ONLINE LEARNING EXPERIENCE: A CASE STUDY OF MASTER OF PUBLIC HEALTH STUDENTS AT A HIGHER EDUCATION INSTITUTION

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ABSTRACT

Background: *Online teaching and learning in Public Health has emerged as an important and perhaps transformative development in higher education in the recent 4.0 industrial era. So far, no studies have explored the perceptions of students with respect to whether online learning enhances academic experience.*

Methods: *The purpose of this study was to determine whether online learning enhances the general student experience and satisfaction. A cross-sectional quantitative study was conducted among the fully online Master of Public Health students at the University of Johannesburg, where questionnaires were used to gather data.*

Results: *The results showed that the majority of the participants were females, and the mean age average was 39 years. There is a statistically significant association (p = .040) between students' perception of ease in obtaining assistance from module facilitators and their satisfaction with timely completion of activities (P= 16.135,), with 4.0% of students reporting ease of obtaining assistance and satisfaction with timely completion. There is also a significant association between ease of obtaining assistance from module facilitators and satisfaction with activity support availability (Pearson Chi-Square = 47.479, p < .001), indicating a need for further analysis to determine the percentage of students experiencing this satisfaction.*

Conclusion: *These findings underscore the importance of accessible support structures in facilitating students' academic success and enhancing their overall satisfaction with their educational experience. Future research should incorporate more research settings amongst online program facilitators, qualitative data, and validation of findings or trends by repeating the survey at a future period.*

Keywords: Assessing, Monitoring, Online Learning, Experience, Higher Education, COVID-19

1. INTRODUCTION

During the Fourth Industrial Revolution, higher education institutions are constantly seeking innovative ways to enhance the overall student experience. One such avenue that has gained significant attention is online learning. Online learning is a mode of education that uses technology to deliver courses and materials to learners who are not physically present in a traditional classroom setting. With advancements in technology, particularly in artificial intelligence, distance learning has become more accessible and interactive than ever before. Online learning offers a myriad of benefits that contribute to an enriched student experience. It provides flexibility and convenience, allowing students to access educational resources and participate in classes from anywhere at any time. This eliminates geographical barriers and enables individuals to pursue higher education while balancing other commitments.

Online teaching and learning, particularly in the context of Public Health education, has become increasingly significant in the era of Industry 4.0 (Gooding, 2013). It offers a versatile learning environment that empowers students to take control of their learning experiences while providing accessibility to education for those with various commitments (Hamdan & Amorri, 2022). This mode of education not only fosters transdisciplinary learning and teamwork but also contributes to better quality management and efficiency in higher education (Heller et al., 2017; Ng & Nicholas, 2013). However, it brings both opportunities and challenges, with ongoing debates regarding its efficacy and quality (Szopiński & Bachnik, 2022). While cognitive traits between online and traditional learning show minimal differences, exploring mixed learning approaches may offer a more effective educational strategy (Mathews, 2022; Krishnamurthy, 2020).

1.1 Significance of the study

Recent studies have focused on factors affecting student satisfaction with online learning, such as learner-instructor contact, course organisation, and technical assistance, highlighting the importance of effective support structures in online education (Trotsek, 2017; Kucuk & Richardson, 2019; ; Frazer et al., 2017; Estelami, 2016). This research aims to critically assess satisfaction outcomes, perceptions of support and technological platforms that could potentially enhance their experience and increase their confidence in completing and submitting their activities on time for online Public Health programs. Even though there are various positive factors in using online learning, it also poses some challenges, such as a lack of social interaction, technical difficulties, isolation, motivation, and self-regulation. Therefore, it is important to investigate whether online learning enhances or hinders the overall student experience, and what factors influence the quality and effectiveness of online learning.

1.2 Aim and objectives of the study

The aim of this study was to evaluate the online learning experience of Master of Public Health (MPH) students at a higher education institution in South Africa.

The objective of this study was exploring the students' perceptions, challenges, and benefits of online learning, as well as the factors that influence satisfaction.

2. MATERIALS AND METHODS

This study examined the opinions, ideas, and views of online students using a cross-sectional study design.

2.1 Study population and setting

The research project targeted the 2023 cohort of online students for MPH at the University of Johannesburg in South Africa. It included the total number of registered students (n=394) who met the minimum requirements for the MPH within the Department of Environmental Health in the Faculty of Health Sciences as of May 1st, 2023.The University of Johannesburg is a South African public university located in Johannesburg, with a student population of over 50,000, including 3000 international students from 80 countries,

2.2 Sampling and sample size

Purposive sampling was employed using student registers. The sample size for the survey was based on the number of online students enrolled for the academic year of May 2020 to May 2023 and registered at the time of the study. This provided an absolute number of online students for the MPH program.

2.2.1 Inclusion criterion

Students at the University of Johannesburg who are at least 18 years old; and who have met the minimum entry requirements for the program which include three to five years’ experience in a management position inclusive of research and/or project management and an average of 65% on the highest qualification.

The students would have been registered for MPH at the University of Johannesburg at the time of study and belong to the cohort of May 2020 to May 2023.

2.2.2 Exclusion criterion

Students who were not enrolled in the University of Johannesburg's MPH program at the time of study and who are not a part of the cohort for May 2020 to May 2022 were excluded from the study.

2.3 Data collection method

The questionnaire was adapted from the survey of the European Student Union and explored the objectives of the study (Aristovnik et al, 2020). The questionnaire was divided into four sections: Section A included biographic information, Section B asked questions evaluating MPH Program students' attitudes, perceptions, and satisfaction with online learning experiences, Section C evaluated the MPH program students' perceptions towards online learning platforms used in the MPH program, and Section D aimed to determine the factors associated with student satisfaction with the online MPH program.

A pilot study was conducted with students (n=?) to measure reliability and determine whether the questionnaire would be understandable for the target group. A link was then created on Google Forms, which was sent out to all participants. This included a section asking for consent before proceeding with answering the questionnaire. The study took place from the 1st of July 2023 to the 30th of September 2023.

2.4 Data Reliability and Validity

To accomplish the goals of this proposed study, additional questions were added to an existing survey of the European Student Union (Aristovnik et al., 2020).

