A Predictive Model for Assessing Satisfaction with Online Learning for Higher Education Students During and After COVID-19 Using Data Mining and Machine Learning Techniques: A Case of Jordanian Institutions

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Abstract: Higher education institutions confronted an escalating unexpected pressure to rapidly transform throughout and after the COVID-19 pandemic, by replacing most of the traditional teaching practices with online-based education. Such transformation required institutions to frequently strive for qualities that meet conceptual requirements of traditional education due to its agility and flexibility. The challenge of such electronic learning styles remains in their potential of bringing out many challenges, along with the advantages it has brought to the educational systems and students alike. This research came to shed the light on several factors presented as a predictive model and proposed to contribute to the success or failure in terms of students' satisfaction with online learning. The study took the kingdom of Jordan as a case example country experiencing online education while and after the covid -19 intensive implementation. The study used a dataset collected from a sample of over "300" students using online questionnaires. The questionnaire included "25" attributes mined into the Knime analytics platform. The data was rigorously learned and evaluated by both the "Decision Tree" and "Naive Bayes" algorithms. Subsequently, results revealed that the decision tree classifier outperformed the naïve bayes in the prediction of student satisfaction, additionally, the existence of the sense of community while learning electronically among other reasons had the most contribution to the satisfaction.

1 INTRODUCTION

Ever since the World Health Organization (WHO) announced Corona Virus disease (Covid-19) to be a pandemic, higher educational institutions encountered many challenges to cope with the drastic change from the traditional (face-to-face) and on-campus learning (Harangi-Rákos et al., 2022). Mobility restrictions within countries significantly impacted the educational sector, among many sectors all over the world (Agyeiwaah et al., 2022). All educational institutions had to switch to full remote processes, ranging from the registration process to conducting classrooms (Azizan et al., 2022), to ensure the continuity of education and avoid a gap of knowledge that could impact many generations to come (Looi et al., 2022). Though, it was evident that not all students were comfortable with this rapid change, given the fact that the situation was unprecedented, educational institutions were challenged to achieve students' satisfaction with the process while lacking the capacity and adequate technologies to go online (Agyeiwaah et al., 2022). Furthermore, those institutions who had the available technologies and were able to commence online education encountered various challenges from the user's side, especially students in their first years (Spencer & Temple, 2021).

Education in the country of Jordan - like many countries- transitioned to online learning as an emergent response to the mobility restrictions after a period of shut down (Basheti et al., 2022). Online learning, that is a learning procedure in which certain online technologies are used to create a virtual

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classroom simulating traditional on-campus teaching (Pagani-Núñez et al., 2022). This type of educational process is unluckily linked with many disciplinary, commitment, and network connection issues among other challenges, from the students' and lecturers' sides, which ultimately prevent the student from having a suitable surrounding environment that guarantees the knowledge and skills are communicated (Augustine et al., 2022).

Evaluating the satisfaction of students and lecturers with online learning since the beginning of the pandemic became one of the focal attention areas of many researchers, this matter was addressed using different statistical and Artificial Intelligence (AI) methods and techniques (Ho et al., 2021). Furthermore, researchers relayed on descriptive analysis using quantitative methods to quantify students' satisfaction with numerous factors impacting the online class some of these factors include student attendance of online classes, online evaluations and exams, and relationship with lecturers (Basheti et al., 2022). Other researchers employed AI techniques to predict students' satisfaction with online learning, using different machine learning algorithms including "Support Vector Machines", "K-Nearest Neighbour", and "Multiple Linear Regression".

In addition, researchers selected features including student readiness, accessibility to online classes and sources, instructor related variables, online assessment, and learning related features, to construct the predictive models used for the satisfaction prediction (Ho et al., 2021). On this regard, one machine learning concept was used widely in studying the satisfaction is the Educational Data Mining (EDM), which is aimed at exploring different education related matters using data mining (Alsammak et al., 2022).

Investigating students' satisfaction with online learning in Jordan during the pandemic was done using descriptive analysis, in which researchers focused on characterizing the experience of online learning during the specific period of the pandemic. Researchers focused on statistical methods to describe students' experience in various universities in Jordan (Basheti et al., 2022),(Alsoud & Harasis, 2021).

