Smart Learning Environments

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Investigating course choice motivations in university environments

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Abstract

Recommendation systems need a deeper understanding of users and their motivations to improve recommendation quality and provide more personalized suggestions. This is especially true in the education domain, the more about the student is known, the more useful recommendations can be made. However, although many studies on the course recommendation exist, studies on the students' course selection motivations in universities are limited. This study investigates the factors that contribute to students' choice when selecting courses in universities to better understand student perceptions, attitudes, and needs and leverage data-driven approaches for recommending and explaining the recommendations in university environments. A qualitative interview for university students (N = 10) comprised of open-ended questions as well as a questionnaire for students (N = 81) was conducted, aiming to investigate the main reasons behind their choices. The results of this study show that students highly value the course contents and the benefits of the course towards their future careers. Furthermore, students are influenced by other reasons such as the possibility of obtaining a higher grade, the popularity of professors, and recommendations from peers. Next, we extract the main categories of students' motivations and analyzed the questionnaire data by employing statistical analysis methods as well as the k-means clustering algorithm to identify different types of students in terms of course selection. Based on our findings, we discuss implications for designing more personalized course recommendation systems.

Keywords: Course recommendation, University environment, Student motivation, Course selection

Introduction

Course selection is a non-trivial task. Prior to every academic term, students make a series of course selection decisions. The course selections they make create a chain of reactions that influence future course choices, skill development, and job decisions (Huang et al., 2019). Due to the increasing number of students and the rise of Massive Open Online Courses (MOOCs), course recommendation systems have been broadly applied within the context of student learning by using various data explicitly and implicitly, for instance, the data about learning activities.

Many of the recent works on course recommendation environments focus on online learning platforms such as MOOCs (Jing & Tang 2017; Piao & Breslin, 2016; Hou et al., 2018; Zhang et al., 2017; Pang et al., 2017). These systems try to make useful suggestions proactively based on the students' contexts and profiles. However, the selection and recommendation of courses in university environments are inherently different from those in MOOCs. 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 (Ma et al., 2020). Also, courses in university environments are closely interwoven with various types of physical, pedagogical, and social contexts, which makes the selection and recommendation of courses in higher education a more complex task as it depends on many intertwined factors that students need to consider (Esteban et al., 2018). Current 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 university environments. This amounts to a collaborative recommendation of the nature of "most people like you did X next." When it comes to university students' diverse intentions in selecting courses, a student's goal may not align with what most people have done (Jiang et al., 2019). Although a few existing works consider the students' motivations in 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 et al., 2011), or predicting the performance of students and give recommendations based on predicted results (Elbadrawy & Karypis, 2016; Elbadrawy et al., 2015; Hu & Rangwala, 2018; Sweeney et al., 2016).

Information about the user and the reason behind their choices is crucial for giving personalized suggestions. Users have different motivations and corresponding information needs, which refer to the rationale behind the way people behave, think, or feel at a specific time and is strongly related to the users' preferences. Therefore, user motivations are being perceived by researchers to influence the variance in the user preferences and behavior in recommendation systems, which can help match users with similar interests and even help with the cold-start problem (Jameson et al., 2003; Chen et al., 2013). It could also help improve the explainability of recommendation systems. To improve recommendation quality, recommendations need a deeper understanding of users and their motivations (McNee et al., 2006). For course recommendations in university environments, acknowledging that students have different reasons for enrolling in courses– for example, to improve their skills, gain access to new knowledge, dabble in an area they find intriguing, or meet the requirement of graduation, and so on. However, there is a lack of study on those factors that influence students' course selection in university environments, and course recommendation methods that fully integrate with students' motivations are relatively unexplored research topics.

In order to overcome the limitations, we aim at enlightening and describing the variety of motivations among students in university environments. Our research questions in this paper are as follows:

- RQ1. General motivations: Why do students decide to take a course? What are their major motivations to choose courses?

- RQ2. Personal differences: Do students have personal differences for those motivations?
- RQ3. What implications for course recommendation system design can be derived?

To achieve this, we employ a two-phased approach. First, qualitative interviews were conducted for 10 university students, the main goal was to gain a deep understanding of the actual reasons for taking a course. Second, we developed a questionnaire based on our interview study and used it to establish a broader understanding of the motivational factors behind the course selections of individual students. The questionnaire asks about students' opinions on the courses they have taken in the past and asked them to rate the significance of each factor behind their decision to choose each course (Note that as the student must take required courses, this study only focuses on elective courses).

The research described in this paper is a part of our larger research project that concerns with course recommendation system in university environments. In this paper, we present the results of our interviews and questionnaires to untangle the complex factors that are of concern to university students for their course selection. By finding ways to classify the reasons reliably, we will be in the position to understand the relationship between why students enroll in these courses and how they seek for the course. Using these results, we could inform the design of alternative course recommendation systems that may consider the versatile nature of reasons and students' different demands involved in course selection. In addition, instructors and course designers could use this information to improve their courses and their students' learning experiences, thus contributing to the discussion about improving instruction for diverse learners.

