Consequential Factors Influencing Student's Learning Experience in Online Team Teaching of Computer Programming Courses

by

Md. Tawhid Anwar
21166002

A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
M.Sc. in Computer Science and Engineering

Department of Computer Science and Engineering
Brac University
January 2023

Declaration

It is hereby declared that

1. The thesis submitted is my own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

Student's Full Name & Signature:

Tawhid

Md. Tawhid Anwar
21166002

Approval

The thesis/project titled "Consequential Factors Influencing Student's Learning Experience in Online Team Teaching of Computer Programming Courses" submitted by

1. Md. Tawhid Anwar (21166002)

Of Fall, 2022 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of M.Sc. in Computer Science and Engineering on January 29, 2023.

Examining Committee:

External Examiner:
(Member)

Ashis Talukder, PhD
Associate Professor
Department of Management Information Systems
University of Dhaka

Internal Examiner:
(Member)

Muhammad Iqbal Hossain, PhD
Associate Professor
Department of Computer Science and Engineering
Brac University

Internal Examiner:
(Member)

Md. Ashraful Alam, PhD
Assistant Professor
Department of Computer Science and Engineering
Brac University

Supervisor:
(Member)

Md. Golam Rabiul Alam, PhD
Professor
Department of Computer Science and Engineering
Brac University

Program Coordinator:
(Member)

Amitabha Chakrabarty, PhD
Associate Professor
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)

Sadia Hamid Kazi, PhD
Chairperson and Associate Professor
Department of Computer Science and Engineering
Brac University

Ethics Statement

I have studied different journals, conference publications, websites for my thesis purpose.

Abstract

This study aims to explore the factors impacting how students learn in online programming courses at the undergraduate level in Bangladeshi universities. In the semester of Summer 2022, an online questionnaire to evaluate online learning was handed out to the students of Computer Science and Engineering at BRAC University. The questionnaire consisted of a total of 47 questions with a mix of both numerical and categorical and multiple-choice questions. This paper adopts multiple data science approaches to find the measure of reliability between the survey items. Twelve factors under five dimensions were examined to analyze the influence of online learning on the students in computer programming courses at the university. A total of 740 responses were collected from the students and 694 valid responses were kept after cleaning the data. Necessary data pre-processing was applied and classification algorithms to select the important features such as CART Classification Feature Importance, Random Forest Classifier, and K-neighbour Classifier were implemented. From the findings, the five most critical factors influencing the student's learning experience in these courses were Effectiveness of Assessment, Digital Content Quality, Adequacy of the Curriculum, Relationship of Lab Assignments with Theory Content, and Theory Instructor's Effort. The dimensions that were most noteworthy for students' evaluation of online learning experience were also ranked according to their significance. Coordination was ranked as the most significant dimension, followed by Lab Works, Course, Faculty, and finally, Technology, which has been found to be the least significant dimension. Finally, the findings of the analysis have been represented in a form of suggestions for adapting effective learning experiences for the students.

Keywords: Online Learning, COVID-19, Learning Experience, Feature Importance

Dedication

I would like to dedicate this thesis to my loving parents and our respected teachers whose guidance and support allowed me to accomplish this work. Without their belief and encouragement, this would not have been possible and I am truly humbled.

Acknowledgement

Firstly, all praise to the Great Allah for whom my thesis have been completed without any major interruption. I would like to express my gratitude to my supervisor, Md. Golam Rabiul Alam of the Computer Science and Engineering department at Brac University. The door to sir's office was always open whenever I was in need of help or had questions about my research or writing. He consistently allowed this paper to be my own work, but steered me in the right direction whenever he thought I needed it.

I would also like to thank my family for the support they provided me throughout my entire life. I will never forget that it is our parents' sacrifices that made my education possible.

Nevertheless, I would like to thank Department of Computer Science and Engineering, Brac University and my teachers for helping me with all the necessary support.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

The way education is offered has been significantly impacted by the COVID-19 epidemic. Due to the shutdown of educational institutions and other social isolation tactics after the emergence of the COVID-19 pandemic, online learning had to be immediately adapted to compensate for the learning gap. This change has brought to light both the advantages and difficulties of distance learning. Starting from March 2020, university closure continued for almost two years in Bangladesh. As preparation was not taken to cope with such an unprecedented circumstance, some institutions had to take a long time to implement a complete online learning system. Professor Emeritus of Brac University stated how the absence of initiatives by authorities to come up with strategies to mitigate the learning gaps and address dropouts during the lockdown has been quite worrying [26]. However, gradually, steps were undertaken to continue the educational process online and prevent interruptions in the learning process with each institution adopting independent strategies to adjust to the circumstances. These remotely adopted strategies might or might not have had a noticeable effect on the student learning experience in any course.

1.1 Research Motivation

For some students, online learning has made education more accessible, but it has also brought attention to the differences in access to technology and internet connectivity. There were struggles with communication between learners and instructors, adapting to new forms of online assessment, and maintaining the lecture quality like conventional lectures. A lot of times, online lectures were not enough to compensate for the learning gaps. Recorded lecture sessions and other supplementary materials had to be made available for the students in a lot of institutions as well. New shift-making policies had to be implemented in terms of course content, which directly affected students' learning process. Various digital platforms gained popularity as a means of communication such as Google Classroom, Slack, Zoom, and even Discord which is usually frequently used by PC gamers. For computer programming courses in a lot of undergraduate schools, course assessments were previously submitted in the paper for quizzes, midterms, and finals where students were given coding and tracing problems to solve. After being shifted to online, submissions were mainly made through applications like google forms, and online learning websites of universities, and submitted course assessment formats were mostly in pdf, .ipynb files, .py files, etc. The epidemic has sped up the implementation of technology in schools, which may have a long-term effect on the educational system.

All of these highly impacted how students perceived virtual learning and therefore, the evaluation of courses was influenced by a lot of factors. In case of future obstructions, it is necessary to evaluate the variables that affect students' perceptions regarding the conductance of any programming course. This will help to respond to unexpected situations faster and also identify the correct strategies to cope with emergency remote learning.

1.2 Team Teaching

Teaching team is a concept where the whole course is controlled centrally. In this case exams, learning platform, grading process are controlled by a course team centrally instead of being authorized by a single faculty member or teacher. Here the teacher is only responsible for the live classes, where the problems faced while learning a topic is discussed. The exams are graded by an automated process and the questions are not section specific. Students are evaluated equally and with same questions or tasks. In this case, the learning platform (buX for Brac University) is the main source for learning materials, assignment submissions and course exams. The problems of this process can be generalized since all of the key components of course management is the same. Unlike a single teacher lead course can create different types of issues. This study is based on this concept, so the problems and the collected data is general, instead of section-specific.

1.3 Research Objectives

This paper is intended to group the variables influencing students' rating of computer programming courses so that special focus can be given to these criteria while making instructional decisions in the future. By making some prior hypotheses regarding the relation of ranking of these courses with the measures of data collected from an online survey, the proposed model will be able to determine how some critical factors like technology, coordination, etc. influence undergraduate students' online learning experience in computer programming courses. By performing the necessary analysis and finding the correlations, the necessary focus can be made to enhance the tools of online learning that need improvement. This will not only benefit institutions in case of future turmoil but also help to integrate a hybrid learning approach consisting of technology-facilitated education and conventional education in computer programming courses at present. Based on some common beliefs about student learning, the following hypotheses have been constructed.

H1: The 3 categories of student learning experience significantly vary in the context of the effectiveness of the assessment.

H2: The 3 categories of student learning experience vary in the context of efficiency of communication

H3: The 3 categories of student learning experience significantly vary in the context of course content quality

H4: The 3 categories of student learning experience significantly vary in the context of the Adequacy of the Curriculum

H5: The 3 categories of student learning experience vary in the context of assessment strategies

H6: The 3 categories of student learning experience significantly vary in the context of the theory instructor's effort

H7: The 3 categories of student learning experience significantly vary in the context of the instructor's lecture quality.

H8: The 3 categories of student learning experience significantly vary in the context of the lab instructor's effort

H9: The 3 categories of student learning experience significantly vary in the context of the Relationship of lab assignments with theory content

H10: The 3 categories of student learning experience significantly vary in the context of the effectiveness of lab content

H11: The 3 categories of student learning experience vary in the context of utilization of digital platforms used.

H12: The 3 categories of student learning experience vary in the context of digital content quality.

The null hypothesis is denoted by H0: There is no relation among the 3 categories in student learning experience. The goal of this study is to examine the validity of these common beliefs.

1.4 Research Outcome

The purpose of this research is to identify the variables and factors affecting undergraduate students' online learning experience of computer programming courses. Here, the contributions of this research have been split down into manageable steps for clarity:

- Suggesting various dimensions of online learning
- Mapping the key components of each dimension
- The variables and dimensions of variables affecting students' virtual experience with programming courses were evaluated and ranked.
- Exploring major features responsible for effective learning in an online environment
- Proposing key factors and strategies to be considered for optimal learning

1.5 Outline of this Book

- **Chapter 2:** This chapter conducts a literature overview of research involving different data science related methods applied to explore learning experiences.
- **Chapter 3:** This chapter examines different data science and machine learning methods used to analyse our conceptual model.
- **Chapter 4:** This chapter details the findings of the conceptual model, hypothesises and analyze the results we have got.
- **Chapter 5:** This chapter concludes our findings and proposes further research to build a better learning experience techniques for students.

Chapter 2

Literature Review

A concise review of previous empirical studies that have employed different machine learning methods to analyze learning experience of students will be presented in this section. Some of these studies have used techniques such as decision trees, neural networks, and k-means clustering to identify patterns and predict student performance [10], [11], [14], [16], [17], [19]. There are some research works focusing the pandemic timeline as well regarding the learning experience [12], [13], [15], [18], [23], [28]. Overall, these studies have shown that machine learning can be a powerful tool for understanding and improving the learning experience of students. We discuss the most relevant ones in this section.

2.1 Related Work

A paper [30] by Fang et al. focuses on a case study conducted to highlight the effects of COVID-19 on undergraduate business students at an Australian University in the state of Victoria by analyzing the experiences and insights of those students. Findings of the study present suggestions directed toward university teachers on how to enhance student engagement and learning in the post-COVID era and amid upcoming disruptions. A way to mitigate the absence of qualitative research on the effects of the COVID-19 pandemic on student learning, particularly in relation to the frequent and lengthy lockdowns, was also one of the goals of this study. A qualitative case study was thus conducted with the participation of fourteen students aged from 18 to 23 years to collect data regarding their online learning experiences which was used in thematic data analysis. This paper was able to dive in-depth into the pandemic's effects on the education of students as it focused on qualitative research methods. The study found that students' perceptions of online learning were mixed. Some thought there were few interactions between students and teachers and that online instruction was delivered ineffectively. On the other hand, some students also found benefits to remote learning, especially those who had to work outside of their studies. Further perceptions by the students were that the learning support during lockdown was adequate whereas some stated they preferred learning after COVID-19. But as the sample size for carrying out this research was limited, a larger sample size of students belonging to different disciplines could provide more diverse and interesting results to this research. Also, studies pertaining to postgraduate or international students studying in Australia from abroad were not the subject matters of this study.

In this paper [24] by Bui et al., insights on how secondary school students in Vietnam experienced online education during school closures due to COVID-19 have been presented. From September to December 2021, 5,327 secondary school students in 5 provinces participated in an online survey via a Google Form using cluster sampling method. Primary focus of the collected dataset has been given on demographic data of the partaking students (mainly gender, school results and residency), access to educational devices, inclination of the students towards digital skills, online learning experience, evaluation activities of students and their overall assessment of online learning benefits. Correlations between these variables were analyzed and statistical variations were found between students' class participation, teachers' assistance and altogether contentment of students towards online learning. It was found that mostly students of junior level, i.e. grade 6 to grade 7 were more indulged in online education and received more support from their teachers than senior level students of grade 8 and grade 9. However, this study was limited to secondary school students and focused more on quantitative research.

A paper [25] by Eteng et al. states how the absence of technological infrastructure and other restrictions present difficulties for universities in developing and some developed nations in properly instructing computer programming languages to students. Programming is a challenge for students as it not only tests logical thinking abilities but also takes patience to learn a new language. This study thus performs a thorough assessment of the programming language related literature and to provide a strategy for efficiently teaching various programming languages with little resources. For this purpose, 18 suitable research papers were collected from 4 databases using exclusion and inclusion tactics. The authors, by conducting a review of the research articles and based on the gaps they discovered, suggest a hybrid teaching strategy that combines teaching the fundamentals of programming, instructing students on how to represent computing problems using these concepts and using mobile compilers to compile code in the absence of working systems. Based on guidelines from the National University Commission (NUC), course descriptions from four universities in Nigeria and reviews from articles in Researchgate, the study suggests using an Online Console Compiler as the Mobile Integration Development Environment (IDE) and also suggests teaching some specific programming languages to students from first to fourth year. This approach is different to other collaborative or interactive strategies suggested by other studies as it proposed a technique that utilizes minimum resources. However, as there are safety regulations on the very minimum set of allowed systems for coders in some developed nations, it also recommends users to exercise caution when using mobile phones.

This paper [21] by Nguyen et al. aimed to analyze the online instruction mediums used to facilitate remote learning during COVID-19 and students' overall experience and perception of those mediums. The mediums mainly included live or synchronous classes, recorded lectures, uploaded notes and learning by communicating through chat. The ultimatum of the research was to assist in making robust decisions not only during COVID-19 but also in the development of remote learning in the near future. Thus, a poll was carried out via a post of an Instagram influencer to analyze which mediums of online learning are more preferable by people. 4,789 undergraduate participants' responses were examined out of a total of 10,563 responses from the poll.

Both qualitative and quantitative data were collected which included asynchronous as well as synchronous methodologies of online education. According to the results from the survey, most students prefer live online courses and that synchronous mode of learning keeps them engaged more. The qualitative data also demonstrated that students long for the social components of on-campus education. The respondents suggested boosting student connection, involvement, and engagement in distance learning. The authors come to the conclusion that active learning techniques, which have been shown to enhance motivation, engagement, and learning in conventional classrooms, also have a positive effect in remote learning environments, and that including these components in online courses will enhance the learning experience for students. However, for this research, most respondents who were followers of the instagram influencer were learning enthusiasts which might have led to an unprecedented biasness. The results may be different in another setting with more varieties of participants.

A paper [20] by Maqableh et al. assesses both the advantages and disadvantages of switching from conventional to online learning during the COVID-19 epidemic from the viewpoint of undergraduate students. To assess online learning and pinpoint its benefits and drawbacks, two online surveys were performed. Data was gathered from 483 participants in the first survey shortly after the emergency change to online learning to evaluate the effect of this change and find the issues faced by students. Following three semesters of online instruction, data from the second survey was gathered from 853 students. Focus group meetings were also held to further evaluate the frustration of students. The examination of the data from both questionnaires reveals that during the COVID-19 pandemic, students struggled with a variety of issues related to technology, time management, monetary problems, mental health and balancing their education and their lives. The findings also indicate that more than a third of the participating students expressed dissatisfaction with their virtual learning experience. 95.9% students relied on resources available online which is unusual in terms of conventional classes and exam questions and assignments were also found to be more difficult for the students. From group discussions, it was found that issues with management, psychological trouble and lack of focus contributed to such discontent. The study therefore puts forward a number of suggestions and solutions to improve online learning and boost student happiness. However, the positive sides of online learning, such as avoiding the spread of COVID-19, and saving time to journey to university were depicted in this study as well.

