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Recommendations as a Key Aspect for Online Learning Personalization: Perceptions of Teachers and Students

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***Abstract*—**Higher education students are increasingly enrolling in online courses, they are, at the same time, generating data about their learning process in the courses. Data collected in those technology enhanced learning spaces can be used to identify patterns and therefore, offer recommendations/personalized courses to future online students. Moreover, recommendations are considered key aspects for personalization in online learning. Taking into account the above mentioned context, the aim of this paper is to explore the perception of higher education students and teachers towards receiving recommendations in online courses. The study was carried out with 322 students and 10 teachers from two different faculties (Engineering and Education) from Mondragon University. Online questionnaires and face to face interviews were used to gather data from the participants. Results from the questionnaires show that most of the students would like to receive recommendations in their online courses as a guide in their learning process. Findings from the interviews also show that teachers see recommendations useful for their students' learning process. However, teachers believe that specific pedagogical training is required. Conclusions can also be drawn as regards the importance of personalization in technology enhanced learning. These findings have significant implications for those who train online teachers due to the fact that pedagogy should be the driven force and further training on the topic could be required. Therefore, further research is needed to better understand the impact of recommendations on online students' learning process and draw some conclusion on pedagogical concerns.

***Keywords*—**Higher education, perceptions, recommendations.

I. Introduction

THE number students in online courses has increased in the last decade. Therefore, data generated about their learning process in those technology enhanced learning spaces is also growing [1]. Data collected could be used in several ways such as identifying patterns of behaviour to offer recommendations to future online students.

In fact, machine learning is one of the fields of Artificial Intelligence (AI) where the idea is to exploit the ability to guess patterns for the future by comparing the problem to examples learned in the past. Analytics data provides opportunities for informed decision-making at both institutional and practice level [2]. In fact, education could benefit from data by means of [2]: An increased understanding of the effects of learning design decisions, learning contexts and what works in relation to stated learning objectives; A deeper insight into the impact of different processes and practices in learning environments; A rationale and agility to respond to changing circumstances; The ability to detect patterns and trends; Enhancing decision-making where logic and supporting data is consistently applied.

The machine learning process is therefore helpful in higher education institutions. As it is known, machine learning could be operating on both, labelled data (e.g. to help with categorization of new entries) and on non-labelled data (e.g. to suggest existence of groups or patterns in datasets). For the labelled data, when the model is built, we ask the algorithm to categorize an entry with information. The algorithm will label it with the closest category that matches its properties. For non-labelled data, the algorithm will group the data according to similarities among them [3].

Educational learning content personalization can be defined as any set of actions that can tailor the e-learning experience to a particular user or group of users. A comparative study of algorithms suitable for learning environments is presented in [1]. This study proposes a data-driven personalized model using Content Based Filtering (CBF henceforth) that is a process to select potentially interesting resources for user out of a very big range of selection. Such an approach requires to be introduced transparently to the user and uses a set of training data to "teach" the program using an algorithm to recognize objects, events etc. similar to previously analyzed ones. Our work covers from the conception to the accomplishment of a learner personalized system that embeds an adaptivity to Moodle so as to achieve better learning results. The mechanism adds a new block that suggests learning resources to each student. In this line, one of the sectors that greatly benefit from content filtering is e-commerce. Algorithms from this family, in order to measure similarity between items utilize available knowledge about them. CBF algorithms could rely on user or item similarities. User-driven CBF performs well with data where the ratio of items per user is high and item-driven CBF does opposite. CBF obtains high accuracy, but each item needs to be analyzed, a vector of its characteristics should be created and comparisons should be carried out to provide results. That implies very big space- and memory complexity. On the other hand, products could be compared completely ignoring their inner properties. Such an approach is available using

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Collaborative Filtering algorithms (CF). To recommend anything, it needs to have data about behavior. That means that, if a course is new, it could not recommend anything as it is unable to compare it to any other user's behavior. The same happens with new items (educational resource). The problem caused by vertical and horizontal sparsity of data is called Cold Start and is a problem related to sparse-data learning environments.