Related work

Several studies have sought to make sense of why students enroll in a course. Specifically, these studies include MOOCs and traditional university environments. We discuss them in the following subsections respectively.

Motivations for enrollment in MOOCs

A growing body of literature has investigated why students enroll in MOOCs. Recent work on MOOCs suggests that learners engage in a wide range of behaviors, which appear to reflect differences in motivation. Liu et al. (2015) found that the main reason for most of the students to took MOOCs could be concluded as personal interest, improve their current knowledge of the job and prepare for future job prospects. Zheng et al. (2015) conducted interviews to understand students and their reasons for enrolling in MOOCs. Their study suggested different types of students' motivation. First, some students were fulfilling their current needs, such as supplementing a for-credit course, or to help with their current position, either as students or in a workplace setting. Second, some students took the course to develop a social connection with others who shared similar interests. Third, some students enrolled in a course to prepare for future job opportunities or to gain experience in a field they might study in a more formal manner in the future. Finally, some students enrolled in a MOOC just because they were interested in satisfying their curiosity. Kizilcec and Schneider (2015) developed the Online Learning Enrollment Intentions (OLEI) questionnaire to ask students about their reasons for enrolling in a MOOC. These questions included career-related interests, formal education, social opportunities, potential career benefits, improve English, and so on. They also found that the subject matter of the course was indicative of the reason a student might take a MOOC. For example, students in a humanities course might have taken the course out of curiosity, while students in a social science or health-care-related course might have taken the course for career benefits (Christensen et al., 2013; Kizilcec & Schneider, 2015).

There have been several studies that have explored the relations among students' reasons for enrolling in a MOOC, their characteristics, and achievements in MOOCs. Students' ages and genders have often been found to share a weak relationship with their reasons for enrolling in a MOOC course. Crues et al. (2018) observed that students' reasons for enrolling in a MOOC and gender did not share a significant statistical relationship. Kizilcec and Schneider (2015) have reported that females selected more reasons for enrolling in a MOOC on the OLEI scale than males. In that study, reasons for enrolling in a MOOC were found not to be related to the age of a student. de Barba et al. (2016) found that students' motivations and interests were related to how they engaged with the course's quizzes and videos. They also investigated how motivation was related to a student's final grade. Others, however, observed no relation between student motivation and the grades earned in MOOCs (Breslow et al., 2013). Crues et al. (2018) found that students' reasons for enrolling in a MOOC clustered into four interpretable reasons, and some of the reasons were related to actively engaging in portions of the course; however, these reasons were not statistically related to remaining engaged in the course overall.

In general, the literature has pointed to interesting findings in MOOCs. However, it is limited to the MOOCs which may significantly differ from the face-to-face learning in traditional university education (LaMeres & Plumb, 2013; Nunez et al., 2016).

Motivations for enrollment in university courses

We also note that a few studies have investigated students' motivations for enrolling in courses and analyzing the students' course selection in physically co-present university classrooms.

According to Babad et al. (1999), one of the vital reasons is the characteristics of the course. McGoldrick and Schuhmann (2002) indicated that course selection is more of a function of relevance toward future careers and perceived interest in course topics. Tallón et al. (2014) conducted a survey to analyze why students choose one elective course. However, it is limited to only the case of teratology. Other study shows that students are driven both by the desire to master content because it is interesting and relevant, and by the desire to demonstrate competency to earn external recognition (Pintrich, 2003). Environmental factors, such as classroom pedagogical strategies, interact with academic and social motivations to influence learning and engagement, as do individual student characteristics (Ryan & Deci, 2000). Shell et al. (2016) investigated the relationship between the students' entering motivation and their subsequent course achievement and retention in college CS1 courses. They measured students' course entering motivation with an instrument include: learning-approach, learning-avoid, performance-approach, performance-avoid, task-approach, and task-avoid. Their studies have found that learning approach goals were associated with higher achievement and retention, whereas, performance goals lead to lower achievement (Ott et al., 2015). Other studies have shown that these goals change across the semester. In addition, demographics, prior knowledge, self-perceptions, and self-regulation–the ability to plan, monitor, and control learning behaviors–have all been shown to have a salient influence on achievement (Tinto, 1997; Bransford et al., 1999; Schunk & Zimmerman, 2012).