In this paper [29], Durand et al. conducted a study at an Irish university in order to learn more about pharmacy students' experiences with technology based education during the COVID-19 epidemic. As the pandemic shifted the conventional education system to an online based technological education may have been easily adaptable for self-supporting learners but it may have been initially a struggle for students who were not adjusted to this sort of learning. Thus, this study aimed to explore the blend of conventional learning with technological enhancement to analyze its advantages and effectiveness in pharmacy programmes. A survey consisting of 16 multiple choice questions were emailed and responses of 32 pharmacy students of third and fourth year of the chosen Irish institution were collected for this purpose. Maximum survey participants stated that the internet speed and stability were good or very good. It was found that prior to the epidemic, 97% of respondents felt comfortable utilizing the web platform 'Canvas' but over half percent of students were uncomfortable with Microsoft Teams. Also, most students preferred interacting in person with instructors and peers as well as live delivery of lectures, seminars, and tutorials, but they also wanted a recording of the session made available online later on. These results led to the implication that pharmacy students preferred a hybrid learning method, where live classes could be recorded and made available for later watch at the same time. However, there are also flaws associated with such a form of learning, mainly the internet network issues, social exclusion and time management. The study also suggested that pharmacy programs should be developed and reviewed for the future taking into account the students' experiences with technology-enhanced learning throughout the pandemic. This research was particularly focused on the final two year students of pharmacy with very few respondents. Results may vary in a different setting and context.

A paper [22] by Reeves et al. discusses the rising interest in realizing virtual reality (VR) labs' potential in the field of science related education in response to the COVID-19 pandemic. Previous surveys have revealed that there is a gap in the approaches to examine how students learn in VR labs. The majority of previous studies focused on evaluating the effectiveness of VR labs in addressing particular needs. But VR labs can co-exist with in-person labs which surpasses its use for specific purposes or situations only. Therefore, it became a necessity to analyze the students' learning experiences in a VR lab. A phenomenographic experiment was thus conducted where six diverse undergraduate chemistry students experienced VR labs in four qualitatively distinct ways: as a hindrance to learning, as an improvement of learning, as a removal of perceived learning hurdles, and as an effect of prior knowledge or experience. A semi-structured interview was conducted and an open-ended questionnaire was handed out to collect the data. This experiment proved that learners have relative perceptions even while having the same experience. It also came to a conclusion on how expanding the horizons of learning contexts and understanding students' perspectives can create informative ways of planning and creation of fresh instructional strategies and cutting-edge curriculum formats for learning which satisfies the students needs. However, this study's findings were constrained by a number of factors, such as the choice of just two sections of a chemistry lab course for participant selection, the employment of graduate teaching assistants, the scarcity of head-mounted displays, and the activities chosen for the VR lab experience that shaped participants' perspectives.

In this paper, [9] Marques et al., discusses the advantages of using real-world software projects in academic work and how they might provide students a better understanding of the difficulties of teamwork in the workplace. While a number of methodologies ranging from disciplined to agile strategies are followed by different institutions, it appears that the majority of instructional approaches used to support these activities center on agile programming. However, this approach may not be suitable for the preliminary software engineering project courses, especially when inexperienced students collaborate in teams while being enrolled in other courses. Even though numerous schemes have been developed to improve a students' educational experience while being introduced to agile techniques, this research aims to support those experiences using disciplined development methods. To implement this, the author suggests the use of Reflexive Weekly Monitoring (RWM), a formative monitoring technique, for project courses that includes flexible work and organized software processes. RWM combines collaborative learning techniques and self-reflection to assist students to become aware of their individual and team performance. This technique was carried out in an undergraduate software project course for over nine successive semesters. Both qualitative and quantitative results were evaluated through an assessment among the students who participated in producing a huge development in their software product after every iteration. Data was collected from peer evaluations, data collected by the course tracking tools and statistical report by SRM, a requirements tracing instrument. The following theories were depicted about RWM: it positively affects team collaboration, it enhances students' learning effectiveness, it helped in improving team coordination and their productivity was better than before. Despite these outcomes, the followed methodology has not shown enough proof of enhanced productiveness of the supervised teams over the non-supervised teams.

A paper [8] by Elhussein et al. presents a thought-provoking study where the use of partition rooms to separate female students from their male faculties had a negative effect on their education. It proves how cultural and social phenomena can play a vital role in the learning experience and growth process of students. In such partition rooms, technological devices play a crucial role to lessen the learning gap caused by the partition. Surprisingly, female students occasionally opted to avoid the use of technology in these rooms to evade revelation of their face. This study aims to bridge the lackings caused due to the indirect interaction between students and teachers, particularly female students and male teachers through the use of technology. A technological university in Saudi Arabia consisting of 45,000 students in total and 600 female students was the intended site for this research. Several variables such as the environment of the partition rooms, grade point average, students' contentment, perception of students regarding their learning and efficient use of technology were considered while conducting this research. Qualitative and quantitative research methodologies were followed where qualitative data was collected from an open group discussion session between the female students and quantitative outcomes were assessed from a questionnaire handed out to students. Statistical analysis was done and results were evaluated which showed that a considerable majority of students had trouble staying focused, reading the whiteboard and hearing their instructors in a partition room. It was concluded from qualitative study that cultural obligations have negatively impacted the communication that was supposed to be facilitated through digital devices as students were skeptical about their faces being seen due to the screen light. Further work was also proposed in this study to conduct this study under more controlled environments.

In a paper [27] by Kilic-Bebek et al., looks at the advantages of quick online courses for graduate students' development of transdisciplinary competency. In terms of improving their knowledge of industrial design, medical considerations, ethics and standards, successful teamwork, and self-dependent learning, it was discovered that these courses can be helpful for students. The study also identified difficulties that students had studied and offered instructional advice to raise the standard of education and professionalism. 31 graduate students from diverse areas participated in the study's online mixed-discipline learning sessions and teams were formed to tackle an authentic industry challenge. Both quantitative and qualitative data were gathered and a scoring rubric was introduced that tested the participants' knowledge level in seven different areas like engineering design, industry perspective, effective teamwork etc. The study's results are hopeful, and they point to the need for more research into the advantages of quick online courses for raising graduation preparation and forming university-industry partnerships in education.

A paper [7] by Nketiah-Amponsah et al. discusses how the context of sub-Saharan Africa is used to explore the relationship between students' experiences using Information and Communication Technology devices and their academic performance. The study used a cross-sectional survey of 320 Ghanaian undergraduates in their final year, and it used the ordinary least squares method to analyze the data and Cumulative Grade Point Average to represent academic success. The perception of students on four factors mainly the use of ICT and its effect on academic results, preferred sector of ICT, use of ICT and areas of innovation and contribution of ICT to teaching were analyzed in an exploratory way. The results demonstrate a favorable and statistically significant correlation between spending on a few particular ICT learning tools and applications and academic achievement. Additionally, it was shown that using email had a favorable impact on academic performance whereas using an iPad had a negative one. This study makes the case that ICT may be utilized to boost students' academic performance and makes the suggestion that, in order to fully realize its potential for academic performance enhancement, students should use email more frequently. Findings of this research could be more revealing with a larger dataset consisting of data from both public and private universities in Ghana along with a longer time span.

Chapter 3

Methodology

This chapter reviews different data science and machine learning methods used to analyse our conceptual model. We summarize the general concepts behind each hypothesis, detail the dataset and how the data is preprocessed for using in this study.

3.1 Conceptual Framework

Based on the questionnaire in the dataset, the study develops the conceptual research framework for adopting undergraduate students' learning experiences in programming courses. The conceptual framework contains 5 dimensions of academic adaption. This study aims to offer helpful direction regarding academicians and decision-makers in improving academic policy and decisions.

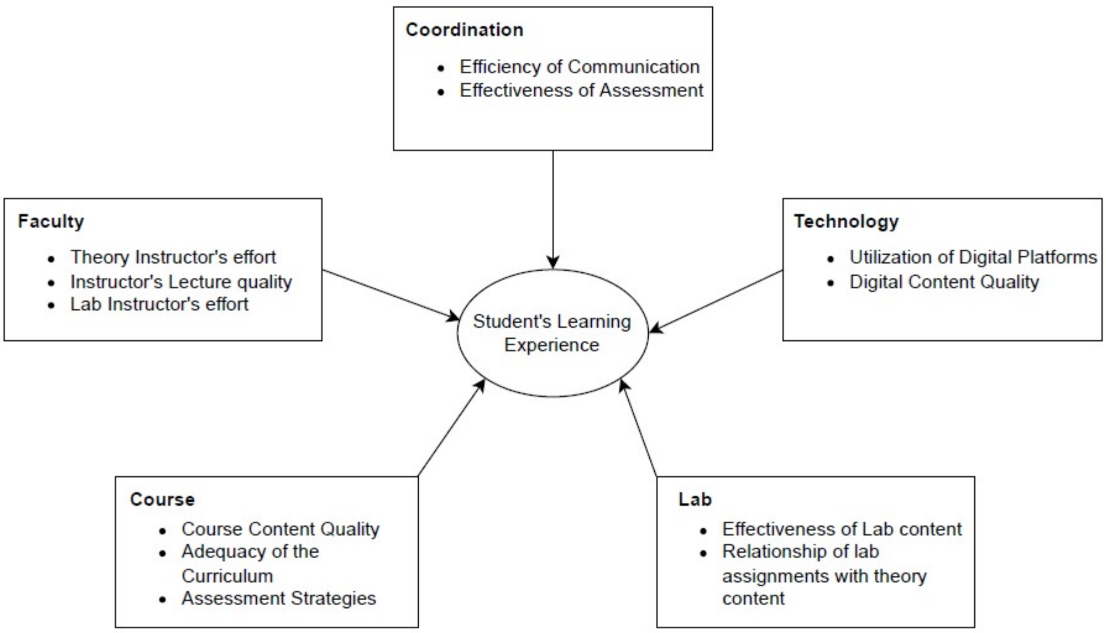

Figure 3.1: Conceptual Model

In this study, the only dependent variable of the proposed framework is the "Students' Learning Experience". There are 12 independent variables. "Efficiency of Communication" refers to effective communication between the lecturer and the students before quizzes, midterms, and final exams. It is measured via 5 items. "Effectiveness of Assessment" is assessed via 3 items to portray the quality of quizzes, midterm, and final exams. "Course Content Quality" is measured using 5 item scale that describes the effective methods of video lectures, Bangla, and supplementary materials. "Assessment strategies" is measured via 7 item scale that represents the number of quizzes taken or assignments given. "Theory Instructor's effort" has been addressed by 7 item scale that represents the instructor's knowledge, helpfulness, dedication, etc. 3 item scale is used to determine the "Instructor's Lecture quality" that reflects on online class rating and how interesting the classes were. Apart from theory faculty, lab faculties' effort is also considered and was measured via 3 item scale considering their knowledge, dedication, and helpfulness. The variable "Relationship of lab assignments with theory content" was considered to be measured by 3 items scale. "Utilization of Digital Platforms" represents whether digital platforms were used properly in the syllabus and it is measured via 3 items scale. Finally, based on the audio and video quality of the content, the variable "Digital Content Quality" has been introduced, which is assessed by 2 items scale.

3.2 Dataset

The study includes survey data of Brac University students' course evaluations of Summer 2020. The dataset consists of anonymous feedback on all courses offered on that semester. The semester was fully conducted online in buX. buX is Brac University's online learning platform where assignments, documents, discussion forums, and lecture videos were included.

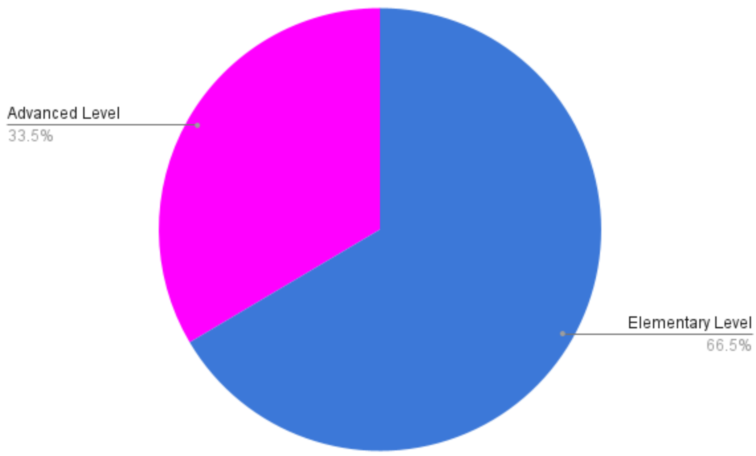

Figure 3.2: Responder Level

All faculty members were to submit their course materials on buX, where students were able to access their courses. The main goals of buX were to make learning engaging and participatory for students from anywhere online. In that semester, class attendance was optional and the course content was buX oriented. The 'Summer 2020' semester started on 1st July 2020 and ended on 24th September 2020. The evaluation data was collected in October 2020. The students were given a set of 47 questionnaires in a google form to express their experience regarding each course. The total amount of collected data on programming languages was 740 out of 3347 students' responses. Back in that semester, there was a total of 854 students who were enrolled in elementary-level of programming courses. Wherever the total number of students in advanced programming was 462.

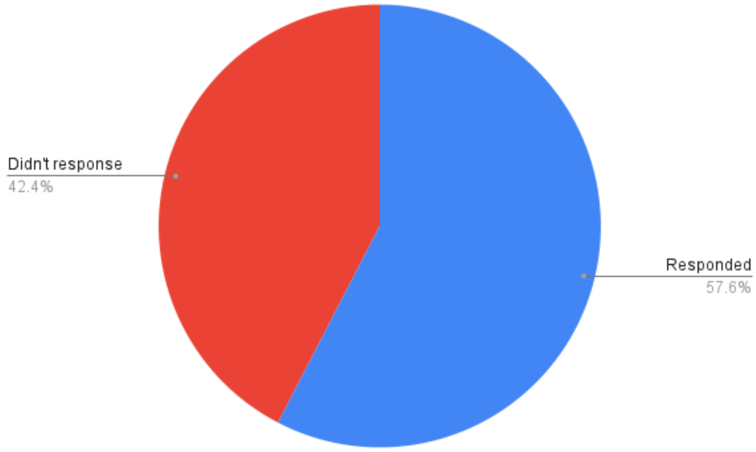

Figure 3.3: Elementary level responses

The data analysis was conducted using information from the form that the students had filled up for the programming courses in order to investigate several hypotheses. From Fig 3.2, we can see that out of 740 responses, we have received 492 responses from the students of the elementary level and 248 responses from the advanced level. After analyzing the whole extracted data, we removed the rows consisting of null values, and 694 rows of data were obtained.