2.5 Statistical analysis

The statistical package that was used for quantitative data analysis and visualisations was R version 4.4.0. Furthermore, the python package, pycaret version 3.1.0 was used for preprocessing and application of machine learning algorithms. Data were summarised using means and standard deviations, medians, and interquartile ranges as appropriate. Descriptive analyses included cross-tabulations, while inferential analyses and prediction involved tests of association and machine learning. Chi-squared, Bayesian analysis and Fisher's exact tests were used to assess the association between sociodemographic and geographic parameters and various aspects or experiences of a student. The Chi-square tests and Fisher's exact tests are suitable for the assessment of the association of categorical variables (Walpole et al., 2022; Rahman & Islam, 2023). The chi-squared, x^2 test statistic and the p-value will be reported, with a p-value that is lower than the threshold of 5% indicating a statistically significant association. The Bayesian analysis is an alternative approach to statistical analysis that takes into consideration the distribution of the prior distribution (McElreath, 2020). It takes into consideration the distribution and variability of estimated parameters. The Bayes factor (BF01) will be reported and will be useful for quantitively assessing the strength of the evidence of an association between variables compared to a null hypothesis of no association (Sivula, 2022). The bayes factor will generally compare the evidence or the likelihood for the null model of no association compared to the alternative model. In this research study, the natural logarithm of the bayes factor that is greater than 3 will provide strong evidence for no association of variables that is the null model, a negative value will provide evidence for an association between variables i.e the alternative model and strong evidence of an association when the value is less than -1 (Liang, 2022).

Supervised Machine learning will be applied for the prediction or classification of satisfaction outcomes and to establish the important factors that influence these outcomes (Murphy, 2024). This is appropriate for this study because the outcomes that are predicted or classified are labelled, machine learning algorithms are suitable for the analysis of complex patterns and classification of the different categories of the labelled data (James et al., 2021). The classification algorithms include ensemble algorithms, linear models, discriminant analysis, Support Vector Machines (SVMs), Naïve Bayes Classifier and Decision tree classifier. The ensemble algorithms that will be applied in this study include the Random Forest Classifier, Light Gradient Boosting Machine (LGBM) and Extra Trees Classifier(ETC), Gradient Boosting Classifier(xgboost) and AdaBoost Classifier (Diaz-Uriarte et al., 2021; James et al., 2024). The Random Forest Classifier constructs an ensemble model that consists of decision trees that are trained on randomly selected subgroups of the features. The AdaBoost and xgboost classifier are based on a gradient learning approach that is based on the sequential improvement of the on the inaccurate predictions of a weak learners (Chen et al., 2022). The LGBM is an improvement of gradient learning algorithms, based on a histogram approach that consists of an ensemble of weak learners that has reduced risk of overfitting, enhanced speed and accuracy in prediction (Junliang et al., 2019).

The Area Under the Curve (AUC) is a metric that is used to assess the performance of classification algorithms. It is calculated from the area under the Receiver Operating Characteristic (ROC) curve that plots the True Positive Rates against False Positive Rates (Jostens & Van Der Burgt, 2022; Fawcett, T. 2023). The threshold for a fairly accurate machine learning model will range from an AUC of 60% to 70% with higher values indicating a higher level of accuracy. Feature Importance plots are graphical visualisations that show a hierarchical plot of features based on their influence on the predictions of the models (Molnar, 2022). The plots provide insights into important factors that influence the occurrence of outcomes and can facilitate the explainability of complex machine learning models.

3. RESULTS

3.1 Demographics

The demographic variables that were considered in the research study included gender, age, and work position. Reliability analysis was conducted on the data for the 195 participants. Out of the 394 individuals that were initially recruited, there was a 50% response rate. From the resulting sample with a total of 195 participants, there were no missing data items. The Table1 below shows the characteristics of the sample for this research study.

Table 1. Sample Characteristics

Variable	Descriptive Statistics	
Total Sample	**n =**	**195**
Gender	Female	68.2%
	Males	31.8%
Age	Minimum	24
	Median	39
	Mean	39
	IQR	9
	Standard Deviation	7
	Maximum	60
Modules Completed to date	Minimum	0
	Median	3
	Mean	4.3
	IQR	4.5
	Standard Deviation	4.8
	Maximum	18
Position at Work	Director	1.5%
	Senior Manager	10,8%
	Manager	37.9%

	General Employee	26.2%
	Other	23.6%
Contract Category	Permanent Temporary Other	79% 13.8% 7.2%
Year of Registration of MPH	2017	1.5%
	2018	3.1%
	2019	1.5%
	2020	8.7%
	2021	23.6%
	2022	61%
	2023	0.6%

The sample consisted of more female respondents (68.2%) compared to male counterparts (32%). The average age of the participants was 39 years, and the median age was 39 years. The standard deviation, which shows the degree of dispersion around the mean, is about 7 years.. The research population covered a wide range of professional groups from directors, senior managers, managers, general workers, and others such as specific professionals e.g. Environmental Health Practitioners. Clinician participants were identified according to their professional roles as shown in Figure. 3 below which illustrates the composition of the study population. The highest number of MPH students were managers (38%) in their workplace and the lowest group were MPH students in strategic positions such as directors (1,5%). Most of the participants were permanently employed (79%). The median number of modules completed by participants was 2 with an interquartile range (IQR) of 4.5. Most of the participants had registered at the university in the year 2023.

3.2 Online Learning Platform Perception by MPH Students

The Chi-square and Fisher’s exact tests examined relationships between various factors such as gender, learning tools, departmental support, etc, and perceptions among Master of Public Health (MPH) students. Null hypotheses assumed no associations, while alternative hypotheses proposed significant relationships. In addition to the Pearson correlation tests, the Bayesian statistical analysis was also applied and the bayes factors were reported.

3.3.1 General support perceptions of students

Most of the respondents in the survey were registered at the university in the years 2020, 2021 and 2022. In the sample, the year 2022 that had the highest number of respondents who registered at the university (n= 119). For these respondents, there was a strong positive perception of general support effectiveness from the department and the faculty from about one third of the respondents. The Fisher’s Exact tests were applied to investigate associations between the general support effectiveness perceptions and year of registration.