The literature highlights the complex reality of course selection in universities, but very little is known about the nature of these motivations, as well as their relationship to individual differences in students. Also, most studies focus on satisfying students' needs to avoid drop-out by understanding their motivations, while few studies oriented from recommending prospects. In this study, we investigate the factors that contribute to students' choice when selecting courses in universities to better understand student perceptions, attitudes, and needs and leverage data-driven approaches for recommending and explaining the recommendations in university environments. We believe that this could inform the design of course recommendation systems in university environments. Also, gaining insight on these issues is crucial for instructors and course designers to consider for attempting to improve courses.

Study 1: qualitative interview

Intuitively, the reasons behind course selection are manifold as it depends on many factors that students need to concern. Likewise, students who are enrolled in the same course may have completely different orientations. First, to get a better understanding of course selection motivations, we conducted a qualitative interview for gathering general information concerning students' opinions. We chose to use a qualitative research approach because it enables us to reveal possible hidden issues that would not unfold if using a quantitative research approach.

Method

We recruited ten participants (N = 10) in this study using a snowball sampling method, through our social media accounts and personal friendship network, and participants are all college students. The age range between 19 and 26 (M = 23.70, SD = 4.32). Six (60.0%) of the interviewees were female.

We conducted a semi-structured interview and all interview questions were open-ended. The interview started with a brief introduction of the interviewer and a short description of the purpose and motivation of the interview. The participants were then asked about their opinions and experience on the course selection and the reasons behind their decisions to choose courses: Are you satisfied with courses you have chosen? Which experience do you have with the course selection process? What is the main reason for you to select (or not) a course? What kind of information will help you for course selection? Our particular focus was on the motivations for enrolling in a course. They are asked to give answers as honestly and truthfully as possible. Interviews ranged from approximately 35 minutes to 1 hour and the average time was nearly 45 minutes. All interviews were annotated and transcribed for data analysis.

Results

We applied the thematic analysis to deal with the qualitative data. After transcribed the data, we first created a set of initial codes and sorted the codes into potential themes, then we reviewed and revised the theme iteratively to determined final theme. The interviews produced a rich set of recollections and descriptions addressing many issues, which have been summarized as a number of emergent themes. We identified several broad types of student motivations for enrolling courses in the following discussion. Note that although we discuss each of these themes separately, it is quite possible that a student might choose to enroll in different courses for different reasons.

Personal interest

Curiosity

Most of the participants explicitly mention their interest towards the subject as a key factor that influences their choice. Some students took courses out of curiosity simply. P2 said that *"I will choose courses whose content closely related to my own interests"*. P8 indicates that *"I choose the course because I just want to have fun"*.

Career-related interests

Some students took courses because they think that the knowledge or skill might be useful in the future. P3 indicates that *"The courses that I am interested in and related to my major is the best choice as it can broaden my horizons and help me have a deeper understanding about my future career".*

However, many students may still be exploring different possibilities in relation to their careers and learning. Especially for first-year students, they may lack learning goals and career planning for the future, and the choice of courses is aimless. Besides, physical and social university environments provide students with a plethora of opportunities to explore, discover and develop intellectual interests and meaningful goals, and student interest and goals can change as they explore and discover something meaningful. P10 mentions that *"When I was a freshman, I was very confused, I did not know what I can do in the future and have no career plan"*.

High grade

Getting relatively high grades for students to improve their GPA is another factor that influences student's choice especially for successful students. It was mentioned by four participants. Some students even prefer to choose what they perceived would be an easier course for fear that a tougher course might lower their GPA. P7 indicates that *"I plan to study abroad after graduation, and an important thing for applying to my favorite school is a high GPA!"*.

Cost avoidance

As learning a course is a non-trivial and time-consuming task, it is expected that some students desire to get through the class with as little time and effort as possible, and 7 participants mentioned this. P4 indicates that *"Although some courses seem very interesting, I will not choose them if I heard that the homework is particularly heavy and the* *instructors are very strict".* P1 mentions that "I don't want to choose difficult courses, I want to choose courses that I am good at and could give full play to my strengths".

Social aspect

Collaborative Learning

Six students mentioned that they would like to enroll in a course with their friends or classmates together. 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 new environment. Social factor also plays a part in course selection process. Tinto (1997) concludes that participation in a collaborative learning group enables students to develop a network of support. This community of classroom-based peers (the network of support) encourages student's attendance and class participation. P9 indicates that *"If I could have a class with my friends, I will not feel nervous or anxious. We can sit together, discuss together, and help each other."*

Social ties

The social ties of classmates and friends can be important and some students are highly influenced by their peers' comments and recommendations when it comes to choosing the most suitable course. Professors' popularity was also highlighted by several students as a reason for course choice. Osborne et al. (2003) concluded that the teacher facilitating a course is a significant factor that can change students' attitudes towards a course, instead of the course itself. P10 indicates that *"I will follow the suggestions of senior students, they have taken some classes and are more experienced. They can tell me which instructors are good at teaching and which courses have less homework".*

In addition, there were other reasons, such as location, time, job-related commitments, and the physical facility such as air conditioner and WiFi connectivity. It is worthwhile to note that many students gave more than one reason, which indicates the complexity of the problem.