A user model can be built statistically or dynamically with techniques that are based on the knowledge or behavior of the learner [3].To build the user model for our development, we measure the user's interaction with learning resources and this model calculated depending on what task he/she has carried out.

a) if no tasks were done, then the value will be 0,
b) viewing the task adds one point to that score,

This user model brings us the possibility to extract based on previous courses similarities between the new student and previous successful students who have already done the course and show similar behaviors. The student to student similarity was calculated using cosine similarity [10].

In the present study we found that the most memory- and time-expensive part of algorithm was data extraction to calculate the matrix for collaborative filtering (a matrix of similarity between all the resources used based on the behavior of users associated with a given course). As estimations with real data are too slow, a sliding time window of 1 week was used in this study.

II. Personalization in Online Learning Recommendations as Key Aspects

With the increase of students enrolling in online courses and the growing quantity of data being originated, more and more researchers and developers from the educational community are exploring possible ways for gaining insights into online learning activities [4]. Moreover, those inputs would lead us to better understand and optimize learning and learning environments to personalize online learning. However, capturing data and using the analysis to inform teaching approaches for individual learners and to adapt it to their experience is still a challenge [5]. That is to say, we believe that Learning Analytics (LA) could provide learners with an ecosystem to advance and reflect on their learning process [4] but consequences for learning and teaching are still far from being understood [6].

As far as research is concerned, several studies have summarized the importance of recommendations in personalizing online learning [4] for example, analyzed 40 key studies related to LA in education and classified them according to the research object. Recommendations were one of the objects classified in the paper. As regards algorithms, the authors [4] state that a combination of students' clustering and sequential pattern mining is suitable for the discovery of personalized recommendations while content-based filtering and collaborative filtering approaches are valid recommendation strategies. Regarding the impact of recommendations on students, conclusions drawn from the diverse studies analyzed show that learner attributes, expected performance on task, navigation history and learner's affective traits should be taken under consideration. However, further research should be conducted in order to get a more holistic picture. And this is particularly the aim of the present paper, to add some more insights into the topic by finding the intersection between pedagogy and computer science by using recommendations as a way to personalize online learning [7].

III. Research

A. Aim

The objective of this paper is to analyze higher education students' and teachers' perceptions towards receiving recommendations in online courses.

B. Context and sample

The present study was carried out in Mondragon Unibertsitatea (MU henceforth). MU is a cooperative university formed by 4 faculties: Engineering, Business, Humanities and Education, and Culinary Science. The present research has been conducted in the faculty of Humanities and Education and in the faculty of Engineering. The sample of study is formed by 322 students and 10 teachers involved in 8 different online courses. It should also be highlighted that half of the students, randomly chosen, received recommendations.

C. Instruments and procedure followed

Two are the main research tools used in this study: online questionnaires and face to face interviews. All students taking part in the study filled in an online questionnaire designed ad-hoc (Table VI) about the use of recommendations in learning processes at the beginning of the study. The questionnaire was sent to the participant by the course teacher with a pre-established guide designed by the research group members. Recommendations were activated for half of the students taking part in each course for a period of 5 weeks. Participants filled in a second online questionnaire (Table VII), also designed ad-hoc, once the courses were finished. This second time, the online questionnaire was different for those who received recommendations and for those who did not. Students' average mark was also calculated taking into account the aforementioned variable. In order to get a more holistic picture, semi-structured interviews (Table VIII) were carried out with teachers at the beginning and at the end of the intervention. All interviews were transcribed and analyzed.

IV. Results

In order to show a clear picture, results will be divided in two sections. First of all, results from the first online questionnaire, that is to say, before the recommendations were activated, will be presented together with some of the answers provided by the teachers involved in the study. Data from the second online questionnaire - after recommendations were activated- and a comparison of the average marks will be provided at the end of the section together with teachers' reflections carried out during the interviews.