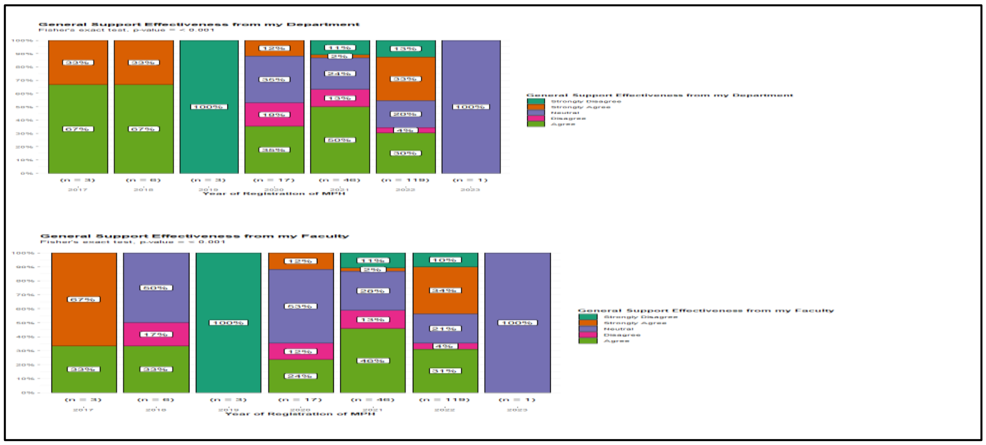

FIGURE 1
GENERAL SUPPORT EFFECTIVENESS AND YEAR OF REGISTRATION

The figure above shows that the students who registered in different years had significant different perceptions of general support effectiveness. The Fisher's exact test indicated that there was a significant association between the year of registration and perceptions of general and departmental support effectiveness ($p < .0001$).

3.3.2 Ease of access to facilitators and student perceptions

The results revealed that the aid from module facilitators was not applicable for 4.1% of respondents (n=8) and 23% (n=45) indicated they had not received any assistance. In contrast, a large portion, 74% (n=142) of the sampled students, admitted to receiving support from either facilitators or the department.

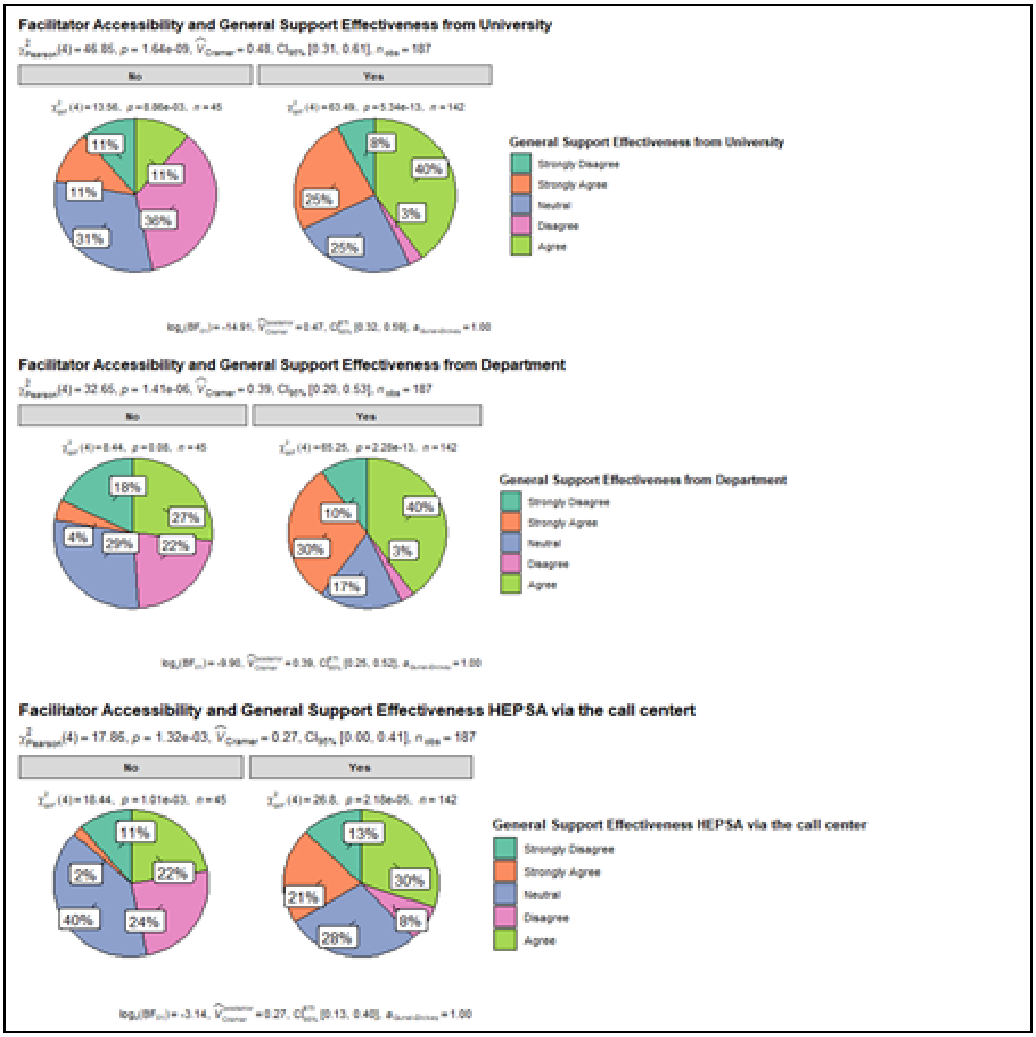

FIGURE 2
FACILITATOR ACCESSIBILITY AND GENERAL SUPPORT EFFECTIVENESS

The x^2 Pearson test revealed that the ease of accessing assistance from facilitators was associated with perceptions of general support ($p < .001$) and departmental support ($p < .001$), as well as with HEPSA call center support ($p < .001$). Furthermore, the Bayesian analysis revealed that there was strong evidence for an association compared to the null hypothesis. The students with facilitators that were easily accessible were more likely to strongly agree with the general support effectiveness from the university, department and HEPSA via the call center. Furthermore, the association of accessibility of facilitators and satisfaction were investigated and the results are shown in Figure 3 below.