Figure 3.4: Advanced level responses

All the questionnaires used in the survey are described below-

Q1: Did the course use a Google Calendar after midterms to push out notifications?

The aim of this question was to ensure that all the students were kept updated about the deadlines after midterms through Google Calendar. The possible answer options were kept binary “Yes or No”.

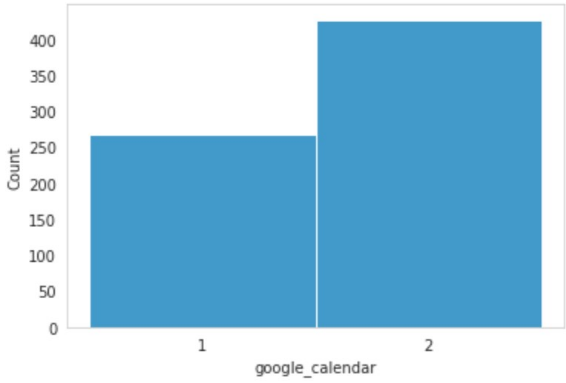

Figure 3.5: Google Calendar

The above histogram represents whether the course used a google calendar to push out notifications. In most of the courses, google calendar was used in order to send reminders regarding class times, exam dates, assignment deadlines, etc.

Q2: Did the instructor use a forum to answer questions? If so, what platform(s)?

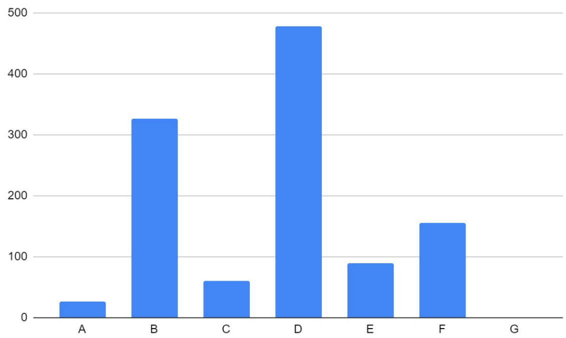

Figure 3.6: Communication Platform

The goal was to check whether the faculty was responsive when he/she was reached by the students. It also narrows down which platform was being used the most in that course. The possible answer options were buX’s native forum, Discord, Facebook group, slack, Gmail, google classroom and WhatsApp.

Q3: Were the digital platforms used appropriate for smooth student-teacher communication?

The aim was to check whether the students’ experience over the digital platform was alright. The answer options were kept binary.

The Fig 3.7 represents whether the digital platform being used was appropriate for smooth student-teacher communication, 1 being no and 2 being yes. As shown in the graph, more students voted for yes.

Q4: Graded quizzes were [Administered fairly]

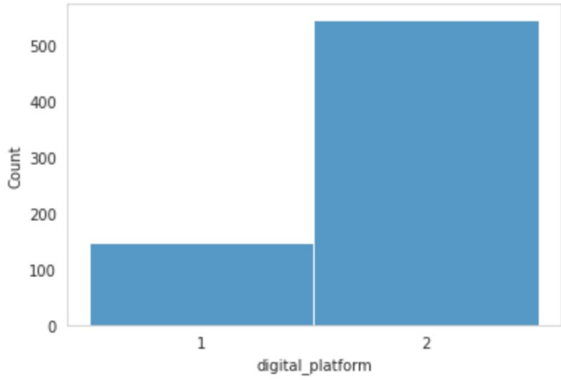

Figure 3.7: Digital platform

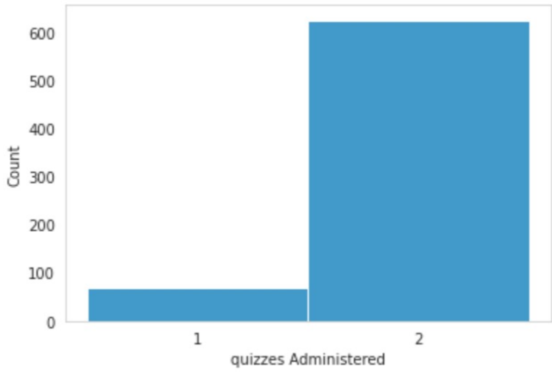

Figure 3.8: Quizzes Administrated

The Fig 3.4 represents how fairly the graded quizzes were administered, 1 being administered poorly and 2 representing that it was administered more fairly. More students voted that the quizzes were administered fairly.

Q5: Graded quizzes were [Notified 2 days before]

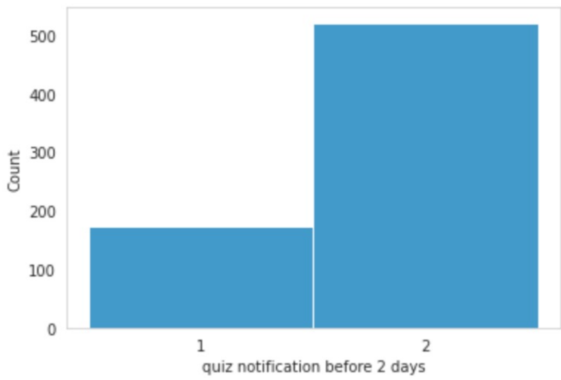

Figure 3.9: Quiz notification before 2 days

The above histogram represents whether quiz notifications were given before 2 days or not, 1 being no and 2 being yes. More students voted that the quiz notifications were provided 2 days earlier.

Q6: Graded quizzes were [Taken during mid week]

The aim of this question was to ensure that all the students were kept updated about the deadlines after midterms through Google Calendar. The possible answer options were kept binary "Yes or No".

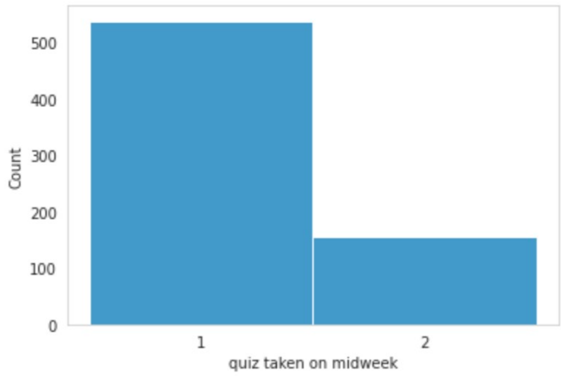

Figure 3.10: Quiz taken on midweek

The above histogram represents whether any quiz was conducted during the midweek, 1 representing no and 2 representing yes. More students voted that no quizzes were taken during the midweek.

Q7: Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Ungraded quizzes]

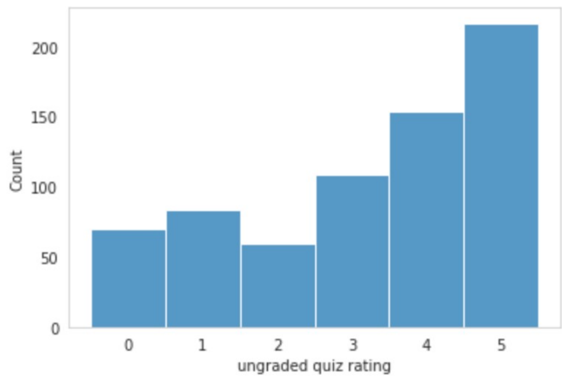

Figure 3.11: Ungraded quiz rating

The aim was to understand how much the students found the ungraded quiz given for practice helpful. The students could only choose one option from the given list of ratings. Maximum votes were towards ungraded quiz being helpful as 5 refers to being most helpful.

Q8: Were the exams and assignments interesting? [Exams questions were]

In the Fig 3.12, 1 refers to exam questions being too straight forward, 2 refers to them to be somewhat interesting, 3 refers to being balanced, having both easy and conceptual content and 4 means very hard and not relevant to course content. Most of the students voted for 4.

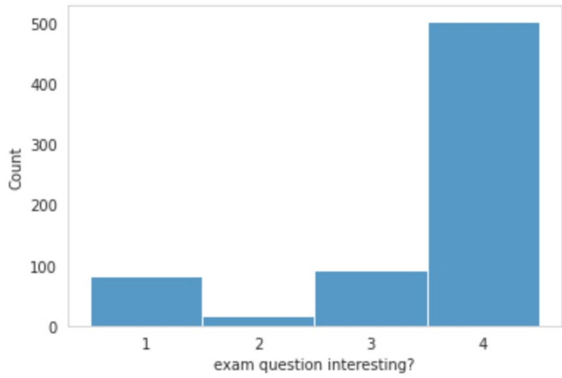

Figure 3.12: Exam question interesting?

Q9: Were the exams and assignments interesting? [Assignments were]

For the above features, the students were to choose one option from the given list of ratings and the aim was to take students' perspectives on the examinations held.

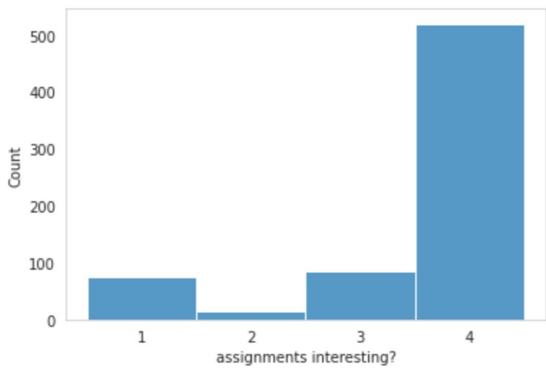

Figure 3.13: Assignments interesting?

In the above histogram, 1 refers to assignment questions being too straight forward, 2 refers to them to be somewhat interesting, 3 refers to being balanced, having both easy and conceptual content and 4 means very hard and not relevant to course content. Most of the students voted for 4.

Q10: Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Video lectures]

In the Fig 3.14 represents count vs video lecture rating graph. Lower values refer to videos being of no help and the higher values refer to them being more helpful. Maximum votes were given to the highest integer, which defines that the video lectures were very helpful.

Q11: Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Bangla supplementary videos]

In the Fig 3.15 represents count vs bangla video lecture rating graph. Lower values refer to videos being of no help and the higher values refer to them being more helpful.

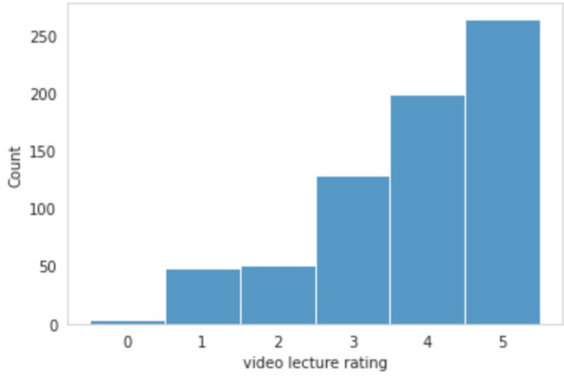

Figure 3.14: Video lecture rating

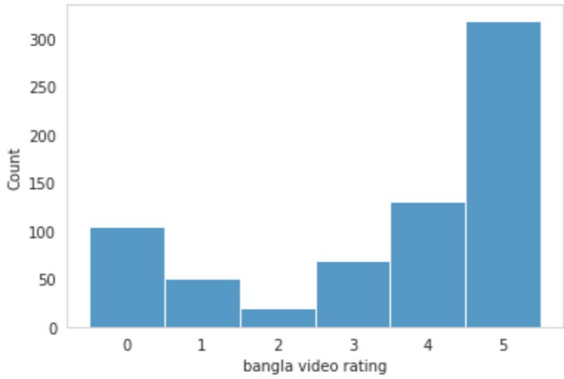

Figure 3.15: Bangla video rating

Q12: How would you rate the administration of this course on a scale of 1 to 10? Administration rating was taken and only one option could be chosen among 10.

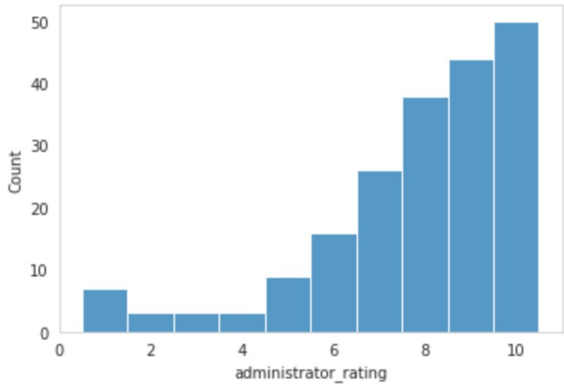

Figure 3.16: Administrator rating

In the above histogram represents count vs administrative rating graph. Lower values refer to coordination being of no help and the higher values refer to them being more helpful. Maximum votes were given to the highest integer, which defines that the administration of that particular course was very helpful.

Q13: How was the audio and video quality for most of the videos in this course? [Audio]

The students could choose one option from the given list of answers and the aim was to understand the audio quality of the course videos.

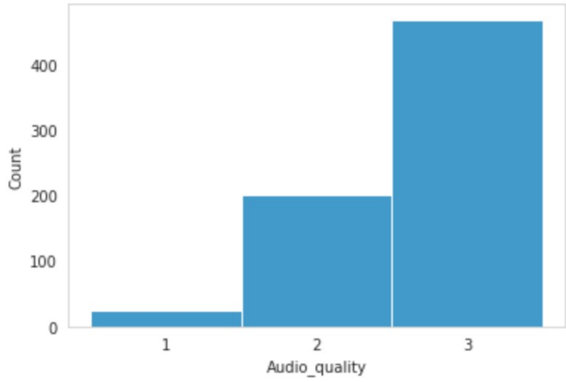

Figure 3.17: Audio Quality

The above histogram for count vs. audio quality describes lower values to be poor and higher values to be better. So, we can see that very few people voted that the audio quality was very poor, around 200 students voted that it was poor and more than 400 voted that it was excellent.

Q14: How was the audio and video quality for most of the videos in this course? [Video]

The students could choose one option from the given list of answers and the aim was to understand the video quality of the course videos.

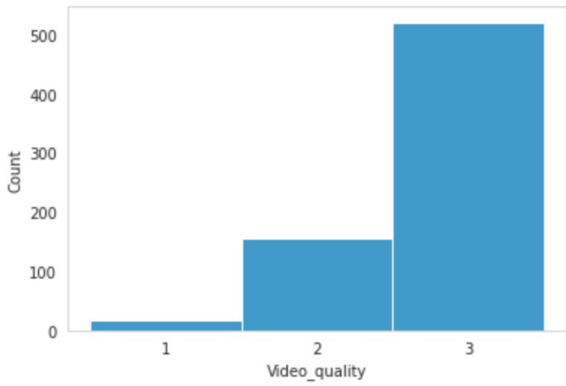

Figure 3.18: Video Quality

The above histogram for count vs. video quality describes lower values to be poor and higher values to be better. So, we can see that very few people voted that the video quality was very poor, more than 100 students voted that it was poor and around 500 voted that it was excellent.

Q15: What was the course's video style? Choose all that apply.