2 RESEARCH QUESTIONS AND STRUCTURE

This section sets the scene of the entire presented paper, by introducing the key research questions and features of its content, offering a brief of the involved aspects. This study aims to contribute to some facets associated with online learning challenges and students' satisfaction by answering the following key questions:

RQ1: What are the potential factors that might affect student satisfaction within their online learning experience?

RQ2: When comparing the Decision Tree and Naive Bayes performance in predicting students' satisfaction based on the potential factors, which predictive model performs better?

The main sections of the study involved aspects that provides insights into relevant literature, and background review, and evaluation of algorithms implemented and their results.

2.1 Online Learning in Higher Education

Online learning is a method of teaching that utilizes different known platforms such as known applications namely (Zoom, Microsoft Teams, Google Meet...etc), to connect students and teachers online on multiple technologies, in a way that simulates actual classroom (Ab Hamid et al., 2022). Online learning, Distance Learning (DE) or E-learning refer to the same concept of a virtual classroom initially created to keep up with the increased number of enrolments, and the inability of some students to be present physically for all classrooms (Spencer & Temple, 2021).

The aim of online learning is not exclusively giving lectures and provide education, rather, e-learning providers aspire to equalize the effectiveness of online learning with face-to-face learning in terms of extracurricular, social, and community practices, that all together contribute to the success of the education process (Tuan & Tram, 2022).

Table 1: Key factors affecting online learning.

Factors	Key Source
Lecturer Performance, Student Interaction, Course Content	(Ab Hamid et al., 2022)
Individual Factors, Course Factors	(Spencer & Temple, 2021)
Facilities, Education Program, Lectures, Interactivity, Tuition Fees	(Tuan & Tram, 2022)
Teaching Effectiveness, Teaching Style, Pedagogy	(Vikas & Mathur, 2022)
Motivation, Autonomy, Digital Pedagogy	(Díaz-Noguera et al., 2022)

Most researchers focused their studies of the online education on multiple factors that may affect the effectiveness and success of this process, Table "1" summarises some key studies and the factors they considered.

According to (Ab Hamid et al., 2022), who adopted a survey constructed to measure students' satisfaction based on the mentioned elements- among others, their study showed that the mentioned three elements contributed significantly to students' satisfaction, additionally the students' ability to interact was the most significant factor. Furthermore, the authors (Spencer & Temple, 2021) designed their survey to include four areas as follows: course format, instructional technology, distance education experience and course instructor technology use. The study showed among many results that students thought technology used in online learning was both dependable and easy to use, and as a result, all surveyed students were satisfied with the online learning.

However, a drawback to online learning was that students appreciated the interaction with their instructor and classmates in the traditional classroom, which they did not experience similarly in the online classroom. Based on Table "1" extracted factors researchers' perceived to be most considered literature are three main factors, these related to the student, lecturers, and courses/ programs. Thus, they have significant effect on students' satisfaction with online learning, and educational institutions may consider these factors to achieve the desired educational result.

2.2 Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) technologies are supercomputers, used for mimicking human intelligence and reasoning abilities using massive processing capabilities. AI technologies consist of agents that function by perceiving surrounding environment, and acting based on these perceptions, whilst increasing the possibility of their success in these actions (Yousaf et al., 2022). Many researchers used AI and machine learning (ML) methods and techniques for the purpose of studying students' satisfaction with online learning (Leo et al., 2021). The use of these information technologies in studying students' satisfaction, provided additional benefits compared to the statistical tools, as these AI based technologies enable the collection of vast amounts of data, from multiple sources in the institution, in order to analyze it for the purpose of enhancing teaching methods, and other processes in the institution (Karo et al., 2022). In addition to the fact that it has a great potential in education and learning (Limna et al., 2022).

ML is defined as a branch of AI and computer science, which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving their accuracy (Leo et al., 2021). Using ML includes a class or a category to be predicted, this is done after data are observed and collected then each record in the dataset is assigned a category or "class", using either supervised or unsupervised ML algorithms. In the same token, one supervised algorithm used widely is educational research is the decision tree, this algorithm is presented graphically as a tree, with branches indicating possible outcomes of a certain decision under a set of conditions (Looi et al., 2022).