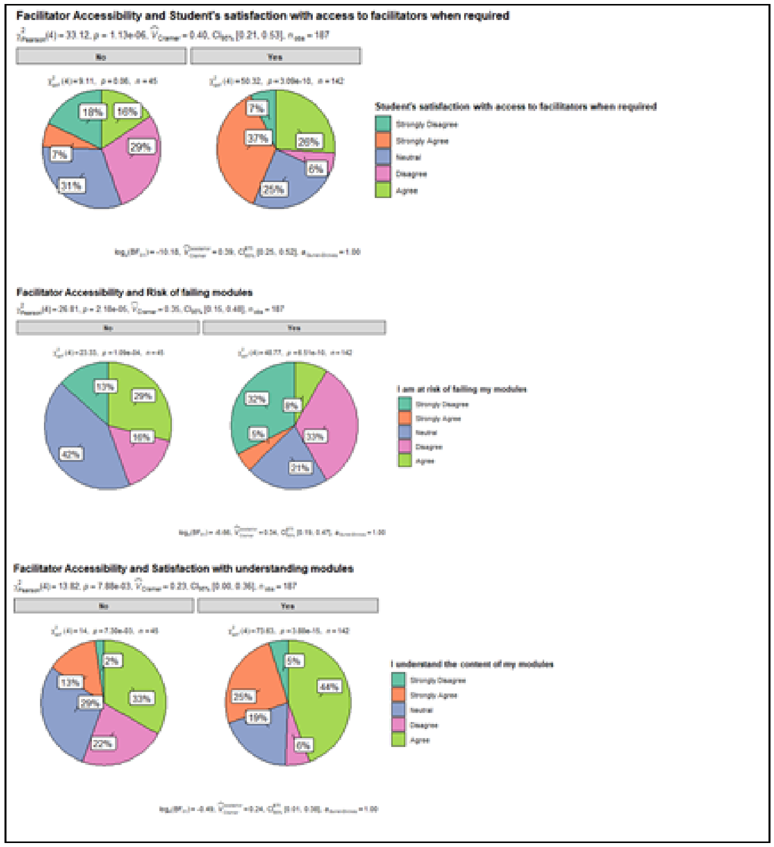

FIGURE 3
FACILITATOR ACCESSIBILITY AND SATISFACTION WITH ACCESS TO FACILITATORS, RISK AND UNDERSTANDING MODULES

The x^2 Pearson test revealed that satisfaction with access to facilitators ($p < .001$), risk of failing ($p < .001$) and understanding module content ($p < .01$) were significantly different based on the perceived ease of obtaining assistance from facilitators. The students who perceived that the facilitators were accessible were almost twice likely to be strongly satisfied with their understanding of the content of modules (25%) than those who perceived facilitators as being inaccessible (13%). The Bayesian analysis reveals that there is strong evidence for an association between facilitator accessibility and risk of failing modules(loge(BF01) = -10.18). Furthermore, there was also moderate evidence for the association between facilitator accessibility and satisfaction with understanding module content(loge(BF01) = -0.49).

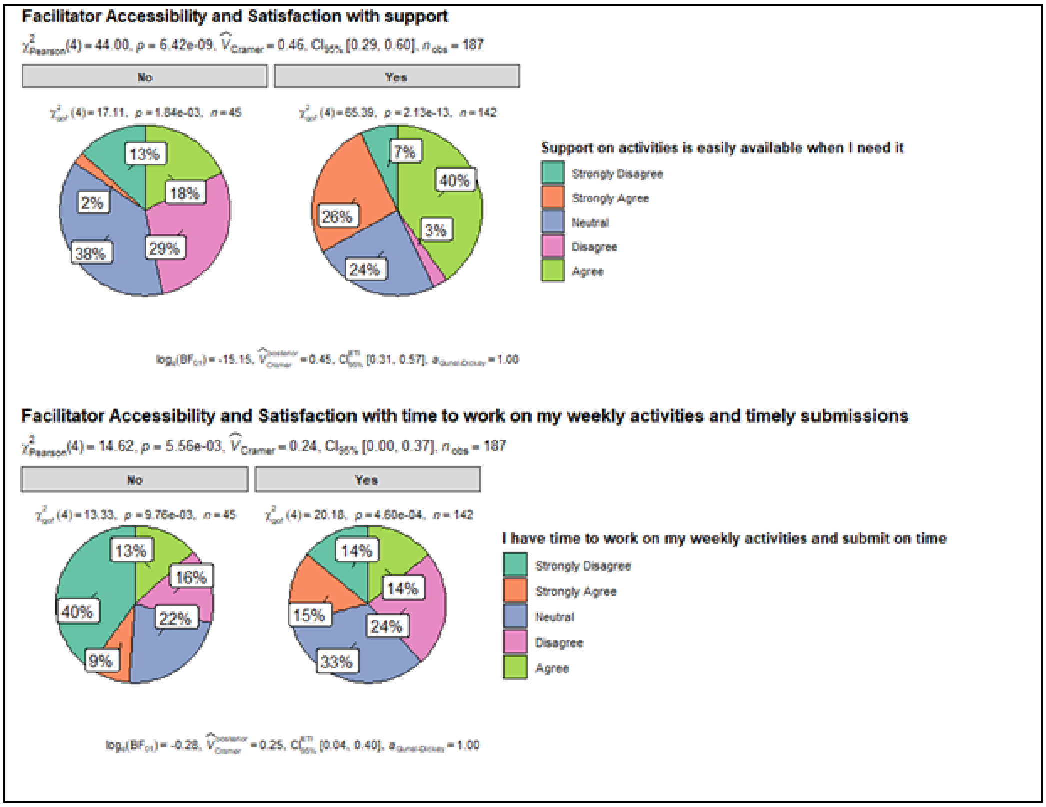

FIGURE 4
FACILITATOR ACCESSIBILITY AND SATISFACTION WITH SUPPORT, TIME FOR ACTIVITIES/SUBMISSIONS

Furthermore, ease of obtaining assistance from facilitators was related to the support availability for activities ($p < .001$), and timely completion of weekly activities ($p = .040$). These findings provide evidence supporting the alternative hypotheses, indicating significant relationships between these factors and students' perceptions. The Bayesian analysis reveals that there is strong evidence for an association between facilitator accessibility and satisfaction with support availability(loge(BF01) = -15.15). Furthermore, there was also moderate evidence for the association between facilitator accessibility and satisfaction with time to work on weekly activities and timely submissions(loge(BF01) = -0.28).

3.3.3 Blackboard experience and student perceptions

The perceptions of the blackboard as the best platform for online learning for MPH were generally positive with almost 7 out of 10 participants (70.8%, n= 138) in agreement. This indicates that there is recognition by majority of participants that the blackboard as a useful technological platform for learning. Furthermore, there was generally a positive perception of with almost three quarters of the participants (72.8%, n= 142) in agreement. This generally indicates that navigation of the blackboard is generally user friendly for most students.

FIGURE 5
BLACKBOARD EXPERIENCE AND YEAR OF REGISTRATION

The figure above generally shows that the perceptions of the ease of the navigation of the blackboard and for submission of activities were significantly varied with different years of registration of MPH. The fisher's exact test revealed that the year of registration was associated with the student perceptions of the ease of the navigation of the Blackboard (p = .03) and using it to submit of activities (p = .04). Almost four tenths of the participants who registered in the year 2022 have a strong positive perception of the ease of submission of activities on the blackboard.

