Eliciting Students' Needs and Concerns about a Novel Course Enrollment Support System

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ABSTRACT: Selecting courses that optimally fit a student's situation can help reduce the risk of dropping out. Data exploration and performance prediction approaches can be applied to help students make these decisions. To ensure that an enrollment support system meets the needs of students, they should be involved as early as possible in the development process. This paper presents an initial assessment of some functionalities of a novel course enrollment support system based on student performance data. The results include a collection of indicators and sources of information, as well as an overview of needs and concerns. The insights gathered will help to develop a system that has the trust of students.

Keywords: Learning Analytics, Student-Centered Design, Course Enrollment Support

1 INTRODUCTION

One of the most promising uses of learning analytics is the personalization of students' learning experiences. In these lines, recommender systems are used to provide students with different courses of action (Wilson et al., 2017). Recommender systems here refer to the use of computational techniques to make suggestions when there is a great volume of options, as in such situations the selection process can become difficult for the user (Goncalves et al., 2018). In educational settings, recommender systems have been proposed to assist students in choosing courses and learning materials, aiming at improving students' persistence and achievement (Abdi et al., 2020; Goncalves et al., 2018).

Why thinking about a novel course enrollment support system? When students have to choose courses at the beginning of the semester, current practice in many German universities is as follows: first, students look up in their transcripts the courses that they have already completed; second, they consult the university course catalogue and the schedule to see which courses are offered, and when they decide how many courses they would like to follow, they choose and enroll. Presently, there is seldom specific official support put in place by the universities to provide more information or to help students reflect on their studies. Experience shows that, before enrolling, many students look for additional information or advice by talking to friends or fellow students. Very few talk to an advisor.

More support could be provided using student-facing learning analytics to ponder on questions like: How many courses should I take? When is the best time to repeat a failed course? Which grades can I expect? Which courses might be difficult for me? Am I at risk of dropping out? Many students are not aware of the advances in learning analytics and the possibilities recommender systems. Further studies should explore current practices and needs, discussing new possibilities when planning the design of a novel enrollment system that could provide such support, helping to reduce the number of dropouts.

Considering that recent work has highlighted the importance of designing transparent recommender systems to improve learners' satisfaction and trust (Abdi et al. 2020), this paper presents the methodology and the results of the testing of the first loop of a student-centered design approach to implement a course enrollment support system with a recommendation component.

2 RELATED WORK

The authors of several studies have described their user-centered approach to involve students in the development of learning analytics tools. The importance of this was also emphasized, e.g., to make learning analytics tools comparable and to evaluate their impact on students.

Bodily and Verbert (2017) conduct a literature review with 94 articles on systems that track learning analytics data and provide their output directly to students. Considering the functionality, the systems were primarily for awareness or reflection (37%), for resources recommendations (29%), for improving retention or engagement (19%), and a few for course recommendations (3%). The authors noticed that the recommendation components are in many cases not transparent in the way they operate, which harms trust and acceptance. They indicated that, although 37% of systems offer grade comparisons, the question of interpretation is open: students with above-average performance might be careless and below-average frustrated. Furthermore, it was mentioned that despite being systems for students, only 6% of the articles included students as stakeholders in the requirements analysis. Finally, Bodily and Verbert (2017) provide 10 questions to guide the development of a possible system and to create awareness that these issues should be published more extensively and transparently in research papers to enable conclusions about student success.

Jivet et al. (2018) summarized the findings of their systematic literature review of learner dashboard development including 26 papers and gave recommendations for dashboard design and evaluation. For example, one should consider that comparisons with fellow students do not necessarily have a positive impact and no learner group should benefit more than others. In addition to usefulness and ease of use, the authors stated that understanding the data and how to interpret it, and finally, trust in the tool plays a major role in dashboard evaluation.

De Quincey et al. (2019) included students in the development of a dashboard that integrates study motivation to track engagement and predicted scores at Keele University (UK). For iterating through analysis, design, and development, four student ambassadors were trained as user experience researchers, who in turn recruited students to elicit feedback. The initial implementation of the system was tested with 94 volunteer students and then evaluated in 10 contextual interviews. Although trust in the system was rated differently, most students recognized the support provided by the tool and for some it also influenced engagement. The authors list a set of success factors such as integrating the system into the classroom, trust in data and computation, and personalization since not all students share the same goals.