Study 2: questionnaire

The interview results have revealed various reasons for course selection and allowed us to extract potential factors for course recommendations in university environments. In order to answer the research questions of this study, we conducted a relatively larger scale user study.

Method

We designed a 5-Likert scale (1-completely disagree, 5-completely agree) questionnaire regarding student motivations in terms of course selection behavior based on information collected by interviews and the OLEI questionnaire (Kizilcec & Schneider, 2015). The questionnaire included both closed-ended and open-ended questions. Closed-ended questions are presented in Table 1 and the open-ended question is used as "Other reason, what"-type.

The questionnaire was sent to all ($N = 336$) students from courses for freshmen in our university and respondents are asked to rate the importance of each factor in selecting courses. Finally, 24.1 ($N = 81$) of students responded to the questionnaire. Most of them were first-year students (96.4%), 34.6% were female and 65.4% were male, which

Table 1 Questionnaire regarding course selection

Item	Description[a]	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[b]
Q9	If instructors recommend the course	Q18	If one has clear goal

[a] These are the English translation, which is originally in Japanese

[b] Such as temperature, humidity, WiFi connectivity

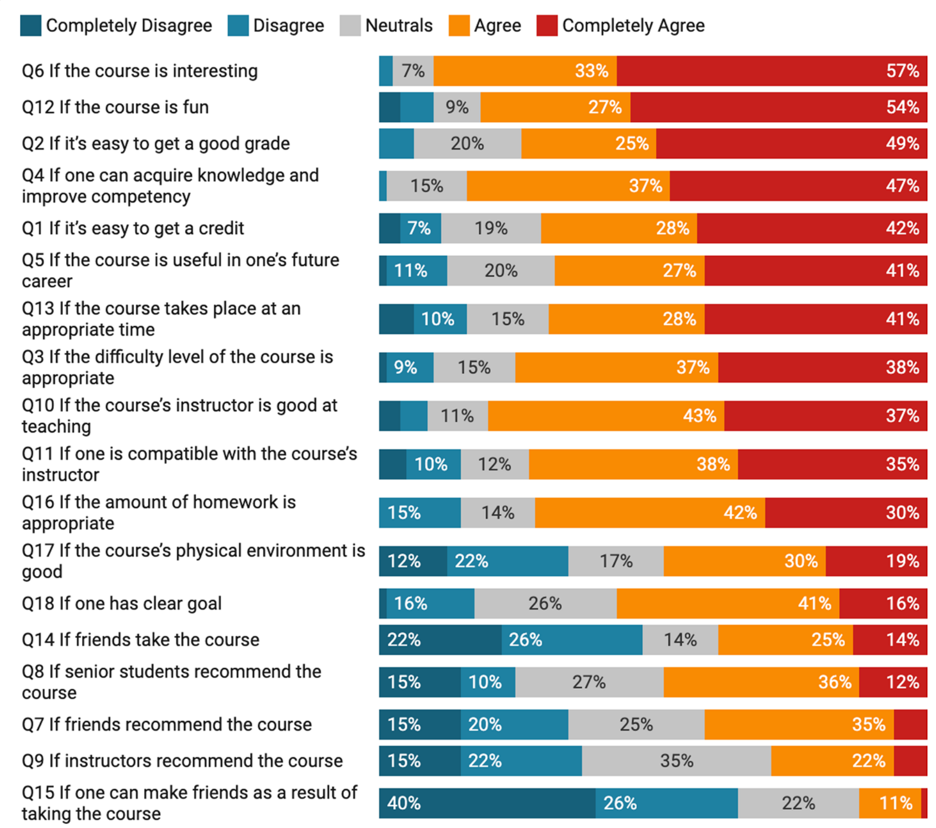

Fig. 1 The questionnaire results

corresponds roughly to the gender division at our university. Cronbach's Alpha value of the questionnaire is 0.783, it indicates an acceptable level of reliability.

Results

The results shown in Fig. 1 indicate that many factors affect students' decision to choose courses. Among them, the overall most important factor was students' interest (Q6). Furthermore, the factors such as usefulness for career (Q5), good grades (Q2), and easiness to get credit (Q1) 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 must be considered together and students have to balance all those factors to make their final decisions.

Gender difference

First, we analyze the data to understand the gender differences regarding the questionnaire using the independent sample t-test. As Fig. 2 shows, male students prefer to enroll in a course with their friends (Q14, M_male = 3, M_female = 2.5, $p < 0.1$), or want to make friends as a result of taking the course (Q15, M_male = 2.2, M_female = 1.8, $p < 0.05$). Also, they seem to consider more about the course's physical environment (Q17, M_male = 3.5, M_female = 2.7, $p < 0.1$). There is no significant difference between female students and male students in other questions.