3.3.4 Perceived levels of general support, blackboard experience and satisfaction

The scales of general support, blackboard experience and satisfaction variables were recoded into a numerical 5-point Likert scale in according to the Table 2 below.

Table 2. Scale for Rating

Strongly Disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

The table above indicates that a score below 3 generally indicated a negative perception towards the variables being measured and the those with a score above 3 indicated a positive perception.

Table 3. Descriptive Statistics and normality test

Research Variable	Mean	Median	IQR	Standard Deviation	Kolmogorov-Smirnov Test D	p-value	Normality
General Support Effectiveness							
General Support Effectiveness from University	3.47	4	1	1.17	0.8952	< .0001	Non-normal
General Support Effectiveness from my Faculty	3.52	4	1	1.22	0.8747	< .0001	Non-normal
General Support Effectiveness from my Department	3.52	4	1	1.25	0.8593	< .0001	Non-normal
General Support Effectiveness HEPSA via the call center	3.24	3	1	1.21	0.8593	< .0001	Non-normal
Blackboard Experience							
Blackboard is the best platform for online learning	3.79	4	1	1.06	0.9106	< .0001	Non-normal
I find it easy to navigate on blackboard	3.84	4	2	1.09	0.9157	< .0001	Non-normal
Blackboard orientation helped me to quickly and easily understand how the blackboard works	3.50	4	1	1.19	0.8850	< .0001	Non-normal
I find it easy to submit activities on blackboard	3.92	4	1	1.16	0.9003	< .0001	Non-normal
I am happy with using blackboard for my online learning experience	3.92	4	1	1.13	0.9054	< .0001	Non-normal
Satisfaction							
Student's satisfaction with access to facilitators when required	3.51	4	2	1.27	0.8849	< .0001	Non-normal
I am at risk of failing my modules	2.35	2	2	1.13	0.8413	< .0001	Non-normal
I understand the content of my modules	3.69	4	1	1.05	0.9362	< .0001	Non-normal
Support on activities is easily available when I need it	3.47	4	1	1.15	0.8952	< .0001	Non-normal
I have time to work on my weekly activities and submit on time	2.76	3	2	1.30	0.8413	< .0001	Non-normal
I prefer online learning compared to attending classes physically on campus	3.86	4	2	1.26	0.8901	< .0001	Non-normal

The levels of positive satisfaction with the ease of submission of activities (Mean = 3.92, Median = 4, IQR = 1) and online learning experience (Mean = 3.92, Median = 4, IQR = 1) using the blackboard were the highest. The risk of failing modules was perceived to be low (Mean = 2.35, Median =2, IQR = 2). On average, there was a negative perception of satisfaction with time to work on weekly activities and submit on time (Mean = 2.76, Std Dev =1.30) with the average rating being lower than rating of 3. The Kolmogorov Smirnov test was used to assess the normality of the distribution of the ratings. The test revealed that the distribution of all the variables significantly deviated from a normal distribution.

3.3.5 The relation between general support, blackboard experience and satisfaction

Spearman's rank correlation coefficient was used to measure the relationship between the general support, blackboard experience and satisfaction variables. The Figure 6 below shows the magnitude of the correlations between the variables at a significant level of 5% and those correlations that are non-significant at the 5% level being crossed out.

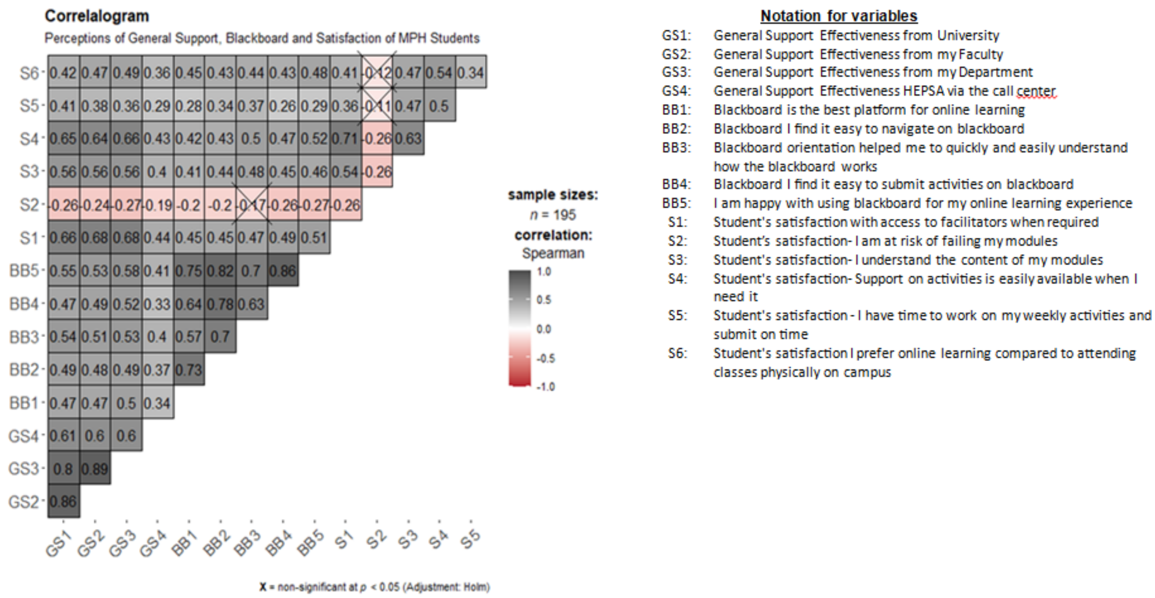

FIGURE 6
CORRELOGRAM OF GENERAL SUPPORT, BLACKBOARD EXPERIENCE AND SATISFACTION VARIABLES

There was a significantly strong relationship between student's satisfaction with access to facilitators and perceptions of general support effectiveness from the university, faculty, and department at the 5% significance level. The risk of failing had a small negative correlation with general support effectiveness from the university, faculty, and university. Furthermore, it was negatively correlated to blackboard platform usage, desirability and how it facilitates ease in the submission. The satisfaction with the usage of the blackboard online learning had strong positive relationship with general support effectiveness from the university, faculty and department.