The possible answer options were kept non-binary; the students could choose several options from the given list of options. The aim was to understand whether the contents of the course needed to be improved or not. The possible options were

A-Just reading the slides out loud, B-Reading the slides and explaining the slides, C-Lecturer can be seen in the videos, D-Whiteboard based lecture, E-Instructor used a tablet effectively in the Khan Academy style., F-Faculty appears like s/he is talking to the students directly (Zoom style conversation), G-Animated videos.

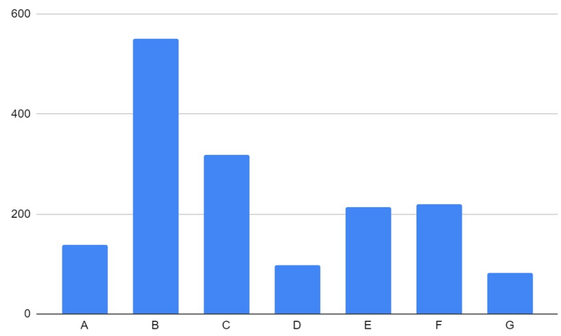

Figure 3.19: Course's video style

Q16: What supplementary material was provided? Choose all that apply.

The answer choices were kept non-binary so that the students could select from a variety of options. The goal was again to understand the course quality and understand what could be done to make it better. The possible options were A-Bangla lecture videos, B-Problem solving videos, C-Additional course or topic related videos, D-Course notes, E-Additional examples, F-Extra problem sets to challenge students, G-No supplementary provided.

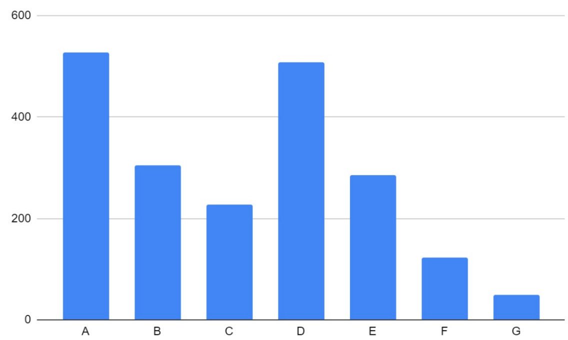

Figure 3.20: Supplementary material

Q17: Was enough material presented in the course?

Students could choose any one option and the aim was to analyze whether enough material was being provided.

The Fig 3.21 represents whether the materials provided were enough or not from the students' perspective. Higher values represent more usefulness. Maximum votes were for the third option which stated that "A reasonable amount of content was taught".

Q18: Did the online lectures cover the course content on the midterm?

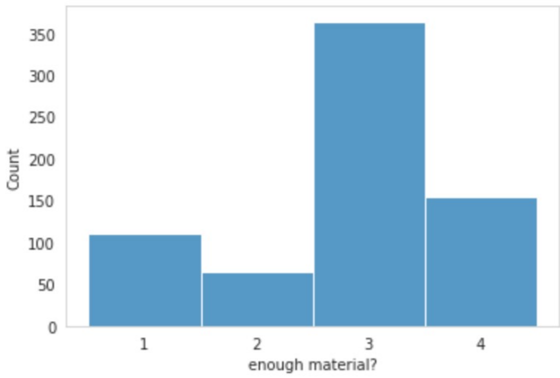

Figure 3.21: Enough material?

Students could choose any one option and the aim was to analyze whether enough material was being provided for midterm.

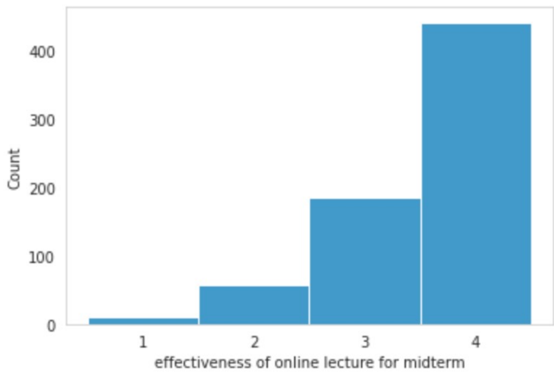

Figure 3.22: Effectiveness of online lecture for midterm

The above histogram represents the effectiveness of online lecture for the midterm; lower numbers represent poor usefulness and vice versa. Maximum students voted that the online lectures adequately covered the contents of the midterm as most votes came for option 4 where the higher values represent more effectiveness compared to the lower values.

Q19: Did the lectures adequately cover the syllabus?

Students could choose any one option and the aim was to analyze whether the lectures were covering everything that the syllabus stated.

The above histogram represents whether the lectures cover the syllabus or not and maximum students voted yes.

Q20: Did you have to memorize a lot for the exams?

Students could choose any one option and the aim was to see whether they had to memorize a lot or the content taught leaned towards research.

The Fig 3.24 represents whether memorization was required or not. Maximum voted for yes as higher values represent a stronger "yes" than lower values.

Q21: Were the lectures enough to learn the material?

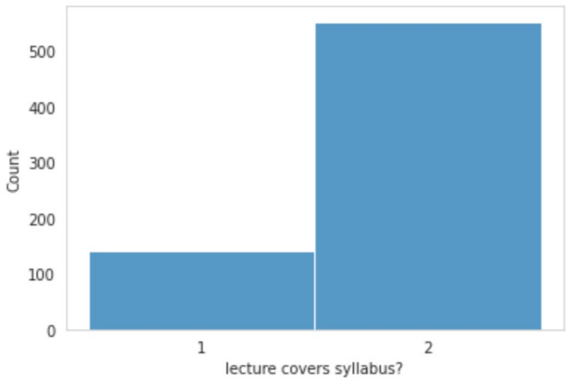

Figure 3.23: Lecture covers syllabus?

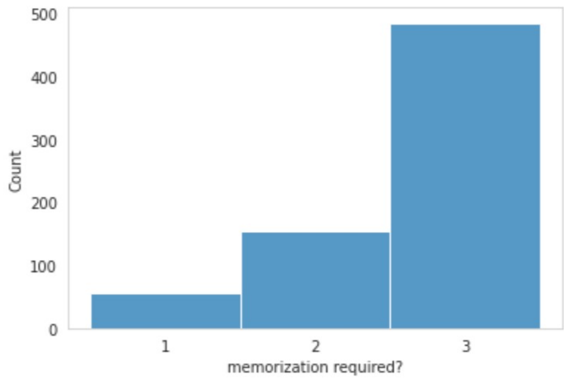

Figure 3.24: Memorization required?

Students could choose any one option and the aim was to see whether the lectures were enough or not.

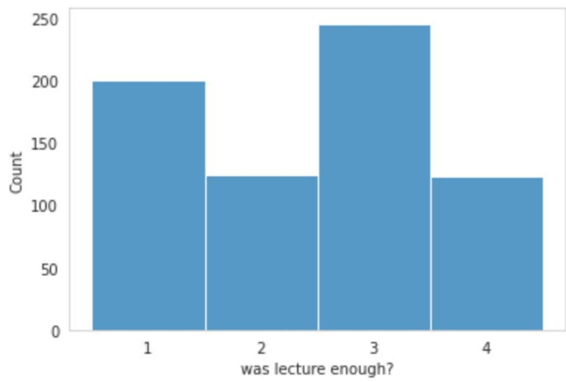

Figure 3.25: Was lecture enough

The above histogram represents whether lectures were enough to learn the material or not. Around 200 students voted for a strong no but almost 250 students voted for quite adequate although not the strongest as shown in the graph.

Q22: How many graded homework assignments and quizzes were assigned during the semester? [Graded Homework Assignments]

Students could choose any one option from a given range.

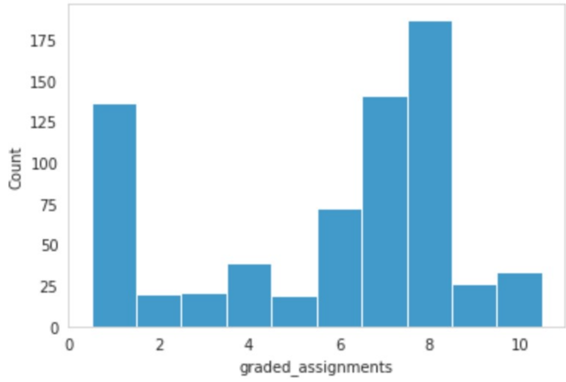

Figure 3.26: Graded assignments

The Fig 3.26 for count vs graded assignments describes the number of graded homework assignments being provided during the semester. Maximum students voted for 8 graded assignments.

Q23: Answer the following for this course [Was enough homework and examples provided to learn the material?]

Students could choose any one among the three options: yes, no or not relevant.

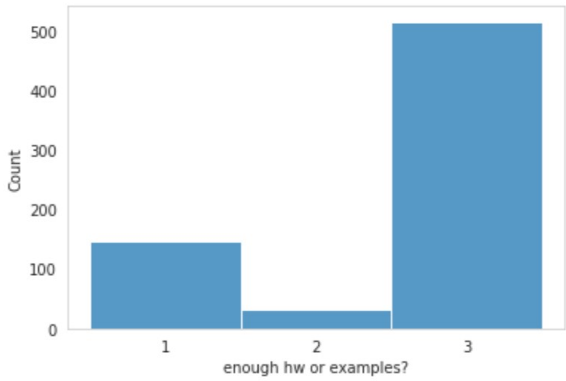

Figure 3.27: Enough HW or examples

The above histogram represents whether enough hw or examples were provided for the course. Maximum of the students voted for a strong yes.

Q24: Answer the following for this course [Was problem-solving help provided for homework assignments?]

Students could choose any one among the three options: yes, no or not relevant. The Fig 3,28 represents whether problem-solving help was provided for homework assignments. Maximum of the students voted for a strong yes.

Q25: Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Homework and problem solving tasks]

The aim was to understand how effective homework and problem-solving tasks were.

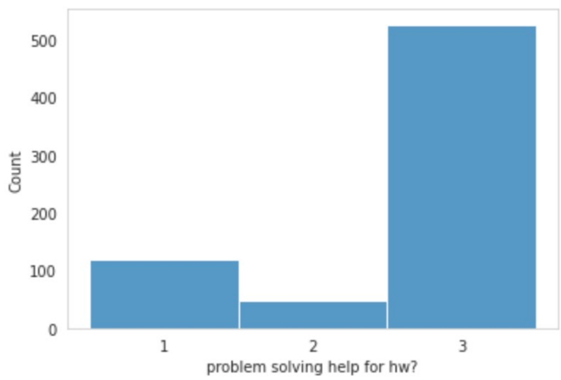

Figure 3.28: Problem solving help for HW?

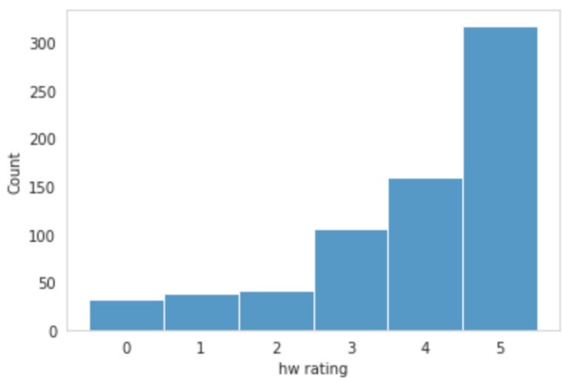

Figure 3.29: HW rating

The Fig 3.29 represents how much homework and problem solving tasks helped to learn the subject matter. Maximum of the students voted for a strong yes.

Q26: How many graded homework assignments and quizzes were assigned during the semester? [Graded Quizzes]

The aim was to keep an approximate count of the graded quizzes taken for that course.

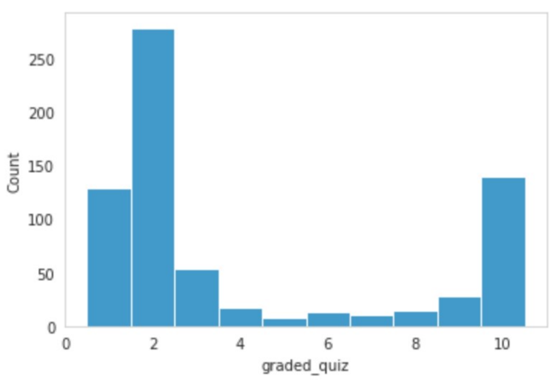

Figure 3.30: Graded quiz

The Fig 3.30 for count vs graded quizzes describes the number of graded quiz being provided during the semester. Maximum students voted 2.

Q27: How many graded homework assignments and quizzes were assigned during the semester? [Ungraded Quizzes]

The aim was to keep an approximate count of the ungraded quizzes taken for that course.

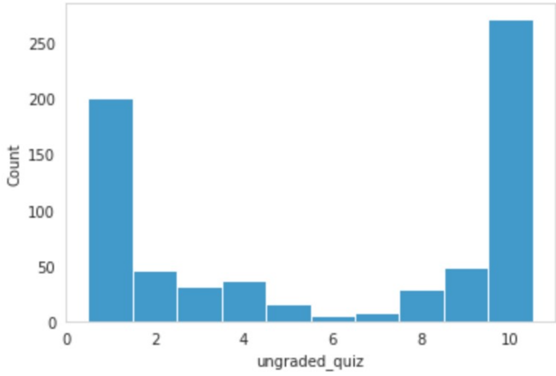

Figure 3.31: Ungraded quiz

The Fig 3.31 for count vs ungraded quiz describes the number of ungraded quizzes being provided during the semester. Maximum number of ungraded quizzes was 10 as per students' votes.

Q28: How much effort do you think instructors gave to produce good video lectures?

Students could choose one option from the given list of choices. The three choices were converted into numbers in such a way that low effort would be represented by lower values and vice versa.

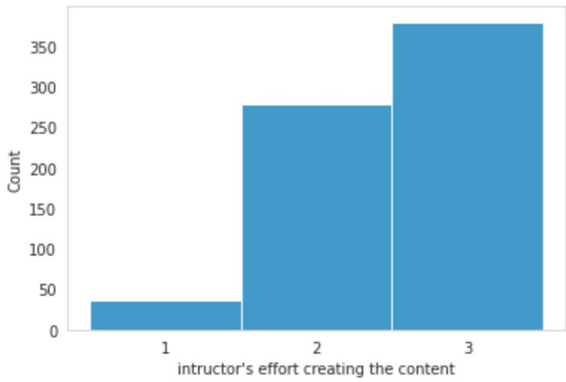

Figure 3.32: Instructor's effort creating the content

The Fig 3.32 represents the instructor's effort on creating the content. Maximum of the students voted for a strong positive rating which defines that the instructors put a great effort while creating the content.

Q29: Did your course instructors try hard to ensure that you could successfully complete your midterm and finals? [Midterm Exam]

Students could choose one option from the given list of choices and the aim was to see whether the instructors were helpful in terms of guidance during their new experience on giving online midterm examinations.