Clear learning goal versus unclear learning goal

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 about this question, the choice of courses for those students is aimless. The students with clear learning goals and the students without clear learning goals may have different criteria

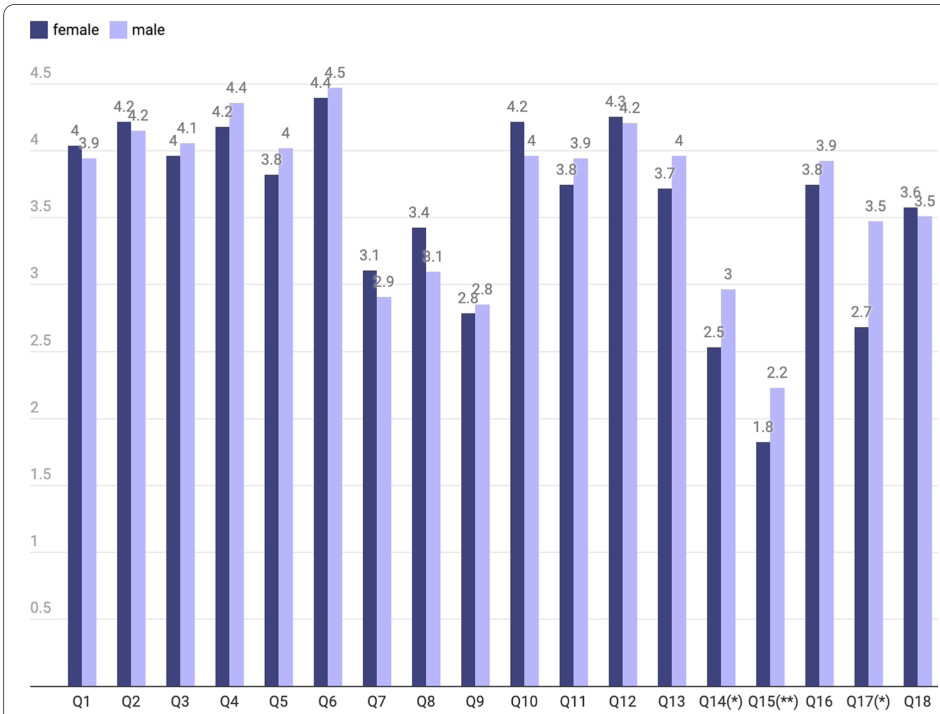

Fig. 2 Comparison results between female students and male students. (Significant Level (*) $p < 0.1$, (**) $p < 0.05$)

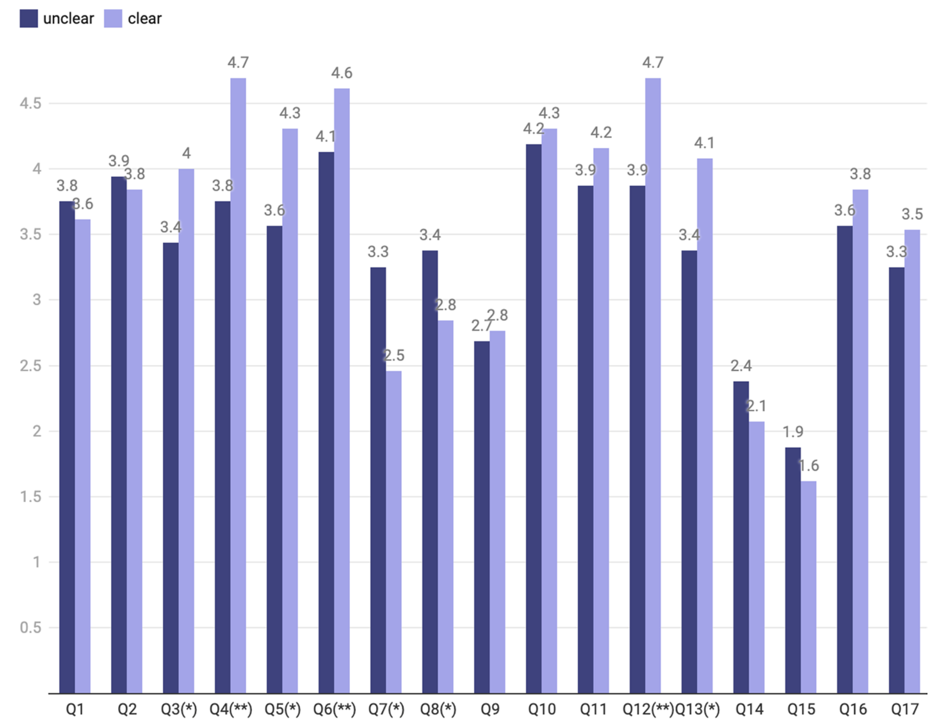

Fig. 3 Comparison results between students with clear learning goals and students without clear learning goals. (Significant Level (*) $p < 0.1$, (**) $p < 0.05$)

for course selection. To have a clear view, we analyze the data to compare these two groups.

