Exploring the Design Space for Explainable Course Recommendation Systems in University Environments

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ABSTRACT: A course recommendation system can assist students in finding suitable courses through a personalized approach. Showing why the course is recommended serves as a bridge between the recommender system and student, could increase student's trust in the system and persuade the student to accept the course. This paper presents a study of the factors that influence students' course selection in universities so as to better understand student perceptions, attitudes, and needs and leverage data-driven approaches for recommending and explaining the recommendations for complex and interactive university environments.

Keywords: Learning Analytics; Explainability; Recommender Systems

1 INTRODUCTION

Due to the increasing number of students and the rise of MOOCs, course recommender systems have become a well-researched area [Polyzou & Karypis, 2019; Jiang, Pardos & Wei, 2019]. Course recommendation is considered a useful tool in the education field for helping students who have no sufficient experience to choose courses that they need as well as reducing time to explore courses that they will take. These recommender systems are supported by the data, explicitly through, but also implicitly through for instance learning activity behavior. Current recommender systems often behave like a "black box" (e.g., those using deep neural networks [Pardos, Fan & Jiang, 2019]): i.e., recommendations are presented to the users, but the rationale for selecting recommendations is often not explained to end-users [Parra & Brusilovsky, 2015]. Several researchers have shown that explanations and user control are needed to support the interpretation of the data and decision-making [Kulesza et al., 2015].

In this context, this paper presents the results of our interviews and surveys to untangle the complex factors that are of concern to university students in order to inform the design of alternative course recommender systems that may consider the versatile nature of reasons involved in course selection.

2 RELATED WORK

2.1 Course selection

Some work has been done on analyzing the college students' course selection. [Kinnunen & Malmi, 2006] conducted a study on the reasons for students' quitting the CS1 course at Helsinki University of Technology. It was discovered that one of the most important factors of quitting the CS1 course is the perceived difficulty of the course. This study suggests that it is a suitable strategy to recommend courses that students will obtain relatively higher course achievement. In [Tallón et al., 2014], a survey was conducted to analyze why students choose one elective course. However, it is limited to only the case of teratology. Kardan et al. [2013] conducted a study on the factors influencing online course selection of college students in the context of e-learning using a neural network. However, it is limited to the e-learning which may significantly differ from face-to-face learning in the traditional college education.

Additionally, there is still a lack of study on the factors that influence students' course selection in university and how the course selection would impact the students' educational achievement.

2.2 Course recommendation system

Recommendation systems have been broadly applied within the context of student learning. Our review of relevant literature shows that many of the recent works on course recommendation environments focus on online learning platforms such as MOOCs [Jing & Tang, 2017]. Other studies on course recommendation use datasets collected in physical university environments, however, they rely on recommendation approaches that are similar to the ones used in recommending MOOC courses without fully considering the versatile nature of the reasons involved in course selection in physically-based university environments [Jiang & Wei, 2019]. This amounts to a collaborative recommendation of the nature of "most people like you did X next." When it comes to students' diverse intentions in selecting courses, a student's goal may not align with what most people have done. Although a few existing works consider the characteristics of university environments, they tend to make simplistic assumptions about learners and their contexts, thereby merely recommending the whole sequence of courses that satisfy the degree requirements [Parameswaran, Venetis & Garcia-Molina, 2011], or predicting the performance of students and give recommendations based on predicted results [Elbadrawy & Karypis, 2016].

In this paper, we elaborate on the explainability of course recommendation and explore how to support the design space for explainable course recommendation systems in university environments.

3 PRELIMINARY STUDY

Intuitively, the reasons behind course selection are manifold. Likewise, students who are enrolled in the same course may have completely different orientations. To get a better understanding of course selection behavior, we conducted a preliminary study. We have employed a two-phased approach to analyze the factors that need to be considered to recommend courses in university environments. First, we conducted a qualitative interview with 10 students (N=10). In the interviews, we asked about their opinions on the course selection and the reasons behind their decisions to choose courses. This procedure has revealed various reasons for course selection and allowed us to extract potential factors for effective course recommendations in university environments. Second, the extracted factors have been used to design 18 survey questions that ask respondents to rate the importance of each factor in selecting courses.