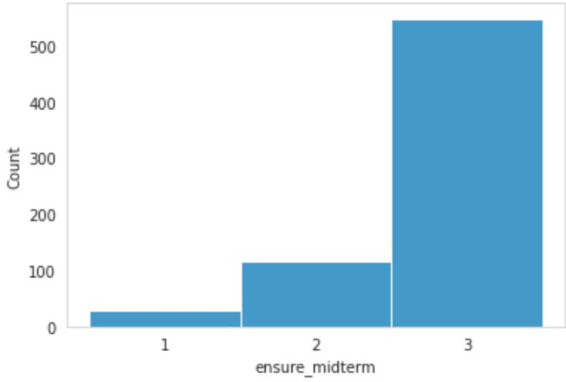

Figure 3.33: Ensure midterm

The above histogram represents how much the course instructors tried to ensure that the students could successfully complete their midterm, lower number representing low effort and vice versa. Maximum students voted a positive response which indicates that the course instructors tried hard to ensure that they could successfully complete their midterm exam.

Q30: Did your course instructors try hard to ensure that you could successfully complete your midterm and finals? [Final Exam]

Students could choose one option from the given list of choices and the aim was to see whether the instructors were helpful in terms of guidance during their new experience on giving online final examinations.

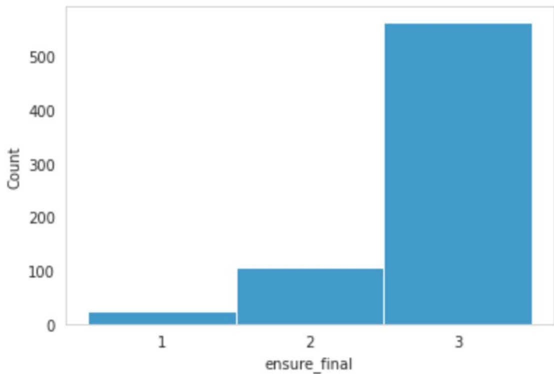

Figure 3.34: Ensure final

The Fig 3.34 represents how much the course instructors tried to ensure that the students could successfully complete their finals, lower number representing low effort and vice versa. Maximum students voted a positive response which indicates that the course instructors tried hard to ensure that they could successfully complete their final exam.

Q31: How long did it take on average for your section instructor to respond to your questions on Slack or email or other forums?

Students could choose one option from the given list of choices and the aim was to keep track

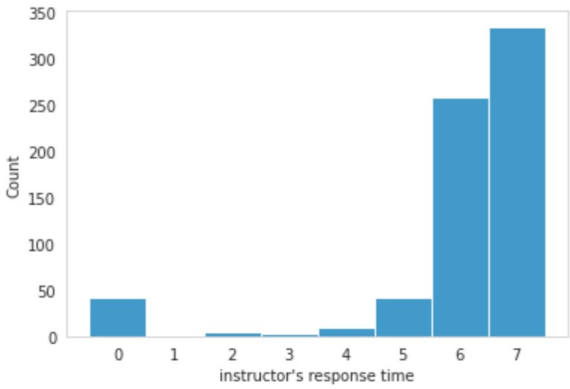

Figure 3.35: Instructor's response time

The Fig 3.35 of count vs instructor's response time represents the time taken by the particular instructor of that course to respond to the students on the platforms being used for that course. Maximum students voted a positive response which indicates that the course instructors tried hard to ensure that they responded as early as possible as greater values represent a positive response.

Q32: How would you rate your section teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Dedication of teaching]

Students could choose one option from possible 10 choices where lower values represent bad ratings and higher values represent a good rating. The aim was to keep track of the instructor's dedication to teaching.

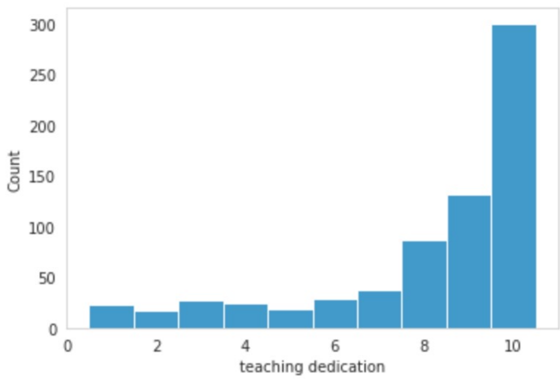

Figure 3.36: Teaching dedication

The Fig 3.36 represents the amount of teaching dedication, lower values representing lower effort and vice versa. Maximum students voted for the highest integer which defines the utmost level of dedication.

Q33: How would you rate your section teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Helpfulness]

Students could choose one option from possible 10 choices where lower values represent bad ratings and higher values represent a good rating. The aim was to keep track of the instructor's helpfulness.

The Fig 3.37 represents the amount of helpfulness provided from the instructor's

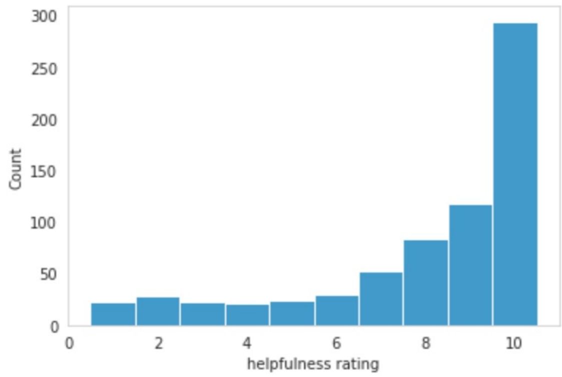

Figure 3.37: Helpfulness rating

end, lower values representing lower effort and vice versa. Maximum students voted for the outstanding rating of their section's teacher.

Q34: How would you rate your section teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Knowledgeable about subject matter]

Students could choose one option from possible 10 choices where lower values represent bad ratings and higher values represent a good rating. The aim was to keep track of the instructor's knowledge about the course.

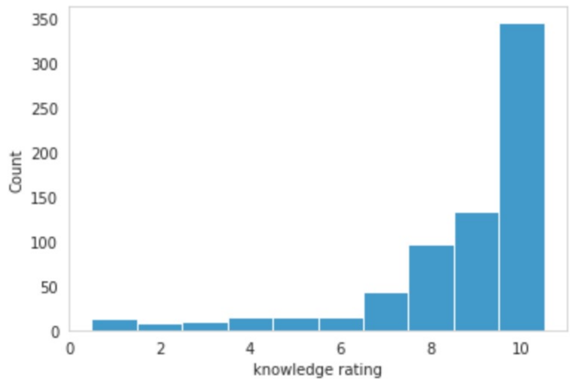

Figure 3.38: Knowledge rating

The Fig 3.38 represents the knowledge rating of the instructor, lower values representing lower effort and vice versa. Maximum students voted for the outstanding knowledge rating of their instructor.

Q35: The following questions are regarding online discussion classes [Section teacher made them interesting and useful]

The options were kept binary. The Fig 3.39 represents whether the online classes were interesting or not, 1 representing no and 2 representing yes. Maximum students voted for yes.

Q36: The following questions are regarding online discussion classes [Personal and irrelevant topics were discussed.]

Figure 3.39: Was online class interesting?

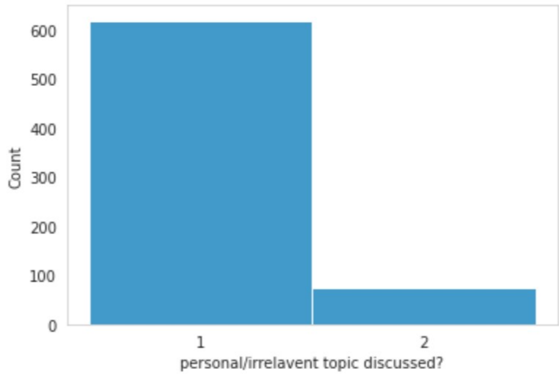

Figure 3.40: Personal/irrelevant topic discussed?

The options were kept binary. The Fig 3.40 represents whether personal/irrelevant information were discussed or not, 1 representing no and 2 representing yes. Maximum students voted for no.

Q37: Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Online discussion classes]

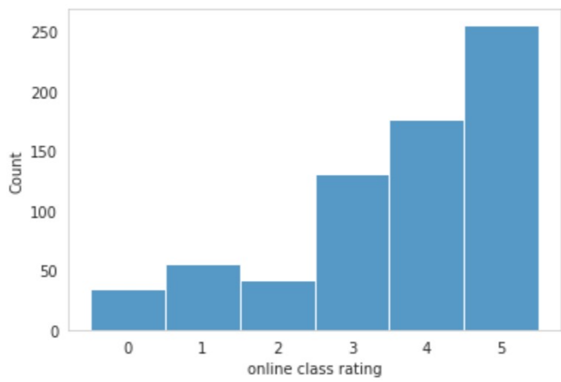

Figure 3.41: Online class rating

The Fig 3.41 represents how effective the learning activities were. Most of the students voted for a strong yes which implies a great online class rating where they found the learning activities to be very helpful.

Q38: How would you rate your Lab teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Dedication of teaching]

Students could choose one option from possible 10 choices where lower values represent bad ratings and higher values represent a good rating. The aim was to keep track of the lab instructor 1's dedication to teaching the course.

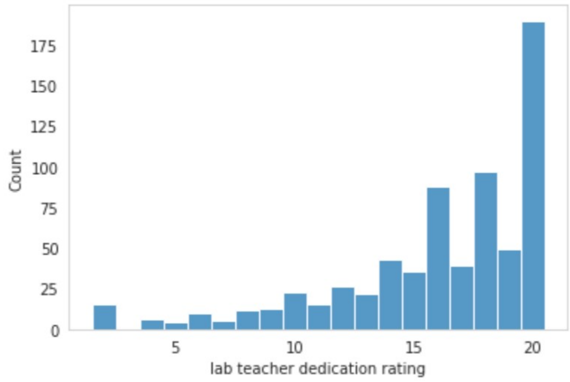

Figure 3.42: Lab teacher dedication rating

The Fig 3.42 represents the rating of the lab teacher's dedication level. Maximum students voted a strong yes which implies that the lab teacher was very dedicated towards teaching the students.

Q39: How would you rate your Lab teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Helpfulness]

Students could choose one option from possible 10 choices where lower values represent bad ratings and higher values represent a good rating. The aim was to keep track of the lab instructor 1's helpfulness.

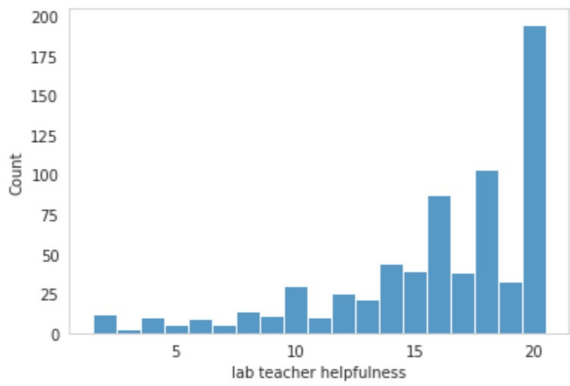

Figure 3.43: Lab teacher helpfulness

The Fig 3.43 shows the feedback of the lab teacher's helpfulness. Maximum students voted a strong yes which implies that the lab teacher was greatly helpful towards the students.

Q40: How would you rate your Lab teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Knowledgeable about subject matter]

Students could choose one option from possible 10 choices where lower values represent bad ratings and higher values represent a good rating. The aim was to keep track of the lab instructor 1's knowledge about the course.

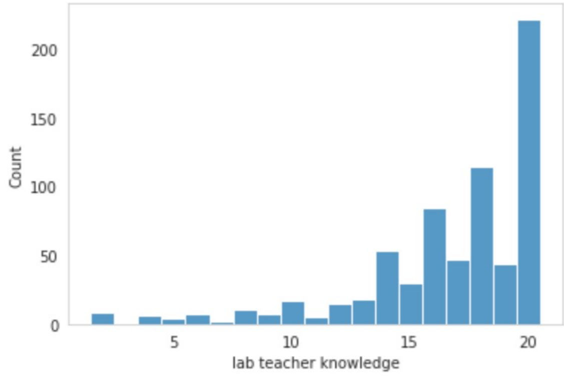

Figure 3.44: Lab teacher knowledge

The Fig 3.44 represents the feedback of the students in terms of their lab instructor's knowledge. Maximum of the students voted for a strong yes which indicates that the lab teacher was knowledgeable.

Q41: Were the lab assignments [Relevant to the course?]

Students could choose an option among three available ones. 1 would represent a bad recommendation, 2 would represent a higher value and 3 would represent N/A. The aim was to check the relevancy of labs with the theory sector.

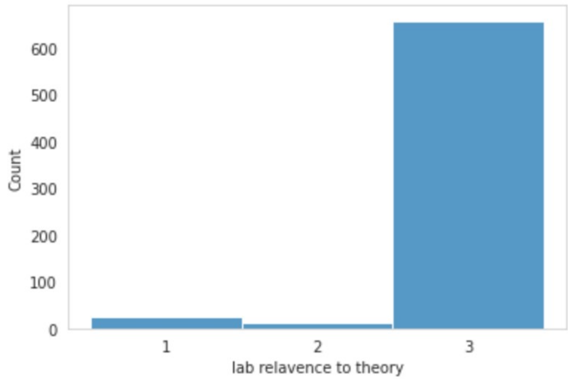

Figure 3.45: Lab relevance to theory

The Fig 3.45 represents how relevant the lab is to the theory. Maximum students voted as strong yes which indicates strong relevance ot the lab to the theory as higher the value, the more positive the feedback is.

Q42: Were the lab assignments [Helpful in learning how to implement the theory??]

Students could choose an option among three available ones. 1 would represent a bad recommendation, 2 would represent a higher value and 3 would represent N/A.

The goal was to check how helpful the labs were from the perspective of theory contents being implemented in labs.

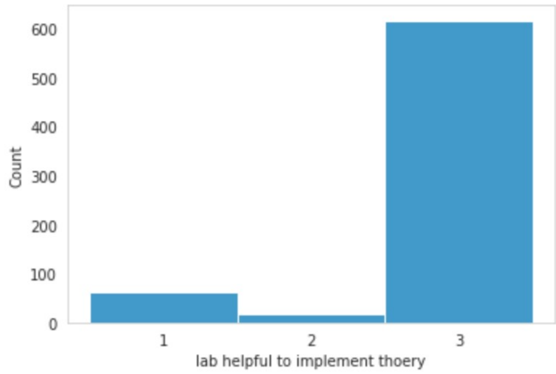

Figure 3.46: Lab helpful to implement theory

The Fig 3.46 represents how helpful the labs were in terms of implementing the theory. Maximum students gave a positive response. The higher the value, the more positive the feedback is.

Q43: Were the lab assignments [In sync with the theory lectures?]

Students could choose an option among three available ones. 1 would represent a bad recommendation, and higher values would represent a better recommendation. The aim was to check whether the theory and labs were in sync.

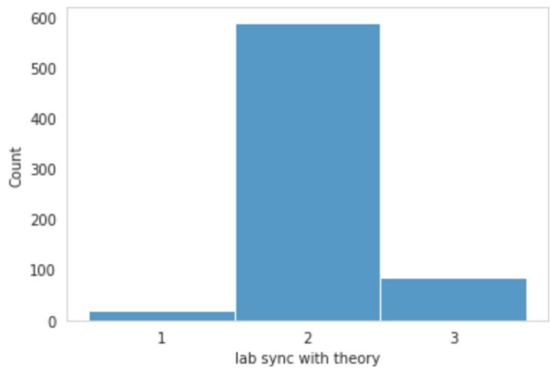

Figure 3.47: Lab sync with theory?

