction included acquiring relevant art knowledge in advance (correlation 0.61). Before the further research on the application of recommendation system to promote students' autonomous learning of art knowledge, we encountered a problem, whether we should recommend relevant art information before art appreciation or provide it after appreciation. According to the classic Stimulus-Organization-Response theory (SOR)[12], people's external stimulation will affect their behavior, and art appreciation is obviously a process of sensory stimulation. So, is there a difference between recommending relevant art information before appreciation and recommending it after appreciation? Therefore, we carried out this experiment in order to get the answer that if the demand for art knowledge recommendation change after students experience art appreciation.

2 EXPERIMENTAL METHODS

2.1 Experimental steps

The experiment was carried out in Beijing Institute of Technology Zhuhai (BITZH). First of all, make the content of the appreciation course. We make an art appreciation teaching video with guitar playing and singing as the main content, which lasts for 60 minutes. The content includes the artist's explanation of musical instruments and music and the students' demonstration performance. The second step is to set the MOOC learning order. Students need to fill out the questionnaire before they can enjoy the course video. After the appreciation is completed, they need to fill out the second questionnaire before they can get the prompt of learning completion. In order to ensure the integrity of the course content watched by the students participating in the experiment, we turned off the fast-forward and double-speed functions in the course playing program. In order to attract more students to participate in the experimental course, we give 0.2 credit to every student who has studied completely and filled out all the questions in the two questionnaires. The course is open online for three days. After the course is offline, all questionnaires will be collected for analysis.

2.2 Questionnaire design

Because everyone's perception of art is different, combined with the stimulus-organism-response effect pointed out by SOR theory, the research team designed two questionnaires after discussion, which were filled out by students before and after enjoying the course content. The designed questions about art learning resources are basically the same, and only one question about teaching details in the course is added to the questionnaire after appreciation, so as to test whether students study hard or not. The question about art learning resources is designed as "Would you be interested if we recommend the history and culture of this art (as well as recent performance resources/famous songs/similar art categories) to you?" , the question answer options are set with the 7-level Likert scale [13], including Strongly disagree, Disagree, A little disagree, Neutral, A little agree, Agree, Strongly agree, it shown as Appendix I.

2.3 Analytical methods

1) Basic processing of questionnaires

First, clean the two batches of questionnaires separately, remove the questionnaires with wrong answers to the knowledge points of the course, and delete the questionnaires with single answers for all options. Secondly, the data of two batches of questionnaires before and after appreciation are combined to generate a data matrix with the student ID as the unique user ID. Thirdly, SPSS is used to test the reliability and validity of the questionnaire. If the results of reliability and validity are good, the next step can be analyzed. Fourthly, calculate the average and standard deviation of each major problem item to obtain a basic overview of the data.

2) Path analysis and correlation analysis

In order to verify whether students' understanding of art and appreciation satisfaction will affect their demand for recommended learning materials, this paper makes path analysis of art understanding and satisfaction, understanding and all kinds of recommended materials (4 items), satisfaction and all kinds of recommended materials (4 items), verifies whether each analysis path is effective, calculates their path influence coefficient, and finds out the key influencing factors. Python is used to calculate the correlation coefficient of each option, and seaborn is used to draw the correlation heat map to analyze the correlation among the elements in an intuitive and easy-to-read way.

3 RESULTS

3.1 Results of the basic questionnaire processing

A total of 1013 valid questionnaires were collected in this study. After deleting the questionnaires with wrong answers, there were 873 valid questionnaires, with a recovery rate of 86.18%. Python is used to combine the summary data of the two questionnaires, and the student number is the only common label, so that the 873×16-dimensional data matrix is obtained. SPSSPro was used to analyze the reliability and validity of the combined questionnaire results, and Cronbach's α=0.886. The value of the reliability coefficient did not increase obviously after the analysis items were deleted, which indicated that the research data had high reliability quality and could be used for further analysis. In the validity analysis, KMO = 0.866, Bartlett sphericity test p-value < 0.05, and the cumulative variance explanation rate after rotation is 70.476% > 50%, which indicates that the information of the research item can be effectively extracted. The comprehensive results prove that the research data has a good level of structural validity, and can be further analyzed. The basic statistical analysis of the obtained data is shown in Table I and Table II. From the results, it can be seen that after the art appreciation study, students' demand for various recommended information has been improved, but the standard deviation changes slightly.

TABLE I. PRE-STATISTICAL TABLE OF DATA

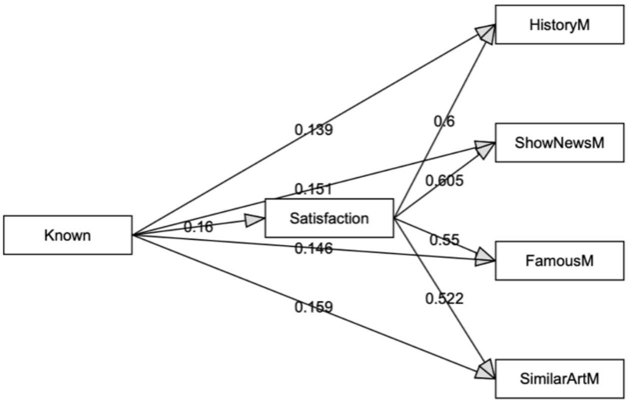
	Known	History	Show News	Famous	Similar
Mean	3.82	4.82	5.03	4.89	4.99
Std	1.21	1.19	1.18	1.22	1.19