Hilliger et al. (2020) identified student information needs regarding course enrollment at Pontifical Catholic University (Chile) using a mixed-methods approach in which a qualitative survey with open-ended questions and 31 student representatives as participants was turned into a quantitative, closed-ended survey with 627 participants in the second step. Information needs were divided into used information and information sources, and additional required information. The most frequently used sources of information out of 9 are class scheduling dashboards (98%) and visualizations of progress in the program, and the least frequently used are other people (12%), i.e. advisors and acquaintances, and friends. The two most relevant pieces of information out of 12 were course schedules (95%) and program progress (66%) and the least relevant are pending academic credits and course assessment tools. Despite the variety of information and sources already available, there were still items that can support course enrollment decisions, such as the information about the real use of teaching assistants' hours (61%), assessment tool types (52%), and course grades in previous semesters (49%). (Hilliger et al., 2020) recognized desired course-level indicators as mostly descriptive and refered to the rejection of predictive indicators mentioned in former papers.

Sarmiento et al. (2020) described their approach of a series of co-design workshops for learning analytics tools with and for students at New York University (USA). Based on in-depth interviews, personas were developed to map the biggest challenges of the learning experiences. Students were invited to co-design workshops to develop solutions for these personas. Students' time constraints at the end of the semester were not only a problem for recruitment, but also for participation in three 5-hour workshops. Out of 106 students initially considered as potential participants, 20 ended up being interested and finally, a total of 10 participants joined the workshops with 4-7 participants each.

3 METHODOLOGY

As the first test phase with users after the design and development of low-fidelity prototype functionalities (Ladner, 2015), a semi-structured group discussion (SSGD) was used to involve students in the development process. The SSGD was organized in two parts: a general part 1 about needed information and a more specific part 2 regarding descriptive and predictive analytics based on real data. The questions of part 2 were extracted from previous research: the feasibility analysis of a course recommendation system based on grade predictions (Wagner et al., 2020a) and the analysis of students at risk of dropping out (Wagner et al., 2020b).

3.1 Group Discussion

The SSGD was held as part of a seminar in an elective machine learning course planned in the $4^{th}/5^{th}$ semester of the curriculum. In this course, the 25 students had already worked in seven groups on a variety of topics and had built some understanding in data exploration and statistical learning. Thus, their data literacy level may be considered above average. Part 2 provides students an opportunity to think about the impact of machine learning algorithms on users, which fits well in such a course. Further, by integrating the discussion into the course and awarding points for participation, student time constraints as in (Sarmiento et al., 2020) were overcome.

The two parts of the SSGD were presented and the students discussed in groups for 30 minutes. All seven groups worked on part 1, which was similar to the 1^{st} survey of Hilliger et al. (2020): 1. "What information do you typically use to decide which courses to take?" and 2. "What additional information would you like to have and why?" Part 2 was divided into three focus topics that were not completely free of overlap regarding their tasks: A Descriptive Statistics, B Grade Predictions, and

C Dropout Predictions. Each topic was divided into four tasks, consisting of several questions supported by figures. Table 1 gives an overview of topics and tasks and the corresponding figures. The figures shown below are examples based on student 2, who had a high dropout risk in contrast to the others, since not all figures can be shown. The slides as provided to the students can be found online.[1]