The Fig 3.47 represents how in sync that labs were with the theory. Maximum students voted for 2. The students somewhat agrees that the theory and lab were in sync.

Q44: Were the lab assignments [Very old, not modern?]

Students could choose an option among three available ones. 1 would represent a bad recommendation, 2 would represent a higher value and 3 would represent N/A. The goal was to check whether the same labs were repeated every semester.

The Fig 3.48 represents whether the lab contents were updated or not. Maximum students gave a strong positive response which indicates that the labs are up to date.

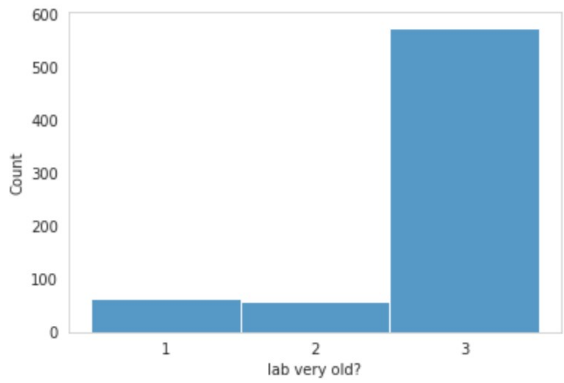

Figure 3.48: Lab very old?

Q45: Were the lab assignments [Appropriate simulation tools were used for online labs?]

Students could choose an option among three available ones. 1 would represent a bad recommendation, 2 would represent a higher value and 3 would represent N/A. The goal was to check whether the tools used to solve the labs were proper.

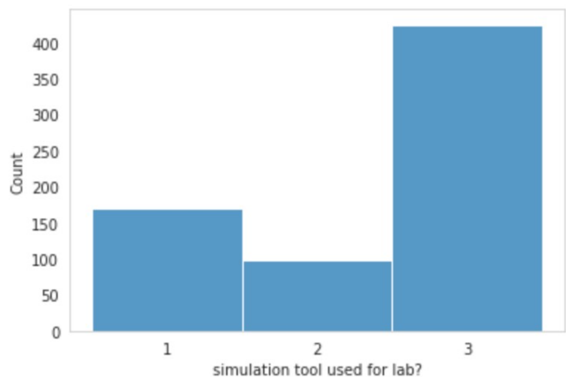

Figure 3.49: Simulation tool used for lab?

The Fig 3.49 represents how appropriate the simulation tools were for the online labs. Maximum students voted a strong yes which implies that the tools were not irrelevant.

Q46: Answer the following for this course [The projects assigned were relevant and did you receive adequate guidance?]

Students could choose any one among the three options: yes, no or not relevant. The Fig 3.50 represents how relevant the project assigned was. Maximum students voted a strong yes which means that the project was relevant to the course.

Q47: Were the lab assignments [Too Few?]

Students could choose an option among three available ones. 1 would represent no and higher values would represent a stronger yes. The aim was to check whether the number lab assignments were enough to cover all the implementations of the theory contents.

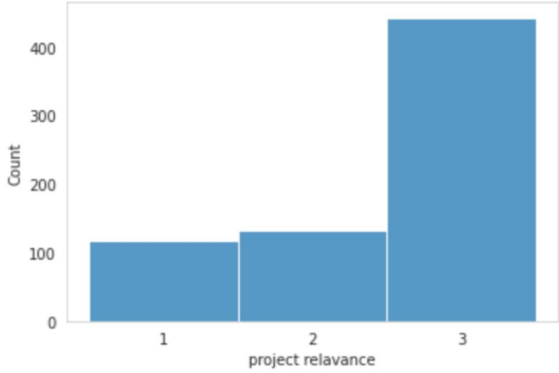

Figure 3.50: Project relevance

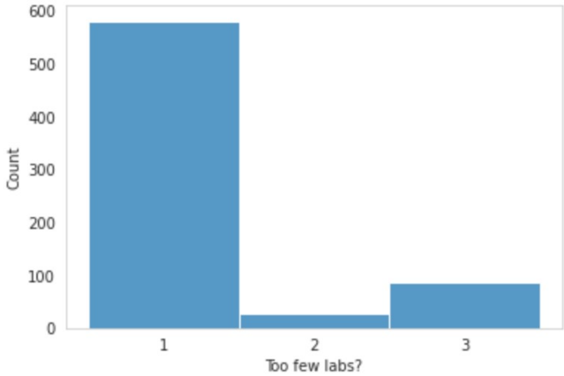

Figure 3.51: Too few labs?

The Fig 3.51 represents whether the total number of labs were enough or not. Maximum students voted no which implies that no, there were not too few labs; there were enough labs conducted to cover the contents.

3.3 Data Preprocessing

In this study, data preprocessing was an important step for further statistical analysis. After removing the rows consisting of null values were removed, 694 rows of data were obtained. In order to convert all the labels to numeric form, the label-encoding method was performed. It was performed on an ordinal scale, meaning the most positive response has a higher number and the most negative response has a lower number.

The questionnaires having multiple options to choose from were separated and one-hot encoding was performed to transform it into categorical data. Such questionnaires were - What was the course's video style? Choose all that apply. What supplementary material was provided? Choose all that apply. Did the instructor use a forum to answer questions? If so, what platform(s)? Some of the features were combined and converted into a single feature, such as - the score of Lab teacher 1's teaching dedication & Lab teacher 2's teaching dedication were added and converted into overall Lab teachers' teaching dedication. Similarly, Lab overall lab teachers' helpfulness and lab teachers' knowledge about the subject matter was generated.

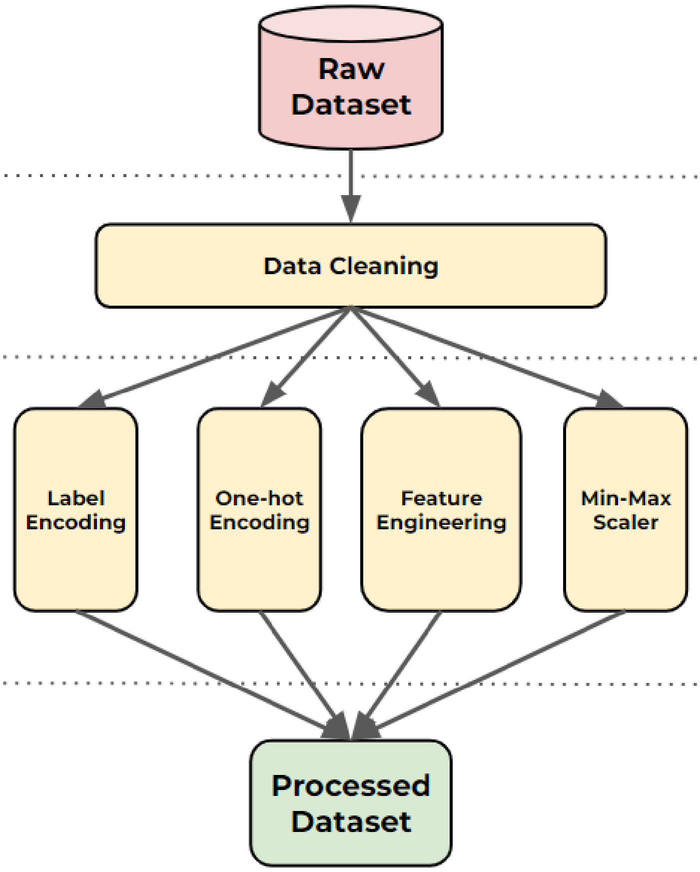

Figure 3.52: Top Down Diagram of Data Preprocessing

Although most of the features contained categorical data, there were some numeric data as well. Features having numeric data were - the number of graded assignments given, the number of graded quizzes given, the number of ungraded quizzes given, the section faculty's dedication score out of 10, the section faculty's helpfulness score out of 10, the section faculty's knowledge rating out of 10, lab faculties' dedication score out of 10, lab faculties' helpfulness score out of 10 and lab faculties' knowledge score out of 10. Min-max scaler was used to normalize these numeric data. In the Min-Max scaler, all the data is scaled in the range of 0 to 1. The equation for calculating normalized value using the min-max scaler would be -

$$x_{norm} = \frac{x - min(x)}{max(x) - min(x)} \tag{3.1}$$

Finally, to find out the learning experience of the students we considered two features- the course coordination rating out of 10, and the overall course rating out of 10. The average of these 2 ratings was calculated and labeled in the following manner: If the average rating score was between [10 - 8], it was considered to be 'Excellent'. If the average rating score was between (8 - 4], it was considered to be 'Good', If the average rating score was between (4 - 1], it was considered to be 'Poor'.

After labeling the dataset, the learning experience to be 'Excellent' was found to be highest with a frequency of 354, followed by 'Good' with a frequency of 258, and

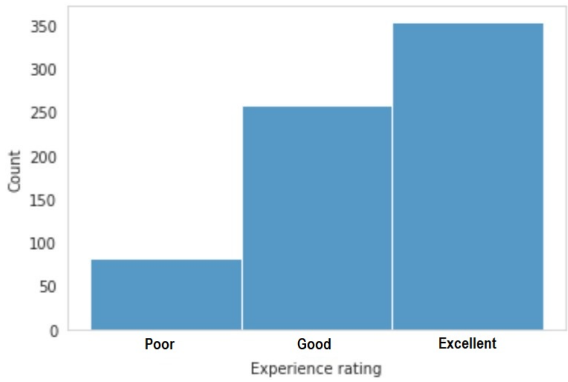

Figure 3.53: Experience Rating

lastly, 'Poor' with a frequency of 81.

In this study, for finding the validity and reliability of the dataset, Cronbach's alpha was calculated for each item and variable. The factor analysis was employed to investigate convergent and discriminant validity. ANOVA test has been used to investigate the mean differences between 3 groups (Excellent, Good, Poor). Afterward, the mean difference was compared in a pair-wise fashion using post hoc multiple comparison analysis (Scheffee's method).

3.4 Data Validation

A group of survey items' internal consistency or reliability is measured by the Cronbach's alpha coefficient. It is used to assess whether a set of items accurately and consistently measures the same attribute. On a uniform 0–1 scale, Cronbach's alpha determines the level of agreement. As the dataset was constructed using the students' response in a survey form, it is important to understand the validity and reliability before the study. Some students may submit invalid or random data though the form. Therefore, it is important to understand whether the dataset is valid enough to perform further analysis. The Cronbach's alpha for each item was found to be more than 0.85, which indicates sufficient reliability of the collected data.

3.4.1 Cronbach's Alpha

A multi-item scale or questionnaire may be evaluated for its internal consistency or reliability using Cronbach's alpha [1], which is a statistical metric. It is a statistic that may take on values between 0 and 1, with higher values suggesting a more reliable result. Evaluation of the reliability of survey instruments and other forms of measuring tools is a typical practice in the social sciences and is supported by this method.

$$\alpha = \left(\frac{k}{k-1}\right)\left(1 - \frac{\sum_{i=1}^{k} \sigma_y^2}{\sigma_x^2}\right) \tag{3.2}$$

Here,

k is the number of items in the measure

σ_y^2 variance associated with each

σ_x^2 variance associated of the total scores

The value of Cronbach's alpha may be determined by first taking the score obtained from each scale item, linking that score with the overall score obtained for each observation, and then contrasting that value with the variation of the scores obtained from all of the scale items individually. It is easiest to understand Cronbach's alpha as a function of the number of questions or items included in a measure, the average covariance between pairs of items, and the overall variance of the entire measured score.

Cronbach's alpha is sensitive to the amount of items that are being measured as well as the distribution of those items since it is dependent on the correlation between the items on a scale. Even though a higher threshold of 0.8 or 0.9 may be more appropriate for certain kinds of research, the general rule of thumb is that an alpha of 0.7 or higher is considered acceptable for most research. However, some experts suggest that a lower threshold of 0.6 may be more appropriate for certain kinds of research.

The Cronbach's alpha coefficient is a measure of dependability that is used by a significant number of academics and practitioners. It is not a measurement of validity, which is the amount to which a test measures what it is intended to assess; rather, it is a measurement of the test's consistency. Validity is defined as the extent to which a test measures what it is intended to measure.

3.5 Hypothesis Testing

Hypothesis testing is a procedure to assess the strength of evidence from the sample and establish a framework for making decisions related to the population. In this study, ANOVA test is used in order to evaluate the hypothesis which are considered as common beliefs. This will provide a method for understanding how each feature influences students' learning experiences to be excellent. Moreover, the scheffe test has been used to make comparisons among groups (Excellent, Good, Poor) in the analysis of variance experiment. This experiment will allow us to make all possible contrasts between group means and represent a pair-wise (Excellent - Good, Good - Poor, Excellent - Poor) comparison.