Decision tree is one the most common algorithms used to create classifiers, that is trained then used to predict a class or value. It is known to be simple, quick and able to classify both numerical and categorical attributes (Yousaf et al., 2022). Another supervised algorithm for classification problems is the naïve bayes algorithm which is a probabilistic technique for solving classification problems (Mengash, 2020).

The current research focused on a sample of over "300" students in higher education in Jordan who have experienced both online and traditional classrooms. Survey elements were carefully selected from literature and tailored to suit the sample and study in progress. After collection, the data were further processed and engineered to fit the prediction model used in which decision tree and naive bayes algorithms were utilized to predict the class attribute.

3 RESEARCH METHODS

3.1 Research Design

The research design employed for the purpose of prediction students' satisfaction with online learning during and after Covid-19 using EDM for studying students' performance and satisfaction. Comprehensive research design is illustrated in Figure "l" below.

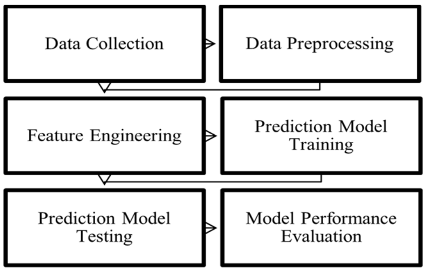

Figure 1: Research Design and Phases.

3.2 Data Collection

A total of "309" responses were collected for the study with no elimination of any records, the sample's demographics indicated almost equal female to male distribution of 51.1% to 48.9% consecutively. Also, most of the respondents were bachelor students (89.6% bachelor to 10.4% master students) that studied in private universities (89.6% private to 14.6% public university). Also, many respondents did not have any type of scholarship and paid their tuition fees in full (89.3% self-paying student to 10.7% with partial or full scholarships). Moreover, most of these students were residents of Amman (93.9%) and owned a personal computer for their studies (97.1% who owned a personal computer to 2.9% who did not). With regards to the responses, it was noted that that percentage of agree to disagree with overall satisfaction with online learning was almost equal of 50.2% to 49.8%. Consecutively the current study developed a questionnaire of "25" items, including demographic information. The questionnaire consisted of "6" main indicators including lecturer's performance, student interaction, intention, internet connection, academic integrity misconduct, and satisfaction with online learning. All questions related to the aforementioned indicators were measured using a 5-point Likert scale. The indicators were inspired from two studies (Ab Hamid et al., 2022), (Klijn et al., 2022), and modified to fit the sample and study's characteristics. The sampling method used was purposive sampling, respondents were selected to be current higher education students or graduates who have experienced both online and offline education. Each of the "6" indicators are introduced with reference to the study's main purposes.:

- Lecturer Performance: Lecturer's role in online education surpasses the function of explaining material, it includes ensuring engagement of the whole class, trigger students' critical thinking and creating an interactive session that allows instant feedback (Ab Hamid et al., 2022).
- Student Interaction: Students' interaction with their colleagues and instructors during the online classroom was reported to be of immense importance in ensuring online classes is effective as traditional classes (Yousaf et al., 2022).
- Intention: Intention was studied not only in terms of attending classes but to make use of the technology at hand for educational purposes (Ab Hamid et al., 2022). The behavioural intention towards online learning was found to be of a significant impact on satisfaction with online learning (Azizan et al., 2022).
- Internet Connection: Having stable internet connection was directly related to increased cost on students and their parents/ guardians, additionally, having a proper internet connection with sufficient data for online classes and assessments have been a challenge for many students and was found to affect their satisfaction with online learning (Leo et al., 2021).
- Academic Integrity and Misconduct: Misconduct in online assessment is facilitated due to the limited ability of instructors to control the environment in which the student is attending assessments in, and since the ability to copy and cheat seems to be high in online exams (Tweissi et al., 2022), results of these assessments will not be as fair as those of traditional exam rooms, eventually affecting students' satisfaction with the process (Basheti et al., 2022).
- Satisfaction with Online Learning: It has been evident that the success of online learning is related to student's needs, expectations and feedback that contribute directly to their satisfaction with their education (Augustine et al., 2022).

