ONLINE EDUCATION – ENGINEERING STUDENTS’ PERSPECTIVE

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Abstract – With online learning moving into the long term, the mental and academic impacts on students are likely to be challenging. Preliminary results obtained from three different student surveys are presented and analyzed for different cohorts of undergraduate engineering students enrolled in an engineering program at the Université de Moncton.

The first survey was administered during the last week of the Winter semester, before the final exams period. This survey was administered by the Engineering Faculty and created to get an overview of students experience during their online learning sessions. Specifically, the goal of this survey was to get information on which technical tools work best for distance learning during their online sessions and to improve future online learning sessions. Another survey was completed at the end of the Fall 2020 online learning semester. About half of all engineering students completed the surveys and a preliminary analysis was conducted. Finally, a third survey was administered during the Winter 2021 online learning semester.

The aim of this study is to evaluate and analyze the results of these surveys using educational data mining. This work will provide an overview of the online learning experience during the end of the Winter 2020 semester and the academic year 2020-2021 and establish relations between classroom and online learning environments. New data analysis may help to accelerate and improve future hybrid classroom-online learning pedagogy since permanent changes are expected in the near future for many engineering programs.

This study shows that students vary in their abilities to adapt to this new reality. Most prefer recorded audio clips of PowerPoint presentations beforehand combined with online synchronous learning using video conferencing software. This suggests that effective online learning requires extra time from educators to better prepare class sessions. Furthermore, there is an important correlation between the level of student motivation and their appreciation level of online learning.

Keywords: Online learning, data mining, engineering education, Covid-19.

1. INTRODUCTION

The Corona virus (Covid-19) pandemic has required a widespread shift from traditional face-to-face instruction to distance learning in higher education institutions. Crawford et al. (2020) conducted a comprehensive study examining higher education response in countries with developed economies, where most reported closing campuses and moving to online instruction with the exception of the United States of America. The higher education sector across the US began a significant online education response from the period of the first suspected on-campus case reported the week of 17 February, until early and mid-March when the infection rate dramatically increased. By the 1st of April 2020, schools and higher education institutions were closed in over 185 countries, affecting over 89.4% of total enrolled students or 1.5 billion learners (Marinoni, Land, and Jensen, 2020).

In replacing classroom teaching by distance teaching and learning due to the disruption caused by COVID-19, there are many challenges and questions that remain unanswered. Although earlier efforts concerned the transition to an online environment, the focus has now shifted to principles for effective online instruction and quality assurance in combination with revenue mitigation measures (Crawford et al., 2020). While most institutions direct efforts to train Faculty staff to ensure quality of the curriculum in virtual classrooms, there has been less consideration to how best to support students who face significant challenges in adapting to this abrupt change. These difficulties include but are not limited to distractions at home as well as privacy and mental health issues that may be aggravated by inequity of resources and access to technology (Neuwirth, Jović, and Mukherji, 2020).

The need to gain insights in this area as well as adopt best instructional design practices for online instruction is most pressing in the domain of engineering, where students rely on traditional hands-on lab experience to facilitate skill and knowledge acquisition (Kapilan, Vidhya, and Gao, 2020; Nogales-Delgado, Román Suero, and Martín, 2020).

Engineering programs contain a list of mandatory courses and electives where understanding complex engineering concepts requires a set of necessary skills that are interdependent. The curriculum is focused on core skill sets that have been traditionally taught in a face-to-face (professor-student) environment. While the surveys were done to improve the online educational experience, the main objective of this study is to analyse the results of the surveys. If the adoption of online learning continues to persist post-pandemic, it will impact engineering education in the future.

2. STUDENT SURVEY

2.1. Survey Context

During the Winter 2020 session, all the students were sent home due to the Covid-19 after completing only two and a half months of their Winter 2020 session. After a pause of two weeks, online learning was implemented for all engineering courses. With this sudden shift away from the classrooms, one can wonder how efficient online learning was during that time and how it was perceived by the engineering students. Furthermore, for most and probably all engineering professors, this was a completely new experience, and many had to rely on their creativity and adaptation skills to quickly modify their approach to teaching. This included preparing additional educational material, learning specialized software, tools to communicate with students, etc. Although online training for professors was well organized and access to technical personnel was available, some professors still had difficulties adapting to this new environment.