3.5.1 ANOVA Test

The analysis of variance (ANOVA) [4] is used for analyzing mean differences between more than two groups. This may be performed by looking at the variation in the data and where it occurs (hence its name). The analysis of variance (ANOVA) is a statistical technique that compares the degree of variation that exists within groups to the degree of variation that exists across groups.
ANOVA is mathematically expressed as

Table 3.1: Construct reliability and validity analysis

Dimensions	Items	Item Description	Cronbach's alpha
Coordination	**Variable (V1): Efficiency of Communication**		
	Item1	Graded quizzes were [Administered fairly]	0.867
	Item2	Graded quizzes were [Notified 2 days before]	0.868
	Item3	Graded quizzes were [Taken during mid week]	0.869
	Item4	Did your course instructors try hard to ensure that you could successfully complete your midterm and finals? [Midterm Exam]	0.866
	Item5	Did your course instructors try hard to ensure that you could successfully complete your midterm and finals? [Final Exam]	0.866
	Variable (V2): Effectiveness of Assessment		
	Item6	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Ungraded quizzes]	0.863
	Item7	Were the exams and assignments interesting? [Exams questions were]	0.863
	Item8	Were the exams and assignments interesting? [Assignments were]	0.867

Table 3.2: Construct reliability and validity analysis (continued)

Dimensions	**Items**	**Item Description**	**Cronbach's alpha**
Course	**Variable (V3): Course Content Quality**		
	Item1	What was the course's video style? Choose all that apply.	0.866
	Item2	What supplementary material was provided? Choose all that apply.	0.867
	Item3	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Video lectures]	0.861
	Item4	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Bangla supplementary videos]	0.862
	Variable (V4): Adequacy of the Curriculum		
	Item5	Was enough material presented in the course?	0.863
	Item6	Did the online lectures cover the course content on the midterm?	0.865
	Item7	Did the lectures adequately cover the syllabus?	0.867
	Item8	Did you have to memorize a lot for the exams?	0.867
	Item9	Were the lectures enough to learn the material?	0.867
	Variable (V5): Assessment Stratigies		
	Item10	How many graded homework assignments and quizzes were assigned during the semester? [Graded Homework Assignments]	0.866
	Item11	Answer the following for this course [Was enough homework and examples provided to learn the material?]	0.864
	Item12	Answer the following for this course [Was problem-solving help provided for homework assignments?]	0.865
	Item13	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Homework and problem solving tasks]	0.86
	Item14	How many graded homework assignments and quizzes were assigned during the semester? [Graded Quizzes]	0.881
	Item15	How many graded homework assignments and quizzes were assigned during the semester? [Ungraded Quizzes]	0.883

Table 3.3: Construct reliability and validity analysis (continued)

Dimensions	Items	Item Description	Cronbach's alpha
Faculty	**Variable (V6): Theory Instructor's effort**		
	Item1	How much effort do you think instructors gave to produce good video lectures?	0.864
	Item2	How long did it take on average for your section instructor to respond to your questions on Slack or email or other forums?	0.864
	Item3	How would you rate your section teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Dedication of teaching]	0.857
	Item4	How would you rate your section teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Helpfulness]	0.857
	Item5	How would you rate your section teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Knowledgeable about subject matter]	0.861
	Variable (V7): Instructor's Lecture quality		
	Item6	The following questions are regarding online discussion classes [Section teacher made them interesting and useful]	0.866
	Item7	The following questions are regarding online discussion classes [Personal and irrelevant topics were discussed.]	0.869
	Item8	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Online discussion classes]	0.864
	Variable (V8): Lab Instructor's effort		
	Item9	How would you rate your Lab teachers on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Dedication of teaching]	0.871
	Item10	How would you rate your Lab teachers on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Helpfulness]	0.871
	Item11	How would you rate your Lab teachers on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Knowledgeable about subject matter]	0.872

Table 3.4: Construct reliability and validity analysis (continued)

Dimensions	Items	Item Description	Cronbach's alpha
Lab/Experiment	**Variable (V9): Relationship of lab assignment with theory content**		
	Item1	Were the lab assignments [Relevant to the course?]	0.868
	Item2	Were the lab assignments [Helpful in learning how to implement the theory??]	0.866
	Item3	Were the lab assignments [In sync with the theory lectures?]	0.87
	Variable (V10): Effectiveness of Lab content		
	Item4	Were the lab assignments [Very old, not modern?]	0.867
	Item5	Were the lab assignments [Appropriate simulation tools were used for online labs?]	0.866
	Item6	Answer the following for this course [The projects assigned were relevant and did you receive adequate guidance?]	0.865
	Item7	Were the lab assignments [Too Few?]	0.87

Table 3.5: Construct reliability and validity analysis (continued)

Dimensions	Items	Item Description	Cronbach's alpha
Technology	**Variable (V11): Utilization of Digital Platforms**		
	Item1	Did the course use a Google Calendar after midterms to push out notifications?	0.867
	Item2	Did the instructor use a forum to answer questions? If so, what platform(s)?	0.868
	Item3	Were the digital platforms used appropriate for smooth student-teacher communication?	0.867
	Variable (V12): Digital Content Quality		
	Item4	How was the audio and video quality for most of the videos in this course? [Audio]	0.866
	Item5	How was the audio and video quality for most of the videos in this course? [Video]	0.866

$$x_{ij} = \mu_i + \epsilon_{ij} \tag{3.3}$$

where x are the individual data points (group and individual observations are denoted by i and j, respectively), ϵ is the unexplained variation, and the model's parameters (μ) are the population means for each group. Each data point (x_{ij}) is therefore the summation of the group mean and the error.

The F-ratio, a test statistic used in ANOVA as well as other traditional statistical tests, allows us to determine the chance of finding the data under the null hypothesis (P-value). A significant P-value (often regarded as $P<0.05$) denotes that the means of at least one group differ from one another in a significant way. Null Hypothesis: All population means are equal Alternate Hypothesis: There is at least one population mean that differs from the others.

ANOVA divides the dataset's variation into between-group and within-group components. These variations are called the sums of squares. By comparing the mean of each group with the data's overall mean, the between-group variation (also known as between-group sums of squares, or SS) is calculated.

$$Between\ SS = n_1(\bar{x_1} - \bar{x})^2 + n_2(\bar{x_2} - \bar{x})^2 + n_3(\bar{x_3} - \bar{x})^2 \tag{3.4}$$

In other words, by multiplying the sample size by the square of the differences between the means of each group I = 1, 2, or 3), then adding the result. The BSS is then divided by the number of degrees of freedom (this is similar to sample size, but it is n-1 because the deviations must amount to zero) to obtain our estimate of the mean variation between groups.
The difference between each observation and its group mean is known as the within-group variance (also known as the within-group sums of squares).

$$SS_R = s^2_{group1}(n_{group1} - 1) + s^2_{group2}(n_{group2} - 1) + s^2_{group3}(n_{group3} - 1) \tag{3.5}$$

i.e., by multiplying the variance of each group by its degrees of freedom . Then, Within SS is Total SS minus Between SS.The mean variation within groups is then obtained by dividing the result by the total degrees of freedom, as previously.

The F ratio is around 1 if the average difference between groups is comparable to that within groups. The F ratio rises over 1 as the average difference between groups exceeds the average difference within groups.

It can be tested against the F-distribution of a random variable whose degrees of freedom correspond to the ratio's numerator and denominator in order to derive a P-value. The probability of obtaining that F ratio or a higher one is indicated by the P-value. Smaller P-values result from higher F ratios.

3.5.2 Scheffé Test

The Scheffé test [2], also known as the Scheffé technique, is a statistical test used in an analysis of variance (ANOVA) context to compare different means or groups.

It is used to identify whether means or groups are substantially distinct from one another when many comparisons are done.

Given the number of groups and degrees of freedom, the Scheffé test utilizes the F-distribution to compute the likelihood of receiving a certain test statistic. The test statistic is the ratio of the square mean between groups to the square mean within groups.

Notably, the Scheffé test is a post-hoc test, which means it's employed after a significant ANOVA result to determine which groups are different. It is not used to determine the overall significance of ANOVA.

3.6 Learning Theory based Validation of Consequential Factors

Machine Learning methods has been used to validate the findings of the data science approach. After this analysis, some ML techniques were applied to find out the most important features for making a course an excellent experience. CART Classification Feature Importance, Random Forest classifier, and K-Neighbors Classifier are implemented. The most significant factors found are - the instructor's effort while creating the content, the effectiveness of video lectures for learning, and the helpfulness of the theory instructor. This result also supports the outcome of the hypothesis and post-hoc testing.

3.6.1 CART Feature Importance

CART (Classification and Regression Trees) [6] is an approach for decision trees that may be used for both classification and regression applications. Feature relevance in CART refers to the relative importance of each feature (or predictor variable) in the input dataset, as measured by its ability to accurately partition and categorize the data. Typically, CART algorithms allocate weight to features based on the decrease in impurity (e.g., Gini impurity or entropy) that occurs when a feature is used to divide the data. The greater the decrease in impurities, the greater the significance of the characteristic.

$$Gini\ Impurity = 1 - Gini = 1 - \sum_{i=1}^{n} p_i^2 \tag{3.6}$$

It is vital to remember that the feature significance estimated by the CART method is relevant to the particular dataset and issue you are attempting to solve, and not absolute.

3.6.2 Random Forest

Random Forest [5] is an ensemble learning technique for classification, regression, and other tasks. It operates by constructing a large number of decision trees at training time and outputting the class that is the mode of the classes (classification) or the mean prediction (regression) of the individual trees. In Random Forest, each tree is constructed using a different data sample and a subset of the characteristics. This generates a diversified collection of decision trees, each with its own strengths and limitations, which may collaborate to produce accurate predictions. The randomization introduced by the random forest makes the model more resilient and less susceptible to overfitting than a single decision tree.

Random Forest calculates the relevance of a feature based on the average reduction in impurity across all trees in the forest, as well as the average number of times a feature is utilized across all trees. This enables a more robust estimate of feature relevance than a single decision tree.

In Random Forest, feature importance is calculated based on the reduction in impurity (e.g., Gini impurity or entropy) that occurs when a feature is used to split the data. The larger the reduction in impurity, the more important the feature is considered to be. It also follows the same formula as CART's Gini impurity.

3.6.3 K-Nearest Neighbors

The k-nearest neighbors (k-NN) classifier [3] is an instance-based, non-parametric learning method. It is used for classification and regression operations. The main principle underlying k-NN is to generate predictions about the sample using the data points nearest to the sample (i.e., the "neighbors").
For a classification job, when a new sample is provided to the model, the k-NN classifier assigns the new sample to the class that is most prevalent among its k nearest neighbors.

For a regression job, the k-NN method selects the k training samples that are closest to the new sample and the output value is the average of the output value of k nearest samples.

In k-NN, k is a hyperparameter whose value is determined by the user. A small number of k will lead to a complicated model with a lot of overfitting while a big value of k will lead to a simple model with high bias.

Chapter 4

Result and Discussion

4.1 Result Analysis

The findings of this study show that ANOVA analysis supports each of the hypotheses. Particularly, the analysis results as shown in Table 4.1, strongly support all the hypotheses ($P<0.001$) except for H12. However, it also supports hypothesis H12 ($P<0.01$). P is assigned by following (*$P<0.05$) (**$P<0.01$) (***$P<0.001$).

Table 4.1: Results of statistical analysis

Variables	F-statistics	Excellent		Good		Poor	
		Mean	SD	Mean	SD	Mean	SD
Efficiency of Communication	1641.339***	2.176	0.739	2.047	0.747	1.78	0.667
Effectiveness of Assessment	10.737***	3.725	1.109	3.2	1.306	2.602	1.398
Course Content Quality	1916.049***	0.91	1.426	0.689	1.199	0.537	0.937
Adequacy of the Curriculum	428.82***	2.945	0.859	2.467	0.949	1.812	0.901
Assessment Stratigies	3241.323***	1.777	1.788	1.434	1.53	1.129	1.238
Theory Instructor's effort	6734.258***	2.018	2.489	1.752	2.319	1.389	2.087
Instructor's Lecture quality	1456.878***	2.405	1.489	2.048	1.296	1.533	0.948
Lab Instructor's effort	47.676***	0.483	0.036	0.475	0.071	0.446	0.121
Relationship of lab assignment with theory content	653.644***	2.645	0.516	2.599	0.597	2.427	0.755
Effectiveness of Lab content	528.298***	2.351	0.883	2.147	0.916	1.848	0.931
Utilization of Digital Platforms	1960.075***	0.585	0.754	0.507	0.714	0.432	0.626
Digital Content Quality	9.462**	2.874	0.352	2.597	0.543	2.128	0.616

Moreover, pair-wise analysis was performed in order to find out the differences between each group and how it affects students' learning experiences. The result from this analysis implies that Excellent experience is significantly different from Poor experience with respect to all the considered variables. However, the mean difference between (excellent-good) and (good-bad) shows some diverse nature in some cases. Particularly, in some factors, excellent experience is different from good experiences, such as Theory Instructor's effort, Lab Instructor's effort, Relationship of lab assignments with theory content, Effectiveness of Lab content, and Utilization of Digital Platforms. The good experience is different from the bad experience in terms of the theory Instructor's effort and Utilization of Digital Platforms. These variables were found to be not significant in the mentioned pair of groups. The summary of the pair-wise analysis is shown in Table 4.2.

In this study, the response of the students indicate that the most critical factors are in descending order: Effectiveness of Assessment, Digital Content Quality, Adequacy of the Curriculum, Relationship of lab assignment with theory content, Effectiveness of Lab content, Instructor's Lecture quality, Efficiency of Communication, Theory Instructor's effort, Assessment Strategies, Course Content Quality, Utilization of Digital Platforms and Lab Instructor's effort. Among the 5 dimensions, 'Coordination' (mean: 2.739) has been recognized as the most significant dimension for better students' learning experience. The rest in descending order are- Lab/Experiment (mean: 2.409), Course (mean: 1.6633), Technology (mean: 1.6105), and finally Faculty (mean: 1.4967).

Table 4.2: Results of ML Methods

Rank	**CART**	**Random Forest**	**K-Nearest Neighbors**
1	How much effort do you think instructors gave to produce good video lectures?	How much effort do you think instructors gave to produce good video lectures?	How long did it take on average for your section instructor to respond to your questions on Slack or email or other forums?
2	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Homework and problem solving tasks]	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Video lectures]	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Homework and problem solving tasks]
3	How would you rate your section teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Helpfulness]	Were the lectures enough to learn the material?	Did the online lectures cover the course content on the midterm?
4	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Video lectures]	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Homework and problem solving tasks]	How much effort do you think instructors gave to produce good video lectures?
5	How would you rate your Lab teachers on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Knowledgeable about subject matter]	How would you rate your section teacher on a scale on 1 (horrible) to 10 (outstanding) in the following criteria? [Helpfulness]	Rate how the following learning activities helped you learn the subject matter. Here 1 means: being no help and means: 5 being most helpful [Video lectures]

4.2 Findings of Learning Theory based Consequential Factor Analysis

After this analysis, some ML techniques were applied in order to find out the most important features for making a course an excellent experience for learners. CART Classification Feature Importance, Random Forest classifier, and K-Neighbors Classifier are implemented. According to the analysis, the most significant factors found are - the instructor's effort while creating the content, the effectiveness of homework and problem-solving tasks to learn the subject matter, the helpfulness of the theory instructor, the effectiveness of video lectures for learning, the instructor's response time in discussion platform or email, amount of lectures to learn the material and clarity of the lecture in the provided video, etc. According to the result of the CART classification feature importance, the instructor's effort while creating the content has been identified as the most important feature to determine the student's experience of the course. Moreover, it was also found that the effectiveness of homework and problem-solving tasks to learn the subject matter and the helpfulness of the theory instructor has also positively affected an experience to be an excellent one. Similarly, the most important features according to the Random Forest classifier in descending order are - the instructor's effort while creating the content, the effectiveness of video lectures for learning, and the amount of lectures to learn the material. However, some new factors were found according to the k-neighbors classifier. It identified the instructor's response time in discussion platforms or email to be the most effective factor for students' learning experience. Moreover, the effectiveness of homework and problem-solving tasks to learn the subject matter was also found to be an important factor in this case.

Table 4.3: Results of pair-wise analysis

Variables	Difference between Excellent and Good	Difference between Good and Poor	Difference between Excellent and Poor
Efficiency of Communication	Significant*	Significant***	Significant***
Effectiveness of Assessment	Significant***	Significant***	Significant***
Course Content Quality	Significant***	Significant**	Significant***
Adequacy of the Curriculum	Significant***	Significant***	Significant***
Assessment Stratigies	Significant**	Significant**	Significant***
Theory Instructor's effort	Not Significant	Not Significant	Significant***
Instructor's Lecture quality	Significant*	Significant***	Significant***
Lab Instructor's effort	Not Significant	Significant***	Significant***
Relationship of lab assignment with theory content	Not Significant	Significant***	Significant***
Effectiveness of Lab content	Not Significant	Significant***	Significant***
Utilization of Digital Platforms	Not Significant	Not Significant	Significant***
Digital Content Quality	Significant***	Significant***	Significant***

4.3 Discussion

This study explores the factors that affect the decision to adopt the model in programming classes for undergraduate students. The findings of the conceptual model that is being presented have a number of interesting implications that are represented in the form of a framework. As a result, some inferences can be derived from the study's findings and outcomes.