3.3 Data Analysis - Preprocessing, Feature Engineering, and Prediction Model Training'

Once the responses were collected, they were extracted into an excel sheet for data cleaning and pre-processing, both manual and digital pre-processing techniques were executed to prepare the dataset for the machine learning. Firstly, all demographical questions with nominal or ordinal values were transformed into binary form (0,1) expect for the location that was discretized and assigned values from 1-12 corresponding to the main cities of Jordan.

After the data had been cleaned and prepared for the model, it was extracted into a K-nime project, the model included further pre-processing on K-nime, including missing value detection and treatment. Afterwards, the dataset was partitioned into training and testing sets using cross validation partitioning node, executed for four times using four different number of validations; “5”,”7”,”10” and “15” folds were run to discover which fold provided the best performance.

The predictive model training included a step of feature reduction, to reduce dimensionality and keep the most relevant attributes to train the model. Table “2” shows the number of features initially included in the survey for each construct, and the number of items remaining for each construct after the elimination, in addition to two out of “6” demographic items.

Table 2: Attributes before and after reduction.

Construct	Initial # of Items	# of Items after reduction
Lecturers Performance	3	0
Student interaction	3	1
Intention	2	1
Internet Connection	3	3
Academic integrity and misconduct	4	2
Satisfaction with online learning	4	2

4 RESULTS

4.1 Model Performance Evaluation and Results

After both classifiers had been trained and assessed, a scorer node was executed to evaluate the performance of each model in predicting the true and false values of the class attribute where (True= Satisfied, False= Unsatisfied). Initially The naïve bayes classifier outperformed the decision tree at each run. However, using the decision tree classifier allowed the researchers to identify the most related attributes, and thus use feature selection to update the dataset and train the model again for enhanced performance. Table 3 and 4 show the performance measures for both classifiers in each run after feature reduction.

The measures included in the performance evaluation are interpreted as follows: Recall shows how many items were correctly classified as” Satisfied” from the total actual” Satisfied” classifications. Precision: shows how many items were successfully predicting as” Satisfied” from total” Satisfied” predictions. F-measure shows how successful the model was in measuring the recall and accuracy. Overall Ac- curacy: how successful the model was in identifying correct values (Satisfied and Unsatisfied).

4.1.1 Decision Tree Classifier

The decision tree classifier uses a predefined quality measure to construct the tree by providing all outcomes of a decision. In this model, decision tree used “Gain Ratio” as quality measure for the branching step. Results showed that the highest gain ratio was that of the attribute measuring the student’s intention to recommend online learning to others, this item measured showed that students were satisfied enough to talk about online learning and encourage others satisfied students with the online learning.

Luckily, using decision tree classifier and gain ratio as a quality measure enabled the researchers to evolve the model, this was done by taking all the items in the decision tree which provide the highest gain ratio to the model and perform further feature selection on the dataset extracted into K-nime. Evidently, the model performed better as the confusion matrix and accuracy measures were notably enhanced for both predictors.

Table 3: True Class Performance Measures.

True Class	Recall	Precision	F-measure
Run 1: 5-Fold			
Decision Tree	0.80	0.89	0.85
Naïve Bayes	0.90	1.00	0.95
Run 2: 7-Fold			
Decision Tree	1.00	0.80	0.89
Naïve Bayes	0.75	0.60	0.67
Run 3: 10-Fold			
Decision Tree	1.00	1.00	1.00
Naïve Bayes	1.00	0.67	0.80
Run 4: 15-Fold			
Decision Tree	1.00	1.00	1.00
Naïve Bayes	0.75	1.00	0.87

Table 4: False Class Performance Measures.

False Class	Recall	Precision	F-measure
Run 1: 5-Fold			
Decision Tree	0.75	0.60	0.67
Naïve Bayes	1.00	0.80	0.89
Run 2: 7-Fold			
Decision Tree	0.83	1.00	0.91
Naïve Bayes	0.67	0.80	0.73
Run 3: 10-Fold			
Decision Tree	1.00	1.00	1.00
Naïve Bayes	0.80	1.00	0.89
Run 4: 15-Fold			
Decision Tree	1.00	1.00	1.00
Naïve Bayes	1.00	0.50	0.67

4.1.2 Naive Bayes Classifier

This classifier works by calculating a set of probabilities, by adding the combinations of frequency and values, the class with the higher probability is considered the most likely class (Karo et al., 2022), and the class is assigned to this value. Based on the performance measures in Tables 3 and 4, we note that the naïve bayes algorithm is a suitable classifier for students' satisfaction with online learning like other EDM related models (Karo et al., 2022) when the dataset is highly dimensional, as the naïve bayes is not affected by the high dimensionality.