To assess the students' perspective on their online learning experience during the past year and to improve the effectiveness of online learning, three surveys were administered. These surveys involve repeated assessment of students' learning experience and at least one third of all engineering students completed the surveys as shown in Table 1. The objectives of these surveys are to improve the students' online educational experience by getting feedback from student and present those findings to engineering professors so they can make beneficial adjustments to their online teaching methods. The surveys were administered from the Engineering Dean's Office. The first survey was administered at the end of the Winter 2020 term and before the exam period. After a two-week break in early March 2020, the resumption of teaching lasted about four more weeks and then the two-week examination period was initiated. Several adjustments had to be made during this period, both for students and teachers. During the two-week break, webinars were given by the University's teaching support group to help professors transition to online teaching. When classes resumed, technical problems arose, and technical support was very much requested by all. Some

results from the Winter 2020 survey were presented at a faculty meeting in August. The second survey was administered at the end of the Fall 2020 term. The experience gained during the end of the last term was beneficial in getting this online term off to a good start for all courses. Before starting the Winter 2021 term, a presentation of the results of this survey was made to the Engineering Faculty staff. The purpose of the meeting was to inform them of the student situation during the online teaching Fall semester and how they could improve the efficiency of their distance education methods for the following term. Finally, the third survey was administered after two months of teaching during the Winter 2021 term.

The Université de Moncton offers three engineering programs (civil, electrical and mechanical). All programs have the duration of five years, and students will normally register for five courses per term. There are approximately 320 students in total registered in the three bachelor's degrees.

Table 1: Number of students that completed the survey.

Program	Survey 1 Winter 2020	Survey 2 Fall 2020	Survey 3 Winter 2021
Civil	34	62	53
Electrical	19	32	29
Mechanical	36	55	35
Total:	89	149	117

Teachers and students have access to the Desire2Learn (named CLIC at the Université de Moncton) educational platform for their educational course materials. This learning management system was already used by some professors before the pandemic but quickly became the preferred tool during the last year, both for document management and for evaluation purposes. In addition, the University has recommended Microsoft Teams as its collaborative communication application and offers technical support to students and professors.

2.2. Data Acquisition and results

Figure 1 shows how often students experienced technical difficulty in each term of distance learning. The question ask was as follows: *Have you encountered any technical difficulties which prevented you from taking certain course sessions?* Students reported less technical issues for the "Always" and "Often" categories for F20 and W21 terms compared to W20 semester. This result was expected and predictable since the experience lived during the Winter 2020 term made it possible to make the necessary modifications and adjustments before resuming teaching in the Fall 2020 term.

Fig. 1. Technical difficulties encountered during online courses.

We also ask this question: *How do rate the workload in your courses this session, compared to other sessions?* The comment that came back regularly from students is that the workload increased for online courses compared to face-to-face courses as shown in Fig. 2. This was brought to the attention of engineering professors and a small decrease in workload during the Winter term was achieved compared to the 2020 Fall term (see Fig. 3) while the workload from other non-faculty courses like Math and Physics remains almost the same.

Fig. 2. Online courses workload vs face-to-face courses.

Fig. 3. Online courses workload vs face-to-face courses.

Fig. 4. Level of motivation during the Winter 2021 term vs the Fall 2020 term.

As shown in Fig. 4, when students were asked: *Compared to the Fall 2020 session, my level of motivation for my courses is better, the same or less*, more than 80% of the student felt that the online Winter 2021 learning experience was better or equal to the 2020 Fall term. For most students (52%), the level of motivation remained the same during the Fall 2020 term compared to the Winter 2021 term. Thirty percent (30%) noted an increase, while eighteen percent (18%) of students indicated that their level of motivation decreased. A significant decrease in the level of motivation from our 2021 graduate students was also noticed (20%).

Fig. 5. Delay for receiving feedback for academic work.

The next question was: *In general, I receive the feedback (correction) of my work on time (2 weeks)*. A noticeable improvement has been made regarding the delays for receiving feedback and corrections for academic work as shown in Fig. 5. The recommend time allowed for giving feedback from the professors is 2 weeks. Ninety percent (90%) of students indicated that feedback was often or always given inside this time frame during the Winter 2021 term compared with seventy-eight percent (78%) during the Fall 2020 term. It is possible that this improvement can be attributed to the Fall 2020 survey

Fig. 6. Effectiveness of different teaching tools and materials.

results presentation given to the professors before the Winter 2021 term. However, this improvement was also found for non-Faculty courses (mark by Other in Fig. 5.). This may also indicate that professors have somewhat adapted to online teaching.

We also asked: *How effective is the teaching tools and material used by the professors for your courses?* Figure 6 shows the results for this question according to engineering students. Overall, Powerpoint with narration is identified as being the most effective while videos and animations are a close second. Students also indicated that Youtube videos and text documents are not as efficient. This coincides with the preferred online teaching methods of the students. For synchronous courses, students prefer online sessions with PowerPoint slides where recordings were made available afterward. They also preferred the use by professors of a document camera during the exercise sessions. For asynchronous lessons, they preferred PowerPoint recordings with narration and videos prepared by the teachers.