3.3.6 The factors that influence satisfaction

Machine learning algorithms were applied to establish the factors that had the largest influence in predicting the variables of student's satisfaction. The following machine learning algorithms were investigated for the student satisfaction variables:

- Random Forest Classifier
- Light Gradient Boosting Machine (LGBM)
- Linear Discriminant Analysis
- Extreme Gradient Boosting (xgboost)
- Logistic Regression
- Random Forest Classifier
- Extra Trees Classifier

- Ridge Classifier
- Gradient Boosting Classifier
- Ada Boost Classifier
- Naive Bayes
- Decision Tree Classifier
- Quadratic Discriminant Analysis
- SVM

The best model for the prediction of each satisfaction variable was selected based on the Area Under the Curve (AUC) metric. The tuning of the hyperparameters of the models applied the grid search method with 10 folds to optimise the AUC. The table below shows the satisfaction variables that were predicted, the best performing machine learning algorithms and the AUC as a measure of the performance of the algorithm.

Table 4. Machine Learning Model Performance of Prediction of Satisfaction

Student's Satisfaction Variable	Best Performing Algorithm	AUC
Access to facilitators when required	Light Gradient Boosting Machine	76.12%
Support on activities is easily available when I need it	Random Forest Classifier	83.48%
Time to work on weekly activities and submit on time	Ada Boost Classifier	63.66%
Preference of online learning compared to attending classes physically	Extreme Gradient Boosting (xgboost)	63.92%

The model performance of the algorithms and the most important factors influencing the satisfaction of the variables are further evaluated using the ROC curve and feature importance plots. The Figure 7 below shows the ROC curve, and the feature importance plots for satisfaction with access facilitators when required.

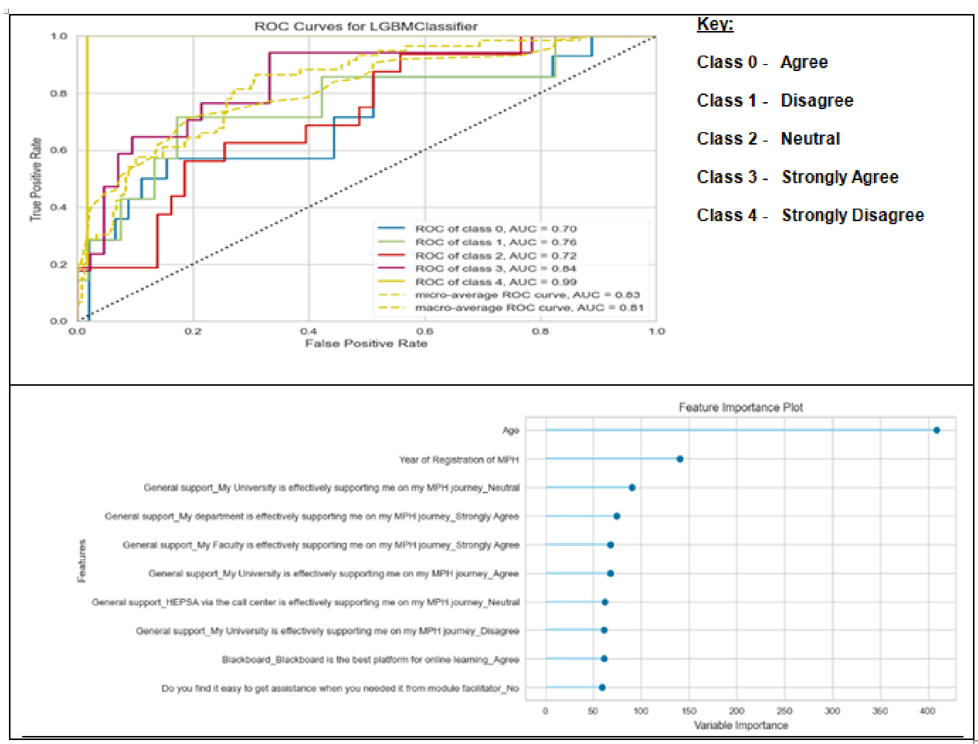

FIGURE 7
ROC AND FEATURE IMPORTANCE PLOT FOR PREDICTION OF SATISFACTION WITH ACCESS FACILITATORS

The ROC in the figure above indicates that the LGBM had a high accuracy in predicting the students who strongly disagree (AUC = 99%) and strongly agree (AUC = 84%) that they have access to their facilitators when they are required. The feature importance plots show that age, year of registration and general support effectiveness were the most important factors that determined the satisfaction of students with access to facilitators. The Figure 8 below shows the ROC curve, and the feature importance plots for satisfaction with support on activities being easily available when required by students.