Figure 3 shows the results using the independent sample t-test. Students with clear learning goals highly value the knowledge (Q4, M_clear = 4.7, M_unclear = 3.8, $p < 0.05$), and consider usefulness and relevance to their future goals (Q5, M_clear = 4.3, M_unclear = 3.6, $p < 0.1$) are important in course selection. They prefer to take a course if they are interested in it (Q6, M_clear = 4.6, M_unclear = 4.1, $p < 0.05$) or if they think it is fun (Q12, M_clear = 4.7, M_unclear = 3.9, $p < 0.05$). Besides, the difficulty level of the course (Q3, M_clear = 4, M_unclear = 3.4, $p < 0.1$) and appropriate time (Q13, M_clear = 4.1, M_unclear = 3.4, $p < 0.1$) is highly rated by them. It may be because students with clear learning goals tend to manage their time and plan their future. In contrast, students without clear goals may be inclined to exploit social means of obtaining recommendations more than the students with clear goals. They might consider more about suggestions from their friends (Q7, M_clear = 2.5, M_unclear = 3.3, $p < 0.1$) and senior students (Q8, M_clear = 2.8, M_unclear = 3.4, $p < 0.1$).

Clustering result

Finally, we analyzed the collected data by employing the k-means clustering algorithm to identify different types of students in terms of course selection motivations. In order to identify the optimal number of clusters, we have performed the elbow method (Bholowalia & Kumar, 2014) and the right number of clusters could be 4.

Table 2 Results of clustering analysis

Item	Description	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Q1	If it's easy to get a credit	3.25	**4.54**	3.32	3.80
Q2	If it's easy to get a good grade	4.34	**4.63**	3.60	4.00
Q3	If the difficulty level of the course is appropriate	3.82	**4.34**	3.75	4.13
Q4	If one can acquire knowledge and improve competency	3.50	3.55	**4.61**	4.44
Q5	If the course is useful in one's future career	4.40	3.13	**4.50**	4.31
Q6	If the course is interesting	4.00	3.81	**4.61**	4.17
Q7	If friends recommend the course	3.93	3.64	2.18	**4.75**
Q8	If senior students recommend the course	1.50	3.85	2.25	**4.41**
Q9	If instructors recommend the course	2.25	2.91	2.61	**3.68**
Q10	If the course's instructor is good at teaching	1.00	3.82	**4.14**	3.88
Q11	If one is compatible with the course's instructor	3.75	3.23	3.89	**4.32**
Q12	If the course is fun	3.25	3.55	**4.61**	4.34
Q13	If the course takes place at an appropriate time	2.75	3.32	3.79	**4.29**
Q14	If friends take the course	3.00	2.82	1.86	**4.37**
Q15	If one can make friends as a result of taking the course	1.50	1.55	1.57	**3.51**
Q16	If the amount of homework is appropriate	1.25	**3.73**	3.43	3.61
Q17	if the course's physical environment is good	3.25	2.50	2.86	**4.32**

The largest value in each row is highlighted with bold text

Table 2 shows the clustering results. It can be seen that both cluster 1 and cluster 2 are highly motivated by grades, but students of cluster 1 seem to want to make a trade-off among high grades (Q2, M = 4.34), usefulness (Q5, M = 4.40), and their interests (Q6, M = 4.00), while students of cluster 2 seem to be grade-oriented type as they consider high grades are the most important factors (Q2, M = 4.63). Also, they consider more about the difficulty level (Q3, M = 4.34) and the amount of homework (Q16, M = 3.73) in the courses, and they are inclined to choose courses that do not require too much effort. In contrast to cluster 2, students of cluster 3 seem to be learning-oriented as grades aren't that important for them (Q2, M = 3.60). Students of this cluster probably prefer to choose courses to seriously study knowledge and are mainly interested in learning and mastering content or a given skill. Besides, they consider mistakes and failure as learning opportunities, therefore, they may even take difficult courses (Q3, M = 3.75) if they are interested in them (Q6, M = 4.61) or think the course is useful for them (Q5, M = 4.50). Another interesting phenomenon is about students in cluster 4. Their average rating of social aspect is much higher than all the other clusters. They appreciate the courses recommended by their friends (Q7, M = 4.75), senior students (Q8, M = 4.41), and instructors (Q9, M = 3.68). They also highly value the student-teacher compatibility (Q11, M = 4.32). In addition, they prefer to enroll in a course with their friends (Q14, M = 4.37) or want to meet friends with similar interests (Q15, M = 3.51).