5 DISCUSSION

The Covid-19 pandemic created many challenges on every aspect for the educational sector, transitioning to online education was the riskiest, researchers started studying the aftermath of the transition, by measuring students and faculty members satisfaction and performance, this was done using both statistical, and machine learning methods. However, using machine learning to predict satisfaction is limited in Jordan, and thus the authors focused in this study on tackling the satisfaction indicators applicable to the characteristics of higher education in Jordan, and the insights provided by similar statistical research.

The model used in this research included the decision tree algorithm, which took part in feature selection helping with the dimensionality reduction and enhancing the prediction performance, additionally, it was used as a predictor for the satisfaction alongside with the naive bayes algorithm. Originally all "25" features from the survey remained in the dataset trained and tested by both classifiers, however, after running the model, results showed that only "11" of the features were relevant and significantly affected the model. The naive bayes performed better than the decision tree at first due to the existence of redundant and irrelevant features, however, after feature reduction both classifiers performed better, and decision tree outperformed the naive bayes in the satisfaction prediction.

Results showed that students who were satisfied were to recommend online learning to others, those satisfied students agreed that group projects were satisfactory, indicating that students were highly affected by their ability to work with colleagues, previous research showed similar results. On the other hand, students who were not satisfied, mostly indicated having issues accessing the internet for their studies due to an instable internet connection in some areas, similarly, studies showed that the internet connection was amongst the most important features contributing to the dissatisfaction of students as having a stable internet connection is costly in some countries (Leo et al., 2021). Furthermore, the researchers noted that academic integrity and misconduct indicator had the least contribution to the satisfaction, indicating the probability of minimal misconduct within the sample selected or a common behaviour done by students that they do not wish to declare.

6 IMPLICATIONS TO HIGHER EDUCATION

Meticulous technological innovations in the sciences that are related to how people learn in different practices, and how to measure such learning in terms of success and satisfaction brings the optimism of developing new varieties that might aid students in succeeding and adapting in higher education by making the nature of the learning practice used, and the progress of their learning as clear as possible. However, Since online learning carried on in Jordan after the pandemic, and bearing in mind that this online learning experience is still primitive in higher educational institutions in the country, this study is proposed to have a valuable contribution to the student satisfaction studies conducted in Jordan, by aiding researchers and institutions identify the most relevant indicators affecting the students' satisfaction and hence draw a clear picture of how online education should be planned and executed.

The machine learning techniques used in this research can be similarly used in predicting faculty satisfaction, and students and faculty performance in online learning, thus providing a novel area for artificial intelligence studies in Jordan. Lastly, the methodology used in this research tackles the importance of feature engineering and pre-processing suitable for each type of machine learning classifier, indicating the importance of treating high dimensionality, and model overfitting before commencing with the processing even if the total number of dataset items is not relatively large it could be overfitting to the model in-hand.

7 CONCLUSION AND FUTURE RESEARCH

The findings of this study revealed several indicators significantly affecting student satisfaction, using decision tree in the prediction allowed a reduced feature dimensionality and thus decreasing the computational cost of the final model and proposing that decision tree can perform better in satisfaction studies in the EDM field when data is well fitted to the model. Lastly, demonstrating that the naïve bayes classifier which also provided relatively superior performance, is suitable for such studies in the field in which the dimensionality in the dataset is high and number of instances is fairly enough for the study.

Future research initiatives will incorporate enlarging the study sample to include more individuals from public universities in order to have normal distribution of private to public universities students, this can possibly alter the results as many indicators are affected by the fact that private universities technological capabilities may not be equivalent to that of public universities. Additionally, future studies may consider students from neighbouring countries other than only Jordan, as engaging more countries and more institutions will have a higher validity to our proposed model in terms of factors and constructs.

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