First, it is a well-accepted fact that the most significant variable during the online semester was the effectiveness of assessments throughout the semester. Students who found the exam question and assignments interesting were most likely to have a comparatively better learning experience. Moreover, ungraded quizzes removed pressure on students during that crucial covid situation. In fact, students found it as one of the most effective ways to learn their subject matter.

On the other hand, lab instructors' effort was found to be the least significant in this study. One of the reasons could be that all the labs during that time were online simulation-based and there was a very small scope of opportunity for the students to interact with their corresponding lab teachers. Attendance in lab classes significantly dropped as it was optional according to the online learning policy. The majority of the students used to rely on tutorial videos provided in buX as an alternative to the physical lab. Therefore, it is very obvious that the efforts of the lab instructors' were unnoticed by most of the students.

As digital lecture videos provided in the buX platform became reliable for the students as an alternative to traditional classes, 'Digital Content Quality' was found to be a major factor determining the overall outcome. Overall video and audio quality of the digital lecture videos made learning more enjoyable and effective for the students. Therefore, courses having good control over the quality of their digital content had the maximum number of students satisfied with the learning outcome.

Another important factor that played an important role was the overall adequacy of the curriculum. According to 71% of the students who had an excellent learning experience, they found enough material presented in the course curriculum. Moreover, courses with better outcomes had enough lectures to learn the subject matter and cover the syllabus. In addition, programming courses that had fewer number of elements to be memorized had a greater impact on the student's learning outcomes. Therefore, the impact of understanding rather than memorizing is also visible in this study.

Alternatively, the utilization of Digital Platforms had comparatively less effect on the student's learning experience as the default discussion board on the buX was not a popular choice for the students. Significantly less amount of comment or discussion was found in the discussion forum. Moreover, usage of google calendar was imposed after the midterm (first half) of that semester. Therefore, most of the students did not find impactful utility in this digital feature.

Course content quality was ranked 10 among the 12 most significant variables as most of the courses did not have Bangla lecture videos and other supplementary materials in the first online semester. Moreover, 67% of the students who had a poor learning experience found out the instructors were just reading the slides out loud in the video lectures. On the contrary, students found the learning to be excellent when the instructor used a tablet effectively in the Khan Academy style.

Table 4.4: Overall Analysis

Dimensions	Mean	Rank	Variables	Mean	SD	Rank
Coordination	2.739	1	Efficiency of Communication	2.081	0.744	7
			Effectiveness of Assessment	3.397	1.279	1
Course	1.6633	3	Course Content Quality	0.784	1.302	10
			Adequacy of the Curriculum	2.633	0.973	3
			Assessment Stratigies	1.573	1.654	9
Faculty	1.4967	5	Theory Instructor's effort	1.845	2.391	8
			Instructor's Lecture quality	2.169	1.394	6
			Lab Instructor's effort	0.476	0.066	12
Lab/Experiment	2.409	2	Relationship of lab assignment with theory content	2.602	0.583	4
			Effectiveness of Lab content	2.216	0.916	5
Technology	1.6105	4	Utilization of Digital Platforms	0.538	0.727	11
			Digital Content Quality	2.683	0.525	2

Considering the dimension of the proposed conceptual framework, coordination was ranked 1st (mean: 2.739), as two major variables, the effectiveness of assessment and efficiency of communication fall under this dimension. As discussed previously, the effectiveness of assessments was crucial in determining students' learning outcomes. In addition, the importance of communication was also important. According to the survey response, a good course must administer graded quizzes fairly to make the experience satisfactory for the students. Moreover, the student should be informed about the upcoming quizzes and exams at least 2 days before the exam date. In some courses, the teaching team ensured the students are being able to complete the midterm and final exams. Those courses were found to be the most effective ones in regards to improving the learning outcome of the students.

On the other hand, the technology dimension was found to be the least significant dimension in our conceptual model. Although the variable 'Digital content quality' had a great impact on the students' learning. However, because of the less effective utilization of digital platforms, the overall score for this dimension has decreased. Therefore, the effect of the technology dimension is less dominant in the observed data.

However, one may argue that the 'Faculty' dimension should be one of the most influential elements for any educational institution. However, in our study, it was ranked 5, out of 5 dimensions. The possible reason for this result could be the policy that has been imposed on online semesters. Most of the courses in buX were created and organized by the team centrally. Moreover, the evaluation and scoring criteria were fixed as most of the exams were taken centrally and checked automatically in buX. Therefore, one particular course faculty had less control and impact over the students learning. This statistical study also supports that statement.

To sum up, after applying various data science techniques and machine learning techniques the major findings that should be considered in online learning platforms for teaching programming courses are -

- Instructors should give a good amount of effort to produce quality video lectures for better learning experience.

- Interesting homework and problem-solving tasks should be given to students for a better outcome.
- Video lectures with good audio and video quality should be provided as a method of teaching.
- Instead of reading out loud from the slide, the lecture style should be similar to Khan Academy videos.
- Instructors should respond within 1 day to learners' queries via email and other digital platforms.
- Section instructors should be helpful to the students queries for better learning experience.
- The lecture should be enough to learn the material and should cover the syllabus.
- Students should be notified at least 2 days before any assessment/exams.
- Lab materials should be modern, relevant, and in sync with theory.
- Bangla lecture videos should be provided as supplementary material for better understanding of a topic.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

To conclude, this study might benefit students studying computer programming with better online learning experiences and greater course performance in the future. It can be done by being aware of and addressing these aspects. Results showed that a total of twelve variables played a vital role to enhance students' learning. Access to dependable technology, clear and consistent communication from instructors, opportunities for interactive learning and collaboration and adequate support from both theory and lab instructors were some of the critical factors influencing undergraduate students' online learning experiences in computer programming courses. Some components had more significance than other components in influencing a student's performance from poor to good, good to excellent, and poor to excellent. Ranking groups of variables based on their significance gave meaningful results that could be used to make impactful decisions in the future regarding online learning.

5.2 Future Work

In the future, similar research could be conducted among undergraduate students belonging to fields other than computer programming to evaluate the significant factors affecting their learning experience. The textual data has not been utilized in this study. The collected data has the feedback of students about how the courses can be improved. The set of unused data also contains faculty comments which can be worked with in future. We can work with Natural Language Processing algorithms to summarize the students' feedback and classify the type of feedback as well.

Bibliography

[1] L. J. Cronbach, "Coefficient alpha and the internal structure of tests," *psychometrika*, vol. 16, no. 3, pp. 297–334, 1951.

[2] G. Enderlein, "Scheffé, h.: The analysis of variance. wiley, new york 1959, 477 seiten, $ 14,00," *Biometrische Zeitschrift*, vol. 3, no. 2, pp. 143–144, 1961. DOI: https://doi.org/10.1002/bimj.19610030206. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/bimj.19610030206. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/bimj.19610030206.

[3] E. Fix and J. L. Hodges, "Discriminatory analysis. nonparametric discrimination: Consistency properties," *International Statistical Review / Revue Internationale de Statistique*, vol. 57, no. 3, pp. 238–247, 1989, ISSN: 03067734, 17515823. [Online]. Available: http://www.jstor.org/stable/1403797 (visited on 01/27/2023).

[4] L. St≫hle and S. Wold, "Analysis of variance (anova)," *Chemometrics and Intelligent Laboratory Systems*, vol. 6, no. 4, pp. 259–272, 1989, ISSN: 0169-7439. DOI: https://doi.org/10.1016/0169-7439(89)80095-4. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0169743989800954.

[5] T. K. Ho, "Random decision forests," in *Proceedings of 3rd International Conference on Document Analysis and Recognition*, vol. 1, 1995, 278–282 vol.1. DOI: 10.1109/ICDAR.1995.598994.

[6] R. J. Lewis, "An introduction to classification and regression tree (cart) analysis," in *Annual meeting of the society for academic emergency medicine in San Francisco, California*, Citeseer, vol. 14, 2000.

[7] M. Asamoah, E. Nketiah-Amponsah, W. Allassani, and L. Aziale, "Examining students' experience with the use of some selected ict devices and applications for learning and their effect on academic performance," *Journal of Computers in Education*, vol. 4, Aug. 2017. DOI: 10.1007/s40692-017-0089-2.

[8] M. A. Elhussein, D. Düştegör, N. Nagy, and A. K. H. Alghamdi, "The impact of digital technology on female students' learning experience in partition-rooms: Conditioned by social context," *IEEE Transactions on Education*, vol. 61, no. 4, pp. 265–273, 2018. DOI: 10.1109/TE.2018.2840501.

[9] M. Marques, S. F. Ochoa, M. C. Bastarrica, and F. J. Gutierrez, "Enhancing the student learning experience in software engineering project courses," *IEEE Transactions on Education*, vol. 61, no. 1, pp. 63–73, 2018. DOI: 10.1109/TE.2017.2742989.

[10] T. Aljohani and A. I. Cristea, "Predicting learners' demographics characteristics: Deep learning ensemble architecture for learners' characteristics prediction in moocs," in *Proceedings of the 4th International Conference on Information and Education Innovations*, 2019, pp. 23–27.

[11] N. Mduma, K. Kalegele, and D. Machuve, "A survey of machine learning approaches and techniques for student dropout prediction," 2019.

[12] S. Choi, J. Y. Hong, Y. J. Kim, and H. Park, "Predicting psychological distress amid the covid-19 pandemic by machine learning: Discrimination and coping mechanisms of korean immigrants in the us," *International journal of environmental research and public health*, vol. 17, no. 17, p. 6057, 2020.

[13] B. Means, J. Neisler, *et al.*, "Suddenly online: A national survey of undergraduates during the covid-19 pandemic," Digital Promise, Tech. Rep., 2020.

[14] N. S. M. Shafiee and S. Mutalib, "Prediction of mental health problems among higher education student using machine learning," *International Journal of Education and Management Engineering (IJEME)*, vol. 10, no. 6, pp. 1–9, 2020.

[15] M. S. Shawaqfeh, A. M. Al Bekairy, A. Al-Azayzih, *et al.*, "Pharmacy students perceptions of their distance online learning experience during the covid-19 pandemic: A cross-sectional survey study," *Journal of medical education and curricular development*, vol. 7, p. 2 382 120 520 963 039, 2020.

[16] M. A. Almaiah, O. Almomani, A. Al-Khasawneh, and A. Althunibat, "Predicting the acceptance of mobile learning applications during covid-19 using machine learning prediction algorithms," *Emerging technologies during the era of COVID-19 pandemic*, pp. 319–332, 2021.

[17] I. M. K. Ho, K. Y. Cheong, and A. Weldon, "Predicting student satisfaction of emergency remote learning in higher education during covid-19 using machine learning techniques," *Plos one*, vol. 16, no. 4, e0249423, 2021.

[18] V. S. Katz, A. B. Jordan, and K. Ognyanova, "Digital inequality, faculty communication, and remote learning experiences during the covid-19 pandemic: A survey of us undergraduates," *Plos one*, vol. 16, no. 2, e0246641, 2021.

[19] H. Luan and C.-C. Tsai, "A review of using machine learning approaches for precision education," *Educational Technology & Society*, vol. 24, no. 1, pp. 250–266, 2021.

[20] M. Maqableh and M. Alia, "Evaluation online learning of undergraduate students under lockdown amidst covid-19 pandemic: The online learning experience and students' satisfaction," *Children and Youth Services Review*, vol. 128, p. 106 160, 2021, ISSN: 0190-7409. DOI: https://doi.org/10.1016/j.childyouth.2021.106160. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S019074092100236X.

[21] T. Nguyen, C. L. M. Netto, J. F. Wilkins, *et al.*, "Insights into students' experiences and perceptions of remote learning methods: From the covid-19 pandemic to best practice for the future," *Frontiers in Education*, vol. 6, 2021, ISSN: 2504-284X. DOI: 10.3389/feduc.2021.647986. [Online]. Available: https://www.frontiersin.org/articles/10.3389/feduc.2021.647986.

[22] S. M. Reeves, K. J. Crippen, and E. D. McCray, "The varied experience of undergraduate students learning chemistry in virtual reality laboratories," *Computers Education*, vol. 175, p. 104 320, 2021, ISSN: 0360-1315. DOI: https://doi.org/10.1016/j.compedu.2021.104320. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360131521001974.

[23] D. Turnbull, R. Chugh, and J. Luck, "Transitioning to e-learning during the covid-19 pandemic: How have higher education institutions responded to the challenge?" *Education and Information Technologies*, vol. 26, no. 5, pp. 6401–6419, 2021.

[24] D. T. Bui, T. T. Nhan, H. T. T. Dang, and T. T. T. Phung, "Online learning experiences of secondary school students during covid-19 – dataset from vietnam," *Data in Brief*, vol. 45, p. 108 662, 2022, ISSN: 2352-3409. DOI: https://doi.org/10.1016/j.dib.2022.108662. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352340922008678.

[25] I. Eteng, S. Akpotuzor, S. O. Akinola, and I. Agbonlahor, "A review on effective approach to teaching computer programming to undergraduates in developing countries," *Scientific African*, vol. 16, e01240, 2022, ISSN: 2468-2276. DOI: https://doi.org/10.1016/j.sciaf.2022.e01240. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2468227622001478.

[26] M. M. Jasim, *School closure longest in Bangladesh, learning vacuum alarming: Educationists — tbsnews.net*, https://www.tbsnews.net/bangladesh/education/school-closure-longest-bangladesh-learning-vacuum-alarming-educationists-372592, [Accessed 25-Jan-2023], 2022.

[27] E. Kilic-Bebek, K. Nizamis, M. Vlutters, *et al.*, "Transdisciplinarity as a learning challenge: Student experiences and outcomes in an innovative course on wearable and collaborative robotics," *IEEE Transactions on Education*, pp. 1–, 2022. DOI: 10.1109/TE.2022.3229201.

[28] M. I. H. Nayan, M. S. G. Uddin, M. I. Hossain, *et al.*, "Comparison of the performance of machine learning-based algorithms for predicting depression and anxiety among university students in bangladesh: A result of the first wave of the covid-19 pandemic," *Asian Journal of Social Health and Behavior*, vol. 5, no. 2, p. 75, 2022.

[29] E. Durand, A. Kerr, O. Kavanagh, E. Crowley, B. Buchanan, and M. Bermingham, "Pharmacy students' experience of technology-enhanced learning during the covid-19 pandemic," *Exploratory Research in Clinical and Social Pharmacy*, vol. 9, p. 100 206, 2023, ISSN: 2667-2766. DOI: https://doi.org/10.1016/j.rcsop.2022.100206. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2667276622001056.

[30] J. Fang, E. Pechenkina, and G. M. Rayner, "Undergraduate business students' learning experiences during the covid-19 pandemic: Insights for remediation of future disruption," *The International Journal of Management Education*, vol. 21, no. 1, p. 100 763, 2023, ISSN: 1472-8117. DOI: https://doi.org/10.1016/j.ijme.2023.100763. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1472811723000010.