Table 1: Questionnaire regarding course selection behavior[1].

Item	Description	Item	Description
Q1	If it's easy to get a credit	Q10	If the course's instructor is good at teaching
Q2	If it's easy to get a good grade	Q11	If one is compatible with the course's instructor
Q3	If the difficulty level of the course is appropriate	Q12	If the course is fun
Q4	If one can acquire knowledge and improve competency	Q13	If the course takes place at an appropriate time
Q5	If the course is useful in one's future career	Q14	If friends take the course
Q6	If the course is interesting	Q15	If one can make friends as a result of taking the course
Q7	If friends recommend the course	Q16	If the amount of homework is appropriate
Q8	If senior students recommend the course	Q17	if the course's physical environment is good[2]
Q9	If instructors recommend the course	Q18	If one has clear goal

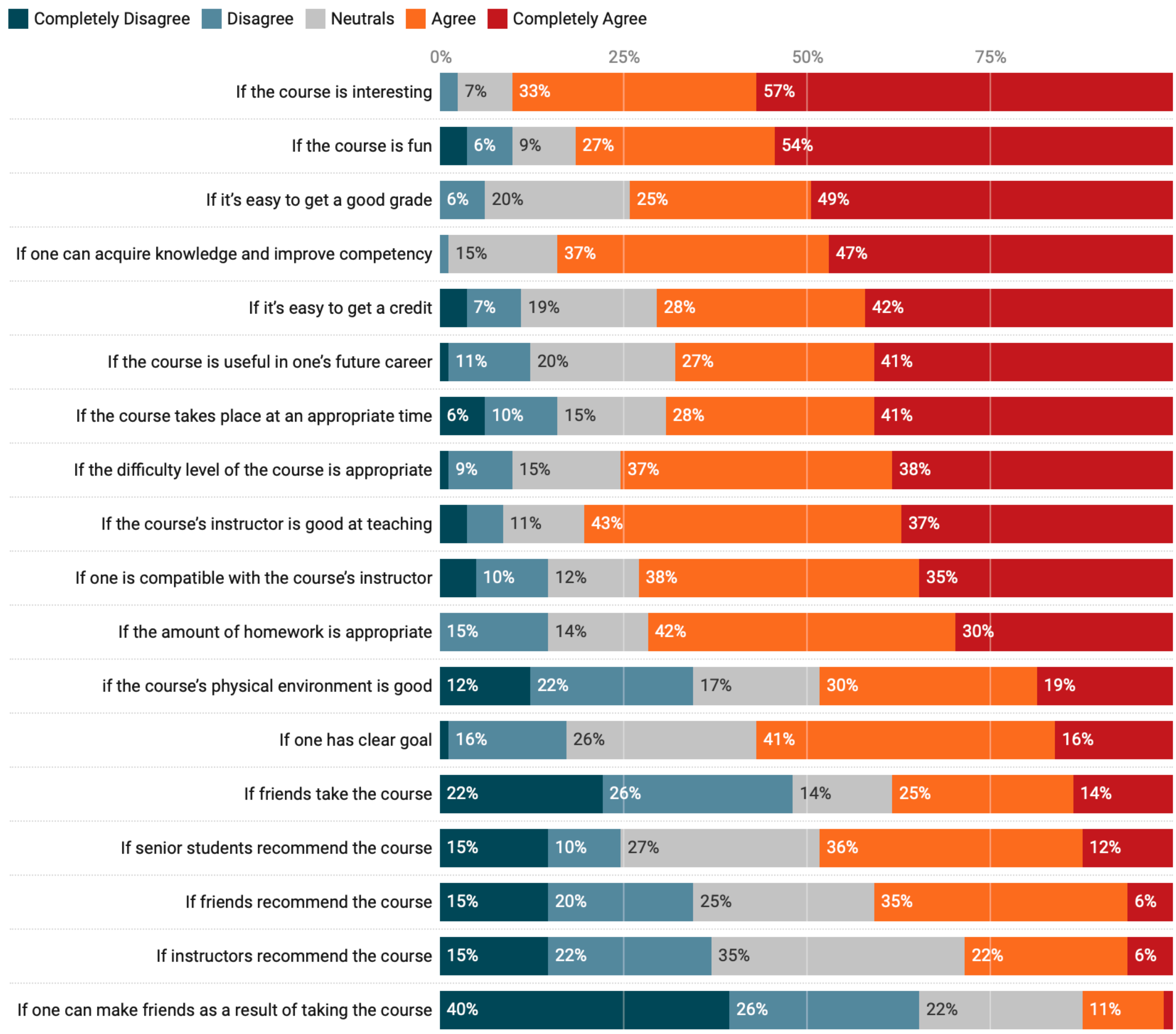

Figure 1: Survey results.

[1] These are the English translation of the description, which is originally in Japanese.

[2] Such as temperature, humidity, WIFI connectivity.

This study took place at Kyushu University and participants are all students. Kyushu University is a national university in Japan and it offers a wide variety of degree programs. The questionnaire was sent to all (N=336) students from two information science courses at Kyushu University and 24.1% (N=81) of students responded to the survey (53 men, 28 women; 78 freshmen, 1 sophomore, 1 junior, 1 senior). A 5-Likert scale (1-completely disagree, 5-completely agree) questionnaire regarding student requirement in terms of course selection behavior (Nstudent=81) with the questions presented in Table 1.

3.1 General Motivation

Course recommendation for higher education is “messy and unorganized” [Babad & Tayeb, 2003] as it depends on many factors that students need to concern. Table 1 indicates that many factors affect students’ decision to choose courses and Figure 1 shows survey results. The overall most important factor was students’ interest (Q6). Furthermore, the factors relevant to students’ career goals (Q5) and grades (Q2) are perceived to be important in course selection. From the above results, one