All participants taking part in the study considered that receiving recommendations could be important for their learning process. In fact, 53% of the students recognized that receiving recommendations is very important and 41% important [Table I]. In the same line, teachers stated that recommendations could have a "great potential" (Teacher3-int.) to help students in the process. Moreover, the impact on the learning process could be deeper and "not only reflected on students' marks" (Teacher 1-int.) due to the fact that students are free to follow those recommendations. However, students stated that recommendations could be especially useful to improve their marks. Besides, participants also considered that recommendations could help them in the following aspects: planning, taking decisions by means of the information provided and clarifying doubts. As far as teachers are concerned, most of them considered that recommendations should be useful to guide students' learning process using their peers' experience as a basis. Furthermore, "identifying particular moments were recommendations may be important could offer students the context to understand the course better" (Teacher 9-int.) and therefore, design their "learning path in a more personal way" (Teacher 7-int.). Nonetheless, teachers taking part in the study considered that the variable of rhythm could be important to bear in mind when analyzing online students' learning process. Indeed, "some of students may not be involved in the course following a constant rhythm, that is to say, they may work on the course for a week, stop the following one and be working for nearly 24 hours during the weekend" (Teacher 9-int.).

TABLE I
IMPORTANCE GIVEN TO RECOMMENDATIONS BY STUDENTS

Degree of importance	Percentage of students
Little importance	6%
Important	41%
Very important	53%

TABLE II
VALUE OF RECOMMENDATIONS

Value	Percentage of students
No value	12%
High value	75%
Don´t know	13%

TABLE III
PERFORMANCE AND RECOMMENDATIONS RELATION

Link between performance and receiving recommendations	Percentage of students
Yes	52%
Yes but depends on other	41%
No	7%

The added value that recommendations could have on students' learning process was also highly valued by the participants of the study. As a matter of fact, 75% of the participants claimed that recommendations could add a high value to their learning process [Table II]. In addition, 52% of the students considered that someone receiving recommendations will perform better than those who do not receive them while 41% mentioned that they could perform better: However, students stated that it may also depend on other aspects such as students' learning styles [Table III].

Results show that the vast majority of the students, 85%, would like to receive recommendations in their online courses. The main reason stated by the participants was that recommendations could be useful to guide their learning process. Just 11% of the participants stated that they do not want to receive recommendations and 4% did not answer the question [Table IV].

TABLE IV
WILLINGNESS TO RECEIVE RECOMMENDATIONS

Degree	Percentage of students
Yes	85%
No	11%
No answer	4%

Overall, teachers think that recommendations are useful to guide their students' learning process. Nonetheless, teachers may need some pedagogical training to understand the use of recommendations in online courses. In the same line, and due to the direct link between the assessment book provided by Moodle and recommendations, teachers taking part in the study asserted that more training on the use of the assessment book could provide more insights about the learning process. Furthermore, sharing those insights with the students might be the way to develop a more autonomous learning process by means of self-regulations tools.

After a 5 week intervention, both groups of students, those receiving recommendations and those who did not received, still considered that recommendations were very useful for their learning process. In fact, those receiving recommendations listed some reasons such as organizational help and changing their way of working to highlight the importance of them. Moreover, 100% of the participants stated that they would like to continue receiving recommendations in future courses. As far as more specific aspects are concerned, students considered that the place where the recommendations were located was appropriate and all of them considered that the frequency and amount of recommendations they were provided with was enough.

A comparison of both groups' - group A: students receiving recommendations and group B: students not receiving recommendations - average mark was calculated to analyze the impact of the recommendations as depicted in Table V.

As could be observed in Table V, there is not a significant difference between both groups. That is, students receiving recommendations did not significantly outperformed students who did not receive recommendations in the different courses.

Teachers also provided new insight from the use of recommendations at the end of the course. Furthermore, teachers highly valued the opportunity to get data about each student to "design personalized interventions" (Teacher 3-int.). Moreover, all the data gathered could help teachers in the redesign of their courses by means of the data provided about each of the resources available in each course.