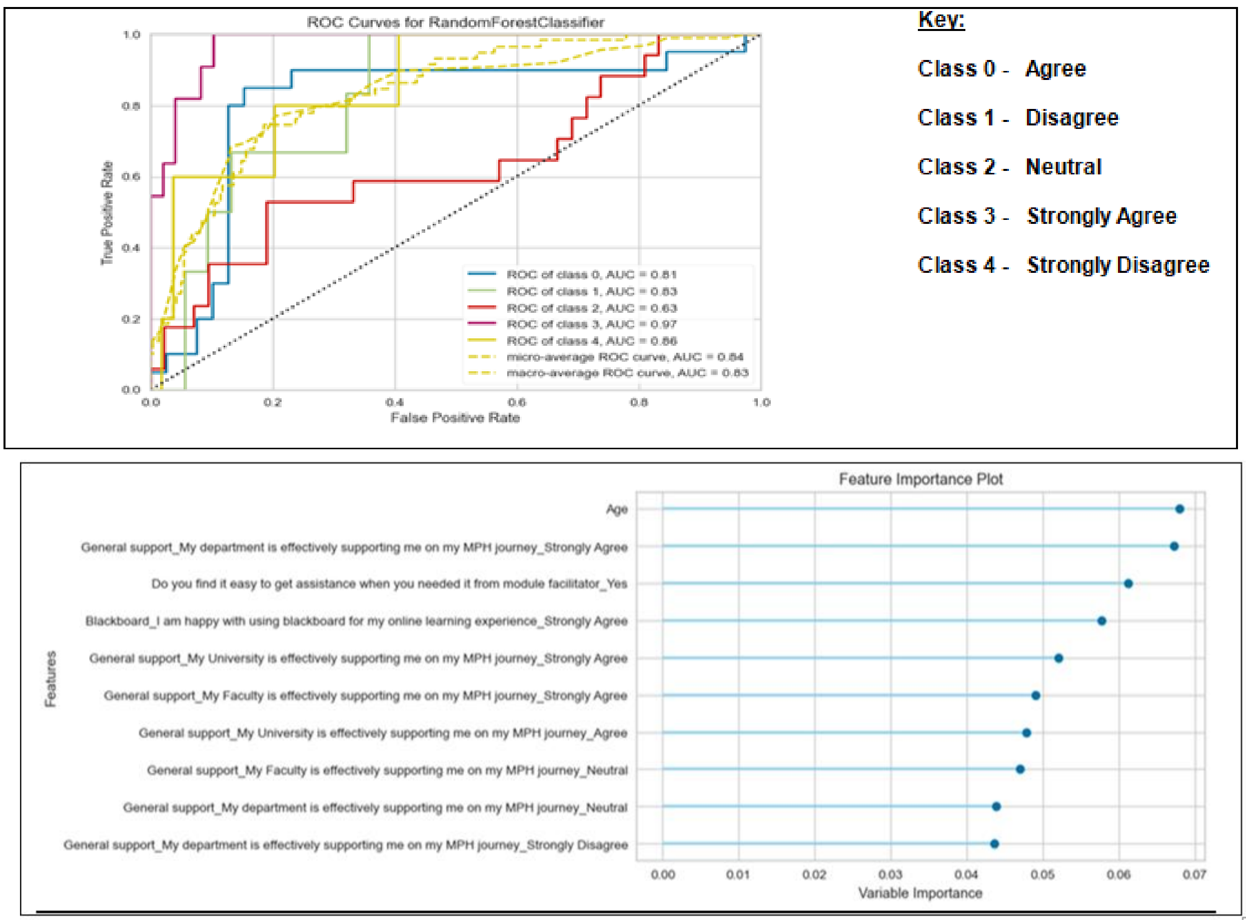

FIGURE 8
ROC AND FEATURE IMPORTANCE PLOT FOR PREDICTION OF SATISFACTION WITH ACCESS FACILITATORS

The ROC in the figure above indicates that the Random Forest Classifier had a high accuracy in predicting the students who strongly agree (AUC = 97%) and strongly disagree (AUC = 84%) that support on activities is easily available when required. The feature importance plot shows that age, general support effectiveness and the blackboard experience were important factors that determined the satisfaction with support being easily available. The Figure 9 below shows the ROC curve, and the feature importance plots for satisfaction with time to work on weekly activities and submit on time.

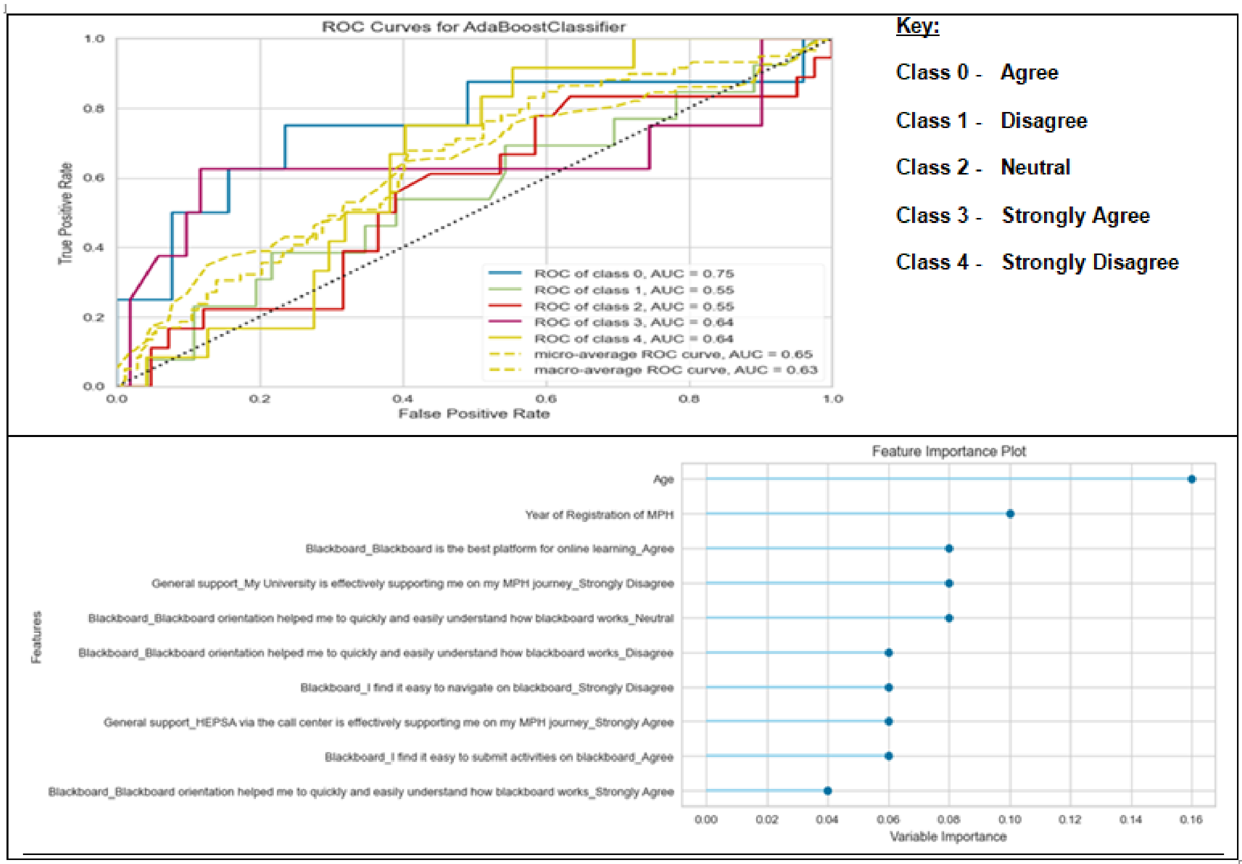

FIGURE 9
ROC AND FEATURE IMPORTANCE PLOT FOR PREDICTION OF SATISFACTION WITH TIME TO WORK ON WEEKLY ACTIVITIES AND SUBMIT ON TIME

The ROC in the figure above indicates that the Ada Boost Classifier had a high accuracy in predicting the students who agree (AUC = 75%) that they have time to work on weekly activities and submit on time. The feature importance plot shows that age, year of registration and the orientation and ease of submission using the blackboard were important factors that determined the satisfaction with having adequate time to work on weekly activities and submit on time. The Figure 10 below shows the ROC curve, and the feature importance plots for preference of online learning compared to attending classes physically.