safe conclusion can be drawn that, there are complex constraints and contexts that have to be considered together and students have to balance all those factors above, made more difficult by the multiple objectives that students want to maximize and risks they want to hedge against. For example, choosing challenging courses of value while maintaining a high GPA.

3.2 Learning Goal and Career Plan

University environments are inherently different from MOOC environments. For example, MOOC users may have clearer learning goals than university freshmen who may still be exploring different possibilities in relation to their careers and learning. Also, physical and social university environments provide students with a plethora of opportunities to explore, discover and develop intellectual interests and meaningful goals.

Answer to Q18 revealed that 17.2% of first-year students are either very unclear or unclear about their learning goals, and 26% of first-year students are neutrals and don't know about this question, the choice of courses for those students is aimless. Also, student interest and goal can change as they explore and discover something meaningful on and off campus. This kind of students has different criteria for course selection than the students who have a clear learning goal. Figure 2 shows the sample of our survey results comparing the students with clear learning goals (the orange bar) and the students without clear learning goals (the blue bars). Students with clear learning goals considered that the usefulness and relevance to their future goals (Q4, Q5) are important in course selection. Also, they would like to ask their professors for advice (Q9). It may be because advice from professors who tend to be local experts with deep knowledge within their subject area is useful. In contrast, students without clear goals considered ease of getting credits (Q1) as important. Also, they prefer to ask suggestions from their friends (Q7). Those students who have no clear goals might be more inclined to choose easy courses that do not require too much effort. They may also exploit social means of obtaining recommendations more than the students with clear goals.