In response to the following statement: *For laboratory sessions, I prefer ...*, the students indicated that live demonstrations with explanations by the professor or technician are preferred. However, most students indicated that they would have preferred face-to-face laboratory sessions. More than thirty percent (30%) of the students indicated that they do not like asynchronous sessions. All the results presented above were consistent throughout the three engineering programs. Thirty percent of students said that the Winter 2021 term is better than the previous session, fifty percent found it to be similar and twenty percent found it to be worse than the previous term.

3. DATA MINING METHODOLOGY

Association rule mining aims to discover relationships between survey responses to closed-ended questions (Chen and Weng, 2009).

3.1. Association rule mining

To identify the link between different student responses, an association rule mining technique was applied. The link between two responses is represented as an association rule ($X \rightarrow Y$) and is measurable in terms of both its support and confidence. Support determines how often a rule is applicable to all item responses featured in the data set. Confidence determines how frequently item responses in Y appear in item responses that contain X . The gain metric captures the difference between both the confidence in the rule and the support of its consequent (Brin et al. 1997). The formulas of these metrics are

- i. Support, $s(X \rightarrow Y) = P(X \cup Y) / N$
- ii. Confidence, $c(X \rightarrow Y) = P(X \cup Y) / P(X)$

where $P(X)$ is the probability of having X . As an example, the support for the rule Smooth running of the Winter 2021 term (SRT) is “Less” given that motivation is “Less”, is equal to the division of the frequency of co-occurrence for both values over the total amount of items $N=78$ in the dataset: Support, $s(\text{SRT} \rightarrow \text{“Less”} \cup \text{Motivation} \rightarrow \text{“Less”}) = 8/78 = 0.103$. Given that the base rate of occurrence of the antecedent or the probability that motivation is “Less” is equal to: Support, $s(\text{SRT} \rightarrow \text{“Less”}) = 12/78 = 0.154$.

Then, the resulting confidence in the rule or probability of observing the consequent (i.e., motivation is “Less”) given the antecedent (i.e., SRT is “Less”) is the following: Confidence, $c(\text{SRT} \rightarrow \text{“Less” and Motivation} \rightarrow \text{“Less”}) = 0.103/0.154 = 0.667$. It stands to reason that values closer to 1 highlight more interesting relations amongst student response to the survey items.

3.2 FP-Growth Algorithm

A minimum support threshold value is specified to generate a set of frequent item responses. The RapidMiner standard implementation of the FP-Growth algorithm was used to create a compressed representation of the item responses (Han, Pei and Yin, 2000). Each support count for item responses that overlap is mapped onto a path in the FP-tree, allowing for increased computational efficiency by extracting frequent item responses directly from the structure in memory and avoiding multiple passes over the data set. At each recursive step, a conditional FP-tree is evaluated by updating the support count along the path and removing infrequent item responses.

As the size of item responses and the corresponding skills increases, it is important to establish subjective and objective criteria for evaluating the quality of association patterns. A minimum confidence threshold is specified and used to extract the most reliable rules from the frequent item responses found in the previous step.

4. ANALYSIS OF RESULTS AND DISCUSSION

Findings are based on the associations obtained from the surveys’ item responses. The data is labelled as a polynomial variable, where each response is associated to an outcome collected from student surveys enrolled in three distinct engineering programs throughout multiple cohorts.

Table 2 shows the encoded response values to each question, including the self-reported outcomes (i.e., whether the student reported less, same, or better performance and motivation for the Winter 2021 term compared to Fall 2020), individual differences (i.e., whether this was the first, second, third, fourth, or fifth year as well as the engineering program including Civil, Mechanical, or Electrical Engineering, preference towards asynchronous and synchronous courses, and workload in engineering or other faculty courses), and predictors (i.e., whether students reported the occurrence of technical issues and availability of help as never, rarely, often, or always). To find the most interesting associations, rules are generated through frequent pattern growth mining and evaluated using support and confidence as interestingness metrics. We focused on rules derived from patterns of responses that are most indicative. The association rules are generated to predict the smooth running of the Winter

Table 2: Encoded values for questionnaire responses

Variable	Indicator	Encoded Value
Outcome	Smooth running of the Winter 2021 term (SRT)	Less, Same, Better
	Motivation	
Individual differences	Year	1, 2, 3, 4, 5
	Program	Civil, Mechanical, Electrical
	Synchronous	Prefer, Do Not Prefer
	Asynchronous	Prefer, Do Not Prefer
Technical difficulties	Issues	Never, Rarely, Often, Always
	Help	
Workload	Engineering courses	Can’t compare, Easier, Same, Higher
	Other Faculty courses	

2021 term according to the students’ perspective with their level of motivation as shown in Tables 3 and 4.