TABLE II. POST-STATISTICAL TABLE OF DATA

	Satisfaction	History M	Show News M	Famous M	Similar M
Mean	5.94	5.45	5.64	5.49	5.56
Std	1.11	1.19	1.17	1.19	1.17

3.2 Path analysis and correlation analysis results

After getting the statistical result that students' demand for various recommended materials has been improved to a certain extent after learning appreciation, we further analyzed the influence paths of two independent variables, namely, the degree of artistic understanding and the degree of appreciation and learning satisfaction, on four dependent variables (including art history and culture, performance information, famous works and similar art information). Because the fourth dependent variable of the two independent variables may have an influence, and there may be influence paths between them, we conducted compound path detection, and the results are shown in Figure 1. Although all paths are effective, it can be seen that the degree of understanding of art knowledge has a low influence coefficient on all recommended factors, while the satisfaction degree of appreciation of art courses directly affects all recommended contents, and the influence coefficients are similar.



* The significance of each path p-value < 0.001***.

Figure 1: Path analysis results

This trend is more obvious from the correlation test results, as shown in Figure 2. As can be seen from the figure, the degree of known of art knowledge is weak in correlation with various items, whether before or after watching and learning art courses. However, the satisfaction index of art courses and the demand of various recommended contents have been obviously improved after the actual viewing, and the correlation coefficient has increased by 0.18 at least and 0.22 at the highest. It can be said that students' satisfaction with the art appreciation course is directly proportional to their expectation to obtain further study recommendation materials. In addition, we can also see that there is a high correlation between all kinds of recommended materials for art learning, ranging from 0.79 to 0.80, and the difference is small, which may indicate that there is little difference in students' demand for all kinds of recommended learning.

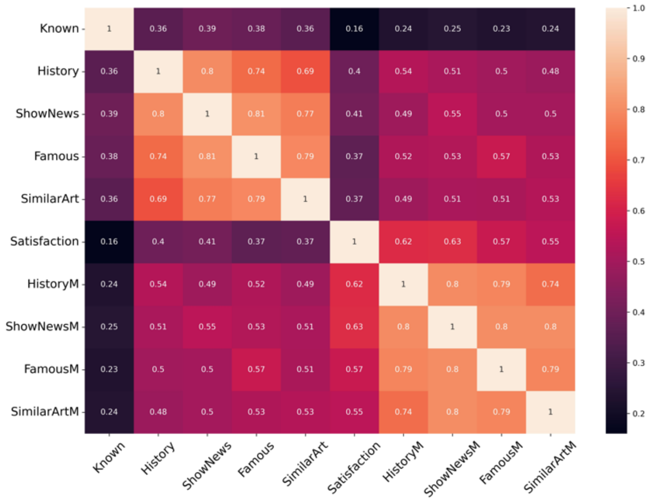


Figure 2: Correlation heatmap of each content of the questionnaire

4 DISCUSSION AND CONCLUSION

According to the results analyzed in the study it can be seen that students have a higher demand for recommended art knowledge after art appreciation classes, which is consistent with the expectations of the SOR theoretical model [12], where students, stimulated by art courses (S), gain appreciation satisfaction and show it through satisfaction (O), which in turn shows a behavior of changing demand for recommended art information (R). This raises a new question, Are all students' needs for knowledge dynamic and so fast? If this finding is true in other disciplines or other teaching models, further validation is needed. In our investigation conducted in the summer of 2021, we found that in art appreciation, active lecturing by the artist increased student satisfaction with art appreciation [14], and the same form of lecturing in this experiment may have facilitated the association between satisfaction and the need for recommended information. According to the pedagogical research tradition, students' course satisfaction is influenced by course stimuli, but also by endogenous factors such as their artistic foundation and artistic perceptual ability, and it is worthwhile to investigate how much weight this component has on the changing behavior of recommended information needs.

At present, the widely used educational recommendation system based on collaborative filtering of user characteristics is still based on machine learning method, which focuses on the single judgment of a product by the user and gives the user characteristics. However, in this experiment, the user's interest characteristics were extracted twice before and after an hour of sensory stimulation by the students, that is, there was a change of correlation of 0.2. Cui et al. found that the user's interest is related to time in the recommendation system of Internet of Things [15], but it seems to change faster in the field of education field. For the education recommendation system, besides the individual characteristics of students, the influence of students' learning progress on their original personal characteristics and the consequent changes in their learning information needs should also be considered, and this change is dynamic.

Based on the results of this study and the discussion, we think that if the education recommender system is applied to the field of aesthetic education, it is necessary to consider the changes of students' demand characteristics for artistic knowledge after receiving short-term audio-visual stimulation of artistic works, and there are few digital traces related to students' artistic accomplishment in schools. Therefore, it is a formidable challenge to design an education recommender system for aesthetic education.

APPENDIX I: CORE CONTENT OF QUESTIONNAIRE

	Strongly disagree	Disagree	A little disagree	Neutral	A little agree	Agree	Strongly agree
• I need to be recommended information about the history and culture of this art	□	□	□	□	□	□	□
• I need to be recommended information about performances of this art	□	□	□	□	□	□	□
• I need to be recommended information about famous artists and famous works of this art	□	□	□	□	□	□	□
• I need to be recommended information about similar art disciplines of this art	□	□	□	□	□	□	□

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