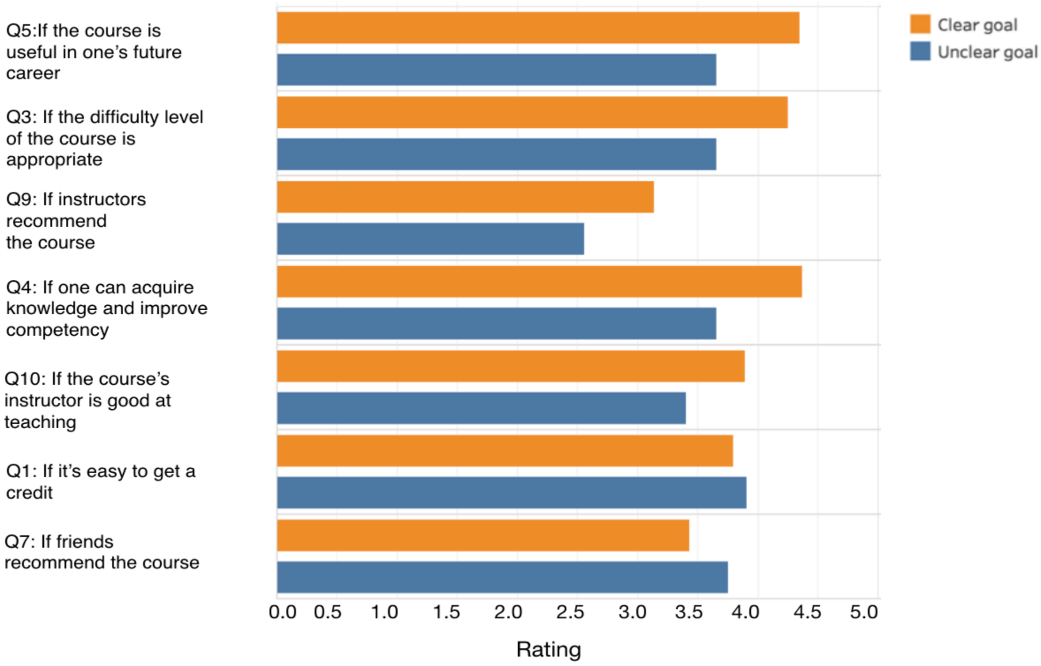

Figure 2: Comparison results between students with clear learning goals and students without clear learning goals.