Motivation structure

In this subsection, we investigate the factor structure of these motivations by using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) method to identify the underlying relationships between measured motivations.

Exploratory factor analysis

First, we have examined skewness and kurtosis values. Most variables' skewness and kurtosis values are between -1 and 1, which means the data is normally distributed. Besides, the result of Kaiser-Meyer-Olkin Measure value is .647, above the commonly recommended value of .6, and Bartlett's test of sphericity is significant ($p < 0.05$), which indicates the sample used was adequate. Also, the communalities were all above .5, further confirming that each item shared some common variance with other items.

A scree plot analysis was performed to determine the number of factors that would be optimal given the covariance structure of the data. The scree plot analysis suggested that the optimal number of factors is five. A factor analysis of the combined correlation matrix with five factors accounted for 63% of the variance. These factors are course quality, recommendation from others, context and setting of the course, social aspect, and effort needed. A varimax rotation provided the best-defined factor structure. The factor loading matrix for this final solution is presented in Table 3.

Table 3 Factor loadings and communalities based on a principal components analysis with varimax rotation

Item	Description	Course quality	Recommendation	Context and setting	Social aspect	Effort
Q10	If the course's instructor is good at teaching	0.712	0.391			
Q4	If one can acquire knowledge and improve competency	0.707				
Q11	If one is compatible with the course's instructor	0.660		0.309		
Q5	If the course is useful in one's future career	0.643				
Q6	If the course is interesting	0.640	− 0.307			
Q12	If the course is fun	0.515		0.336	0.344	− 0.338
Q7	If friends recommend the course		0.838			
Q8	If senior students recommend the course		0.782			0.346
Q9	If instructors recommend the course		0.690			
Q3	If the difficulty level of the course is appropriate			0.478		0.356
Q15	If one can make friends as a result of taking the course				0.746	
Q17	if the course's physical environment is good			0.738		
Q16	If the amount of homework is appropriate			0.694		0.484
Q13	If the course takes place at an appropriate time			0.578	0.327	
Q14	If friends take the course		0.467		0.569	
Q18	If one has clear goal				0.716	
Q1	If it's easy to get a credit					0.612
Q2	If it's easy to get a good grade					0.761

Table 4 Model fit summary

Fit statistic	Value
Chi2 (*df*)	253.480 (45)
RMSEA	0.097
(90% CI)	(0.051, 0.141)
AIC	273.480
BIC	276.668
CFI	0.905
GFI	0.891
TLI	0.896

Table 5 AVE and CR result

Factor	AVE	CR
Factor1	0.505	0.743
Factor2	0.498	0.662
Factor3	0.505	0.759
Factor4	0.635	0.702
Factor5	0.719	0.802

Confirmatory factor analysis

We also performed Confirmatory factor analysis (CFA) to confirms the factor structures. Goodness-of-fit statistics were obtained, as can be seen in Tables 4 and 5 .

Discussion

Answering the research questions

In this section, we discuss the results of the interview and questionnaire, and we link them together to answer our research questions.

General motivations (RQ1)

In summary, the results of our studies indicate that many factors affect students' decision to choose courses. Among them, the overall most important factor was students' interest. Furthermore, the factors such as usefulness for one's future career, good grades, and easiness to get credit are perceived to be important in course selection. In addition, there were other reasons, such as location, time, job-related commitments, and the physical facility such as air conditioner. It is worthwhile to note that many students gave more than one reason and students must balance all these complex constraints and contexts together to make their decisions. Also, different students have different ranking strategies as their own criteria.

Personal differences (RQ2)

Align with the previous study (Crues et al., 2018),we can observe only a few differences with respect to the gender of different participants. Male students seem are more socially engaged as they would like to enroll in a course with their friends or want to make friends with others. Also, they emphasize more about the course's physical environment than female students.

We do see differences in subjective responses in relation to the clear learning goals of participants. Students with clear learning goals consider the knowledge, usefulness, and relevance to their future careers are important in course selection. They would rather take a course for fun and interesting. Besides, the difficulty level of the course and appropriate time is highly rated by them. In contrast, students without clear goals may be inclined to exploit social means of obtaining recommendations suggestions from their friends and senior students.

We identify four different types of students in terms of course selection. (a) All-around type: They want to make a trade-off among high grades, usefulness, and their interests. (b) Grade-oriented: They consider high grades are the most important factor. Also, they seem to be task- or work-avoid because they consider more about the difficulty level and the amount of homework in the courses, reflect a desire to get through the class with as little time and effort as possible. (c) Learning-oriented: Grades aren't that important for them. They probably would like to choose courses to seriously study knowledge and are mainly interested in learning and mastering content or a given skill. Besides, they may even challenge difficult courses if they are interested in them or think the course is useful for them. (d) Social-oriented: They consider more about suggestions from their friends appreciate the courses recommended by their friends, senior students, and instructors. They also highly value student-teacher compatibility. In addition, they prefer to enroll in a course with their friends or want to meet friends with similar interests.