Table 1: Group Discussion Questions: Topics from A to C and tasks from A1 to C4

A Descriptive Statistics	B Grade Predictions	C Dropout Predictions.
A1 Performance Do you find a comparison of your own performance with that achieved by other students helpful, for example, to better assess your own performance? (similar to Figure 1b)	**B1 Information Demand** Do you think that there are different information needs depending on the performance, i.e. does student 2 need different information than student 1? (similar to Figure 1a)	**C1 Individual Study Conditions** Do you think that a recommendation system should be able to take different study motivations / framework conditions into account? Which parameters can you think of / do you find important? (similar to Figure 1a)
A2 Performance Do you find explanatory texts helpful, e.g. to better assess your own performance? (similar to Figure 1b)	**B2 Grades Distribution** Do you find a rough overview of the results in the modules of the coming semester helpful? What evaluations would you be interested in? (similar to Figure 3)	**C2 Dropout Risk** Especially at the beginning of their studies, students often change their study program or drop out. Do you find a corresponding forecast helpful? Should explanations be provided as to how the system makes the forecast? What kind of explanations could be helpful for students to better manage their studies? (Figure 2b)
A3 Grades Distribution Do you find a rough overview of the results in the modules of the coming semester helpful? (Figure 3)	**B3 Grade Predictions** Do you find a grade prediction for the upcoming semester helpful? What effect might the prediction of a good grade, a bad grade, or the prediction of not passing have on you? Should only the positive predictions be given? (similar to Figure 2a)	**C3 Support in Case of Dropout Risk** What support would you want in such a situation?
A4 Further Exploration What other evaluations would interest you?	**B4 Grade Predictions** Do you need explanations to understand the prediction? If so, which ones? If the explanations do not seem helpful to you, would you need a simulator to enter your desired grade, and understand the effect on your degree? (similar to Figure 2a)	**C4 Study Behavior Illustration** Do you find examples of students in similar situations helpful? How could this be illustrated? (similar to Figure 1c)

Two groups focused on topic A, three on topic B and two on topic C. The opinions and ideas were then presented by one group at a time in a whole class discussion and supplemented by the other groups or individual students as needed. The groups provided their notes, which serve as the basis for this paper. All groups were given the enrollments and grades of the first two semesters of three student-examples drawn from the data of their own study program, so that they could easily understand the three examples. Student 1 had almost only very good grades, while student 2 enrolled in fewer courses and failed one course in semester 1 and semester 2. Student 3 enrolled in the same courses as student 1 and got mostly good grades.

[1] Further material: https://projekt.beuth-hochschule.de/index.php?id=4863

Figure 1a shows the enrollments and grades for student 2. The column “S” means the study semester of a given student, the column “P” is the semester in which a course is planned in the curriculum, the column “Course” is the code of a course, with “WP” representing an elective course and “B” a mandatory course, and the column “Grade” is the grade obtained by the student. Grades are given according to the German system: 1.0 is the best (green), 4.0 the worst possible grade to pass a course (orange) and 5.0 means fail (red). If a course has been enrolled but no exam has been taken, the cell is gray. The last row means: he/she completed the course WP01 in his/her 1st semester of study with the grade of 1.3, and this course is planned in the 4th or 5th semester according to the curriculum. Figure 1b compares the student's results with the course median based on all students and all semesters and gives the difference (red less, green better, gray equal to the course median). Figure 1c shows the results of the remaining semesters.

a)

S	P	Course	Grade
1	1	B01	2.3
1	1	B02	2.7
1	1	B03	1.7
1	1	B04	2.0
1	1	B05	2.0
2	2	B06	1.3
2	2	B07	4.0
2	2	B08	2.7
2	2	B09	2.0
2	2	B10	2.0
2	4/5	WP01	1.7

b)

S	P	Course	Grade	Median	Diff
1	1	B01	3.3	2.3	1.0
1	1	B02	2.7	2.7	0.0
1	1	B03	3.0	1.7	1.3
1	1	B04	2.0	2.0	0.0
1	1	B05	5.0	2.3	2.7
2	1	B05	2.7	2.3	0.4
2	2	B06	5.0	2.7	2.3
2	2	B10	1.7	2.0	-0.3
2	4/5	WP01	1.7	1.7	0.0

c)

S	P	Course	Grade
3	2	B07	4.0
3	2	B09	
3	3	B15	2.0
3	3	B17	2.7
3	4/5	WP06	1.7
4	2	B06	3.3
4	2	B08	1.7
4	2	B09	1.3
4	3	B13	3.7
4	4	B20	2.0
4	5	B24	1.0

S	P	Course	Grade
6	3	B14	3.0
6	3	B16	3.7
6	4	B18	2.7
6	4	B19	1.7
6	5	B23	2.0
6	4/5	WP14	
6	4/5	WP15	
7	4/5	WP03	
7	4/5	WP10	1.7
8	4/5	WP09	3.3