TABLE V
AVERAGE MARKS IN BOTH GROUPS

Course	Average mark of group A (receiving recommendations)	Average mark of group B (not receiving recommendations)
ITA1A2008-F	6.82	6.08
GEA103-E	5.8	5.07
GMA102-H	4.34	4.15
GL/H4101	7.57	7.11
GH4202	7.2	8.15
GH3403	8.04	8.04
GH2/3302	7.95	7.74
GH3302	7.88	7.75

V. CONCLUSIONS AND FURTHER RESEARCH

Some important conclusions could be drawn from the present research. Results have shown that the participants of the study, both students and teachers, highly valued the importance of receiving recommendations. Moreover, recommendations were perceived as very useful by students and teachers both, before and after the courses. In fact, participants see the added value of recommendations owing to the fact that they could guide students' learning process. However, some explicit training on the use of recommendations would help teachers and students to better understand the rationale behind. In that line, teachers believe that LA in education could open two areas of interest: on the one hand, pedagogical aspects of students' learning process and on the other hand, teachers' pedagogical intervention. Therefore, pedagogical aspects should be analyzed before using data because this opportunity will potentially affect the design and implementation, and of course, training in the future [5]. Findings from the present study could have significant implications for those training online teachers because as seen in this study, pedagogy should be the base of the development [6]. Moreover, further research is required based on pedagogical concerns to gain a deeper insight of the impact recommendations have on online students' learning process. Besides, the importance of personalization in technology enhanced learning is also highlighted in this research although the need to adopt a holistic framework should be underlined. Teaching and learning processes, from the theoretical perspective, need to be coherent with the use of data to become powerful means to support learners and teachers, as well as institutions, in better understanding learning needs [6]. Moreover, the adoption of these educational technologies has afforded new opportunities to gain insights into students' learning [8] but special attention to policy implications needs to be paid [6,8].

Future research should analyze the accuracy of recommendations - although in this study were considered adequate - by adopting a more personalized view of each student and by interpreting results in within the existing research of learning. Moreover, although the present research is an attempt to find the intersection between computer science and pedagogy, future studies should look closer to understand systems in their full complexity [4]. Moreover, recent studies show that regularity is related to performance [2]. In this line, one of the aims of this work was also to provide students with an additional mechanism for their time management; that is to say, encouraging their regularity by means of providing them recommendations. Furthermore, adaptive learning could benefit from A as suggested in [9] because Adaptative Learning Analytics focuses on the features and the process of learning helping to track the progress of the students.

APPENDIX

TABLE VI
QUESTIONNAIRE FOR STUDENTS (BEFORE RECEIVING RECOMMENDATIONS)

1. How important do you consider receiving recommendations in your learning process? Why?
2. Which type of recommendations would you like to receive?
3. In which sense could recommendations be helpful for your learning process?
4. Which is the added value of receiving recommendations in your learning process?
5. Do you think that students receiving recommendations could perform better?
6. Recommendations are based on students' data from Mudle, would you like to receive them?

TABLE VII
QUESTIONNAIRE FOR STUDENTS (AFTER RECEIVING RECOMMENDATIONS)

1. Which is the degree of importance that you give to the recommendations that you have received? Why?
2. Were the recommendations you received useful and meaningful? Why?
3. Do you think that the locations of the recommendations in the platform was adequate? Why?
4. What do you think about the amount of recommendations that you have received?
5. What do you think about the frequency of receiving recommendations?
6. Which was the added value of the recommendations in your learning process?
7. Would you like to receive recommendations in other courses?
8. Would you like to receive any other type of recommendations?

TABLE VIII
GUIDE FOR SEMI-STRUCTURE INTERVIEWS (TEACHERS)

1. We can get data from students' activity in the platform and use them for educational purposes. In your opinion, which could be the most appropriate use in the educational field?
2. How can we improve our students' learning process by means of recommendations?
3. What do you think about recommendations?
4. How do you think the future could be like when using learning analytics in educational fields?

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