As an example, it can be seen from the first association rules in Table 3 that for students who preferred synchronous courses and considered that the Winter 2021 term was running less smoothly than the Fall 2020 term, the outcome was a lesser motivation level for these students during the Winter 2021 term (confidence level of 0.727). The higher workload associated with synchronous courses also resulted in less motivation from students. No significant association with the degree of technical

Table 3: The association rules generated that predict less motivation and a difficult Winter 2021 term.

Rule	Support	Confidence
Then (Motivation = Less)		
If (Synchronous $\rightarrow$ Prefer $\cup$ SRT $\rightarrow$ Less)	.103	.727
If (Year $\rightarrow$ 5)	.128	.667
If (SRT $\rightarrow$ Less)	.103	.667
If (Synchronous $\rightarrow$ Prefer $\cup$ Year $\rightarrow$ 5)	.128	.667
If (Synchronous $\rightarrow$ Prefer $\cup$ Faculty Workload $\rightarrow$ Higher)	.103	.667
Then (SRT = Less)		
If (Synchronous $\rightarrow$ Prefer $\cup$ Motivation $\rightarrow$ Less)	.103	.320
If (Motivation $\rightarrow$ Less)	.103	.308

Note. Minimum support set to 0.10 and confidence to 0.25, rank ordering for most confident.

Table 4: The association rules generated that predict better motivation and a better 2021 Winter term.

Rule	Support	Confidence
Then (Motivation = Better)		
If (Asynchronous → Prefer U SRT → Better)	.103	.471
If (Synchronous → Prefer U Asynchronous → Prefer U SRT → Better)	.103	.471
If (Performance → Better)	.115	.391
If (Synchronous → Prefer U SRT → Better)	.115	.391
If (Faculty Workload → Same)	.103	.333
Then (SRT = Better)		
If (Asynchronous → Prefer U Motivation → Better)	.103	.667
If (Synchronous → Prefer U Asynchronous → Prefer U Motivation → Better)	.103	.667
If (Motivation → Better)	.103	.600
If (Synchronous → Prefer U Motivation → Better)	.115	.600
If (Synchronous → Prefer U Asynchronous → Prefer U Issues → Never)	.115	.562

Note. Minimum support set to 0.10 and confidence to 0.25, rank ordering for most confident.

difficulty experienced by students was detected in the survey data with the associations presented in Table 3. However, for students that indicated that their level of motivation was better during the Winter 2021 term compared to the preceding term, either for asynchronous or synchronous courses, they indicated that the Winter 2021 term is running smoother than the Fall 2020 term as shown in Table 4.

5. CONCLUSIONS

The objective of this study was to develop a set of diagnostic assessment tools that specifically target the engineering students' perspective of online learning during the COVID-19 pandemic, and how their responses build upon one another throughout the three academic terms (Winter 2020 through Winter 2021). Results were presented based on a limited amount of data since only one third of the students replied to the surveys. The underlying assumption is that the proposed association rule mining method enables us to empirically find relations between different student responses. The major conclusion drawn from the comparison of the results of the surveys, despite

the differences in scales and time frame, is that students vary in their abilities to adapt to online learning. Most prefer recorded audio clips of PowerPoint presentations beforehand and videos prepared by professors. They also preferred synchronous online learning using video conferencing software to asynchronous courses. This suggests that effective online learning requires extra time from educators to better prepare class sessions. Furthermore, there is an important correlation between the level of student motivation and the appreciation level for the third term. Unfortunately, the students who indicated that they were not very motivated also noted that the third term (Winter 2021) in general, is going poorer than the previous sessions.

One important item that can be drawn from this study is that keeping the students motivated during online learning is key to a successful learning experience. There are plenty of ways professors can keep students motivated during online lectures e.g. making your lesson interactive by regularly asking questions, adding pop quizzes, adding group projects, taking feedback from students, encourage collaboration and communication between students and professors, etc. Throughout the term, plan each lecture, provide timely feedback on assignments, respond to student questions within one day, give easy access to resources, etc. Professors are encouraged to incorporate these strategies in future online learning lectures to favour student engagement.

One of the limitations of this study is that it does not capture several factors that pertain to the students local learning environment, availability of getting help from other students and professors, time difference for international students and other effects not considered in this study.

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