Figure 1: Presentation of the Students' Results using the Example of Student 2:
a) Results from the first two semesters (used in tasks B1, B3, B4, C1, C2, C4),
b) Performance summary of 1st and 2nd student semesters comparing grades of the student to the course median and reports the difference between students grade and course median (used in task A1),
c) Results from later semesters (used in task C4)

Figure 2 combines two prediction results used for topics B and C. The grades prediction result for each course in the upcoming 3rd semester based on linear regression are shown for student 2 in Figure 2a. The grades are colored with the same scheme as in Figure 1. The dropout risk, or probability of graduating, of each student based on logistic regression, are shown in Figure 2b.

a)

Course	Grade
B13	2.33
B14	2.12
B15	2.14
B16	3.09
B17	2.07

b)

Student	Prediction	Probability
1	Graduate	89.07%
2	Dropout	72.35%
3	Graduate	91.30%

Figure 2: Presentation of the Prediction Results:
a) Grade predictions of 3rd semester courses for example student 2 (used in task B3, B4),
b) Dropout prediction for all example students (used in task C2)

Figure 3 shows a summary of the statistics of the students' performance of all courses planned in the 3rd semester: minimum, maximum grades, median, mode, and percentage of the students who got each grade from 1.0 to 4.0 and colored as a heatmap. These statistics have been calculated with historical data.

P	Course	Min - Max	Median	Mode	1.0	1.3	1.7	2.0	2.3	2.7	3.0	3.3	3.7	4.0
3	B13	1.0 - 4.0	2.0	1.3	5.9%	17.8%	17.5%	14.1%	16.6%	10.2%	9.4%	5.2%	1.7%	1.7%
3	B14	1.0 - 4.0	2.0	1.0	25.4%	11.0%	12.5%	12.2%	10.3%	9.6%	5.4%	7.5%	3.7%	2.4%
3	B15	1.0 - 4.0	2.3	2.3	6.8%	5.5%	11.9%	12.9%	16.5%	14.4%	16.4%	12.2%	3.0%	0.5%
3	B16	1.0 - 4.0	2.7	3.0	6.3%	6.9%	7.4%	10.7%	11.8%	9.8%	15.7%	9.0%	9.3%	13.1%
3	B17	1.0 - 4.0	1.7	1.3	10.8%	24.7%	22.3%	16.1%	9.2%	7.1%	4.2%	2.6%	2.1%	1.1%

Figure 3: Summary Statistics of Grades Distributions
for Courses of the 3rd Program Semester(used in task A3):
P = Plan semester (semester in which the course is scheduled according to the curriculum),
Min-Max = Grades range, [1.0, 1.3, …, 4.0] = Grades and their distribution over all semester

3.2 Evaluation

The two parts of group work and discussion have been evaluated differently so far: the submitted notes from part 1 were coded in several steps based on the indicators and information sources from Hilliger et al. (2020), and those from part 2 were used to describe key challenges for further work.

To code the notes from part 1, the most important indicators and sources given by Hilliger et al. (2020) were used as starting point. In the first step, the most comprehensive answer to each question was mapped to the codes by two researchers together. The other notes were coded independently, and those that did not lead to the same result, e.g., because of to unclear meaning due to other study conditions, were discussed afterward. If previous codes could not be adopted, they were merged or renamed. If necessary, new codes were created. The mentioned indicators and sources were evaluated by their number of occurrences and assessed in terms of their integrability into a novel enrollment support system. For part 2, students' comments were grouped into addressed subjects and improvement ideas are briefly outlined.

4 RESULTS

4.1 Part 1

The presentations by the groups and discussions with the students lasted about 15 minutes for part 1. Table 2 gives an overview of the original codes (Hilliger et al., 2020) for indicators as well as the used codes in this paper and their short description and Table 3 contains the same for the information sources. 11 of the original codes were adopted, 6 were merged to 3 new codes, one was renamed and 6 new codes were introduced to fit the context. 14 codes (10 indicators and 4 sources) were not used in our context and are not given here.