Implications for course recommendation system develop (RQ3)

Student motivations are a useful lens for understanding students and inform design directions for course recommendation systems.

Multi-criteria personalized recommendation First, a useful course recommendation system should better account for student motivations in their designs. Results of our studies show that different students may have completely different orientations based on their own reasons, which serve as different criteria for course selection and those should be considered in course recommendation systems in physically-based university environments. This suggests that recommendations that are aimed only at one or a few factors are likely not enough to help the students find useful courses. Also, take different factors into account when training models may get better results (Esteban et al., 2018). In addition, individual differences indicate the need of designing a personalized system to fit different students (Esteban et al., 2018).

Utilize social information A substantial number of students were found to take courses for social reasons, even though the learning experience was designed primarily for individuals. Many course recommendation systems separate social features, even though learners can be an invaluable resource to each other. Our results indicate that, in such physically-based learning environments, students would ask their peers, mentors, or senior students to recommend courses for them. Such social information can be extremely useful and could be considered for future course recommendation systems.

Issue warnings and provide preparatory Another finding is, in universities, the cost to students of making a bad decision is much higher as it can have a long-lasting effect on the student and seriously affect their course achievements. As a result, a lot of students were found to care about their GPA. In such a situation, if a course recommender system could issue a warning for courses too advanced and provide suitable preparatory courses would therefore be extremely beneficial.

Support exploration and explanation Also, course recommendation systems should support exploring and provide relevant information to explain the recommendations. Our results indicate that some students may have no clear idea of what they want to study. For those students, course recommendations that help to explore various candidate courses can be extremely important. In addition, have a good understanding of why they should take the course is important to help them with the decision process. Explain the reason why the course is recommended could increase student's trust in the system, improve their understanding of the course content and knowledge structure, persuade them to accept the course. Also, it enables students to develop their own vision, reasoning and finally pave their way for future learning goals and career plans.

Provide user control Finally, allowing students to involve in the recommendation process is another strategy for supporting the transparent and diversity of student needs. For example, allow students to provide feedback in the recommendation process by choosing different criteria for recommendation and changing the influence of selected criteria. There are some recommendation systems allowing user intervention into the recommendation processes by rating, removing, sorting recommended items, or editing input data sources (Tsai & Brusilovsky 2018; Bostandjiev et al., 2012; Parra & Brusilovsky, 2015). Although they are not designed for education domains, those works propose a good solution and provide insights for educational course selections.

Limitations

Although conducted on a relatively small-scale, our study has revealed the complexity and variety of factors involved in students' decision to choose courses in university environments. The main limitation of our work is that conclusions are based on data that was collected in our university. This challenges the generalizability of our findings, we will carry out a more large-scale study on students' selection decisions as future work.

Conclusion

In this paper, we present the results of our interviews and questionnaires to untangle the complex factors that are of concern to university students for their course selection. Our study has revealed the complexity and variety of factors involved in students' decision to choose courses in university environments. Students who enrolled in the same course may have completely different orientations, and those should be considered in course recommendation systems in physically-based university environments. Using these results, we could inform the design of alternative course recommendation systems that may consider the versatile nature of reasons and students' different demands involved in course selection. In addition, instructors and course designers could use this information to improve their courses and their students' learning experiences, thus contributing to the discussion about improving instruction for diverse learners.

Future work should examine other factors that affect both behavioral choices and motivations. Beyond demographic differences, levels of prior knowledge, preference, and learning style are other individual differences between students that have been identified as important. A final topic for further investigation is the extent to which the suggested design changes for course recommendation systems could actually measuring and accounting for individual differences and supporting students with specific motivations. Based on those results, we could design and develop a better course recommendation system.

Abbreviations
MOOCs: Massive Open Online Courses; OLEI: Online Learning Enrollment Intentions.

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Authors' contributions
This study reported in this article is a part of the Ph.D. project conducted by BM. SK is his supervisor. An initial manuscript was written by BM. SK has a significant contribution to plan and prepare the materials for conducting the experiment, recruiting participants, and reviewing the manuscript. ML and YT have significant contributions to provide feedback to analyze the data and review the manuscript. Each named author has substantially contributed to conducting the underlying research. All authors read and approved the final manuscript.

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Availability of data and materials
Data and material are not available as our consent forms did not include information regarding sharing data outside of the research study.

Declarations

Competing interests
The authors declare that they have no competing interests.

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