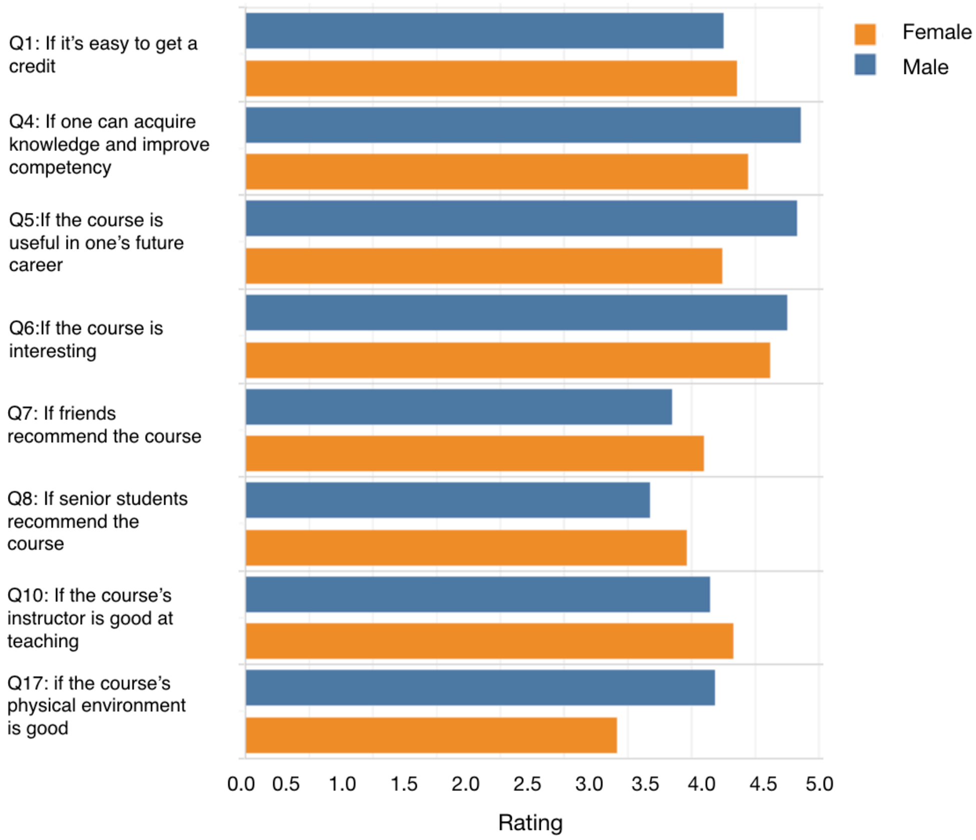

Figure 3: Comparison results between female students and male students.

3.3 Social Aspect

Potts et al. [2018] conclude that the risk of social isolation is a problem in the learning process especially for first-year students at university, who have difficulty navigating their new academic and environment. In fact, the social factor also plays a part in the course selection process. For example, some students prefer to enroll in a course with their friends or classmates together. Tinto [1997] concludes that participation in a collaborative learning group enables students to develop a network of support. This community of classroom-based peers encourages student's attendance and class participation.

Our results show that 39% of first-year students considered the social factor as an important thing in their course selection process. The results in Figure 3 also show some interesting gender differences regarding the social aspect. Female students seem to ask suggestions from their friends and senior students more than male students (Q7, Q8). Also, female students consider factors related to the instructors of courses as important more than male students (Q10). The above results indicate that the classmates or friends based social link could be important information in course recommendation.

3.4 Student Preference

We also analyzed the survey data by employing the k-means clustering algorithm to identify different types of students in terms of course selection motivations. Table 2 shows the clustering results. It can be seen that students of cluster 1 consider high grade as the most important factor (Q2, M=5.74) and they are inclined to choose courses that do not require too much effort or difficulty (Q1, M=4.65; Q3, M=4.30). Students of cluster 2 prefer to choose courses to pave the way for their future career (Q4, M=4.58; Q5, M=4.47), but they also want to make a trade-off between high GPA (Q2, M=4.13) and their interest (Q6, M=4.34). Students of cluster 3 seem to be challengers, as they may even take difficult courses (Q3, M=3.57) if they are interested in them (Q6, M=4.27) or think the course is helpful for their future career (Q4, M=4; Q5, M=4.22).

Table 2: Sample clustering results.

Item	Q1	Q2	Q3	Q4	Q5	Q6
Cluster1	**4.65**	**4.74**	**4.30**	3.57	3.22	3.43
Cluster2	3.72	4.13	4.25	**4.58**	**4.47**	**4.34**
Cluster3	3.09	3.70	3.57	4.00	4.22	4.27

4 DISCUSSION AND CONCLUSION

Although conducted on a relatively small-scale, our preliminary study has revealed the complexity and variety of factors involved in students' decision to choose courses in the university environments. Existing course recommendation approaches without considering such factors may not fit different perceptions of students, and therefore could not provide convincing explanations that are needed to support the interpretation of the data and decision-making. Our survey results show that different students may have completely different orientations based on their own reasons, which serves as different criteria for course selection and those should be considered in course recommendation systems in physically-based learning environments such as universities. This suggests that recommendations and explanations that are aimed only at one or a few factors are likely not enough to help the students.

Based on our results, it is important for course recommendation approaches to: (a) take different factors into account when training models. e.g., social factor and physical constraints in university environments; (b) consider the courses are well-aligned with their interest and learning goal; and (c) account for the student's expected grades in each course that they recommend. Accordingly, physically-based course recommendation systems should provide relevant information to explain the recommendations: (a) course descriptions and structures that make students have a better understanding about the course (b) personal preference of students (e.g., their interest, major, the courses they have already taken and their grades) and (c) interactive representations that help students make sense of recommended courses from multiple perspectives.

Our future research will concentrate on two issues. First, we shall carry out a more specific analysis of large-scale data on students' selection decisions and a more detailed analysis of the selection process. In addition, we shall link the results to the actual use in building the explainable course recommender system.

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