Table 2: Indicators overview: integrability in a novel system [* easy, ** not easy, * out of scope], U = usage of original codes [A=adopted, M=merged, N=new, R=renamed], Q1, Q2 = number of occurrences in questions 1 and 2**

Code	Description	U	Q1	Q2
Academic Workload *	Credit points according to study regulations	A	1	
Assessment Types ** (original: Assessment Tool Types, Course Assessment Tools)	Way the course is examined, e.g. written exam, group project	M	3	3
Course Content *	General description of the content	N	3	
Course Preview **	Preview of what will be covered in the up-coming semester	N		1
Course Requisites *	Recommendations for prior knowledge according study regulations, e.g. other courses or general requisites descriptions	A		1
Course Schedules **	Timetable of offered course	A	5	
Course Type *	Mandatory or elective course	N	1	
Fellow Students' Decisions * (original: Students' Comments)**	Decisions made by fellow students about course enrollments	R	1	
Past Course Grades	Results in previous semesters	A		2
Pending Academic Credits *	Credit points of courses not yet passed	A	1	
Percentage of Passed *	Part of students that passed this course in previous semesters	N		2
Perception of Workload **	Workload perceived by students	A	1	2
Prior Course Syllabus **	Course syllabi in previous semesters	A		1
Program Progress *	Progress according to study regulations	A	1	
Teaching Methodologies **	Teaching methodology used in a course, e.g flipped classroom	A	1	1
Teaching Staff Information **	Information about lecturers, e.g. teaching experience	A	4	1

Table 3: Source overview: U = usage of original codes [A=adopted, M=merged, N=new, R=renamed], Q1, Q2 = number of occurrences in questions 1 and 2

Code	Description	U	Q1	Q2
First Lectures	First 2-3 lectures of a course	N	1	1
Friends and Acquaintances (original: Friends, Other people)		M	5	
Official Evaluation Report (original: Program WhatsApp Group, Student Facebook Group)	Evaluation report provided by the university and filled by students at the end of a course	N		2
Students' Social Media Group	Grouping of various informal social media	M	2	
University Course Catalogue	Study offer and regulations	A	5	

The most important indicators currently used are “course schedules” and “teaching staff information”, while the most important information sources are “friends and acquaintances” and “university course catalogue”. The most often requested indicator is “assessment types” and the most often requested source is “official evaluation report”. Based on these results, indicators were identified that can be easily included in the enrollment system (marked with * in Table 2), which will be elaborated in the discussion section.

One notices that four indicators and one source have been mentioned in some groups as an already existing usage (question 1), and as a request for additional information (question 2) in other groups. From the discussions, this can be explained as follows: At the time the enrollment starts, i.e. before the beginning of the semester, only the general information from the university course catalogue is available to students. During especially the first lecture, lecturers provide additional information on assessment, teaching methodologies, and so on. As students have almost 3 weeks after the beginning of the class to cancel their enrollments, for some groups, this is enough. Other groups would like to have this information beforehand, for example in the form of a course preview. Similarly, some groups ask friends about their perceived workload and teaching staff and consider having this information. Other groups would like official information on those items for example, by making parts of the Official Evaluation Report public.

4.2 Part 2

The presentations by the groups and discussions with the students lasted 20 minutes for topic A, and 30 minutes for topics B and C. Needs and concerns as well as the further ideas have been extracted from the students' notes and are listed in Table 4 and Table 5 together with the task in which they were mentioned. "Individual interpretation" refers, for example, to "A1 Performance Comparison" and "B3 Grade predictions". The number of groups in which the item occurred is not shown because only two or three groups worked on the respective tasks in part 2, in contrast to part 1, which was completed by all groups. The improvement ideas will be presented at the end of the discussion section.

Table 4: Needs and Concerns and Related Task (from A1 to C4)

Needs and Concerns	A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4
Equality					x							
Explainability							x	x		x		x
Impact on motivation						x	x					
Individuality					x			x		x		
Individual interpretation	x						x					
Lecturer and course type dependancy			x	x		x	x					

Table 5:Students' Ideas and Related Task (from A1 to C4)

Ideas	A1	A2	A3	A4	B1	B2	B3	B4	C1	C2	C3	C4
Additional recommendations types					x			x	x			
Basic/Expert mode					x							
Dynamic plan for study sequence					x				x		x	
Evaluate individual strengths									x	x		
Other					x		x			x	x	

Needs and concerns are presented in turn, with any conflicting ones listed together:

- Explainability, Individual Interpretation, and Impact on Motivation: Students have little trust in the predictions because not all influencing parameters are known to the system. In their opinion, explanations of how the predictions are made are necessary. Depending on one's performance, grade distributions and predictions may affect students differently. One assumption students make is that performance comparisons are motivating for students with good performance and demotivating for those with poor performance. Another is that students with good performance may become careless. Both assumptions were also mentioned by Bodily and Verbert (2017) and Jivet et al. (2018).
- Equality and Individuality: Students general state that the same information should be available to everyone so that no one feels disadvantaged. However, they have ideas about what additional information could help students with lower grades and also assume that the system cannot take all individual factors into account.
- Lecturer and course type dependency: Students see the lecturers as the biggest factor influencing the grades. Thus, in their opinion, summary statistics of grades in the past and grade prediction should be lecturer dependent, although the course type must also be taken into account: Students consider data exploration and grade predictions to be more helpful for elective courses than for mandatory courses, since for mandatory courses, a choice is possible only if at least two lecturers teach the same course in parallel.

Students' ideas about additional functionalities are mapped against the tasks in which the ideas were discussed in Table 5. A "Dynamic plan for study sequence" – a visualization that brings together courses already taken and a prediction of grades or the best time to take courses that are still open, depending on a maximum number of courses to be taken in the future – could be helpful regarding the individual information demand, individual study condition and supportive in case of a high dropout risk. "Additional recommendations types" refer to recommendations that are not already contemplated, e.g. special recommendations to improve weaknesses or elective courses according to personal interests. "Basic/Expert mode" means a display that can be expanded by the user. "Evaluate individual strengths" refers to one's strengths by competencies, e.g., mathematics, and upcoming courses: if math skills are good, refer to courses with a math component and if math skills are week, refer to the fact that there is not as much math left in the rest of the program. "Other ideas" present further aspects, such as advising sessions or highlighting of career opportunities.

5 DISCUSSION

The result from part 1 provides the basis to answer the research question, identifying indicators that should be included in the enrollment support system. Although all indicators and sources seem reasonable to support course enrollment, there are tradeoffs to be made in realization: some of them can be used more quickly since the data already exist or can be easily obtained (marked with * in Table 2) – all of them are part of the University Course Catalogue. Some items are indicators, that are semester-specific and for which there is currently no structured data, so they cannot be easily included (marked with ** in Table 2). And the last item – Fellow Students' Decision – is out of scope for our future work (marked with *** in Table 2).

Results from part 2 show needs and concerns as well as student ideas to support course enrollment. Contradictions are seen as a challenge: 1. to be equal and fair as well as individual, and 2. to be understandable in order to be trustworthy. Equal information for all is required, but how can e.g. a ranking like “You are in the Top10” of the course motivate the students with good performance and the absence of such a statement not demotivate them? Already the non-appearance of such an evaluation means: “You do not belong to those with the best performance”. How to ensure that no learner group benefits more than others as requested by Jivet et al. (2018), considering equity and when low-performing students need more support? To build trust in recommendations, the system must not only be accurate but also explain how the predictions are made so that they are understandable and interpretable. Finally, the SSGD revealed ideas from the students, some of which can be included in the upcoming design phase: A “Dynamic plan for study sequence” was an interesting side finding, that can be an approach to support students. “Other ideas” go beyond of course enrollment support and are outside the scope.

6 CONCLUSIONS AND FUTURE WORK

The purpose of the study was twofold by not only evaluating various functionalities of a novel course enrollment support system through a semi-structured group discussion with students, but also illustrating how to engage students in the design of recommender systems to enhance trust in further implementation stages. This paper includes a description of user involvement as demanded by Bodily and Verbert (2017) and de Quincey et al. (2019), and a set of indicators and sources of information based on the research of Hilliger et al. (2020) and relevant to students at the time of course enrollment. The approach of semi-structured group discussion, which was integrated into a course, is considered to be purposeful: A suitably large number of students was involved to gather relevant aspects for a course enrollment support system. The illustrations of the functionalities with real examples contributed to a lively discussion and provoked both needs and concerns. Future studies will have to look at ways to turn predictions into supportive, understandable, performant, and trusted recommendations, e.g. by using model-agnostic methods. In addition, a quantitative survey supported by an improved prototype and including a larger number of students can provide a better understanding of trust in course recommendations.

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