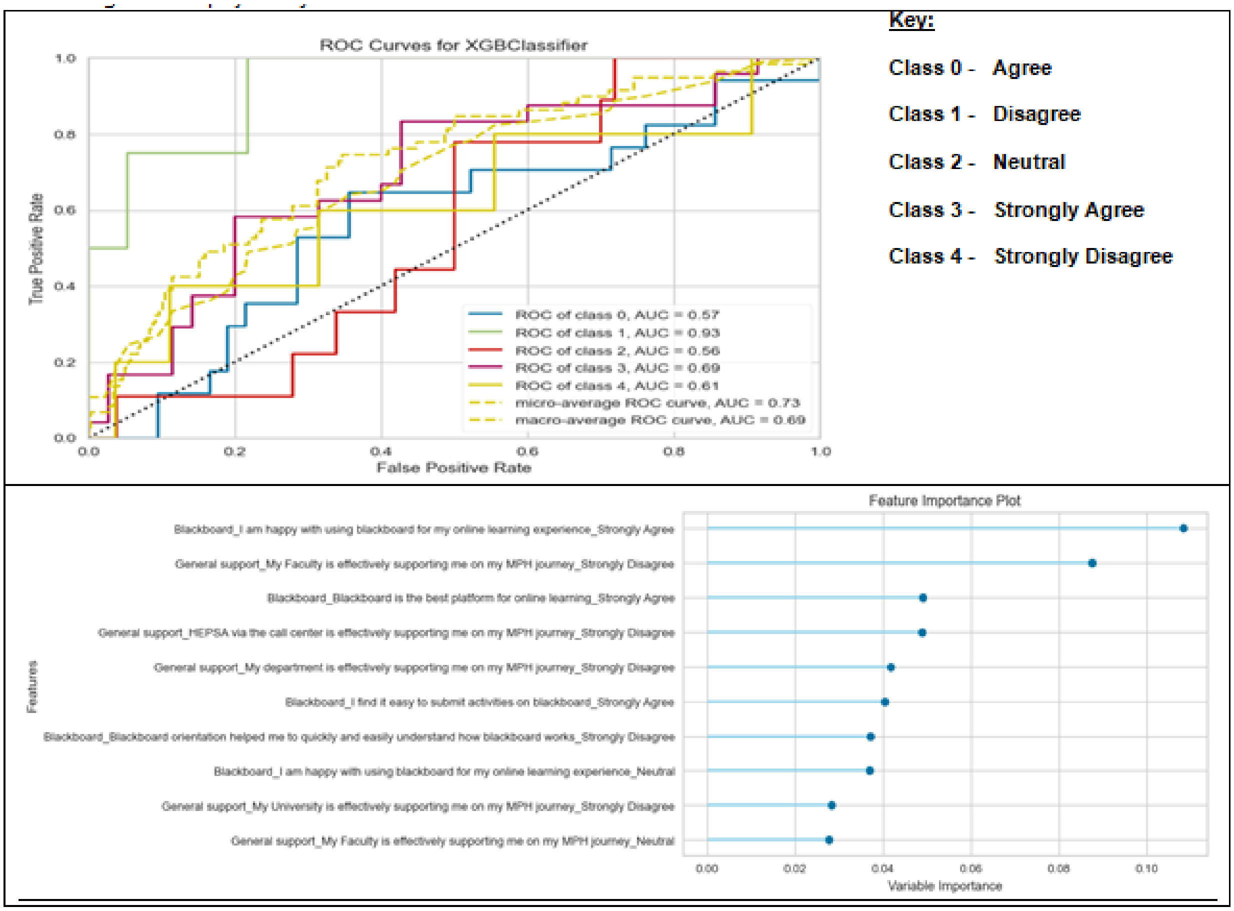

FIGURE 10
ROC AND FEATURE IMPORTANCE PLOT FOR PREDICTION OF PREFERENCE OF ONLINE LEARNING COMPARED TO ATTENDING CLASSES PHYSICALLY

The ROC in the figure above indicates that the xgboost classifier had a high accuracy in predicting the students who disagree (AUC = 93%) that they prefer online learning compared to those attending classes physically. The feature importance plot shows that blackboard experience, use and ease of submission were important factors in determining the preference of online learning compared to attending classes physically. Furthermore, general support effectiveness through the call center and by the university were important factors.

4. DISCUSSION

4.1 Perception of online learning

A study by Alghamdi et al. (2021) found that students appreciated the flexibility, convenience, and accessibility of online learning, as well as the opportunity to develop their self-regulation and digital skills. While Kaur et al (2020) found that students had mixed feelings about online learning, such as frustration, boredom, anxiety, and satisfaction.

4.2 Supportive online learning environment

The relationship between academic success, distance education learning, or eLearning environments is also connected to interaction and communication between the department, lecturers, and students (Ghasempour et al, 2023). The observed trends in perceptions of support effectiveness and satisfaction among Master of Public Health (MPH) students align with previous research highlighting the influence of temporal factors and academic progression on student experiences. A study by Smith et al. (2019) found that students' satisfaction with university support services varied based on the timing of their enrollment, suggesting a similar temporal influence on support perceptions. Furthermore, Jones and Brown (2020), demonstrated that students' satisfaction with academic support services was positively correlated with their progression through the program, echoing the findings regarding module completion in the current study. Consistent with the importance of responsive support services identified in this research, a study by Johnson et al. (2018) emphasised the pivotal role of accessible assistance from faculty in shaping student satisfaction and academic success. While the absence of clear linear trends in some relationships parallels findings in previous studies (Johnson et al., 2018), the limitations due to low expected frequencies highlight a common challenge in analysing student satisfaction data (Smith et al., 2019). Together, these findings emphasise the nuanced nature of student support experiences within MPH programs and underscore the importance of tailored support strategies informed by factors such as registration year and academic progression.

The analysis of students' perceptions regarding support accessibility and its impact on academic satisfaction resonates with findings from other studies, indicating the crucial role of accessible support structures in fostering student success and satisfaction within educational programs. Ghasempour et al, (2023) found that students reported moderate levels of academic success and positive perceptions of their distance education learning environment. They also found that the distance education learning environment and field satisfaction were significantly associated with student's academic success. They concluded that improving the learning environment of distance education and increasing students’ satisfaction could enhance their academic outcomes. Alghamdi et al. (2021) found that students faced technical, pedagogical, and psychological difficulties, such as poor internet connection, lack of interaction, and increased stress and anxiety.

4.3 Socioeconomic factors impact on online learning

Notably, Aristovnik et al. (2020) highlight the influence of socioeconomic factors on learning outcomes, with gender disparities observed in support perceptions, as reflected in the majority of higher education students being female. Furthermore, the transition to online learning, accelerated by the COVID-19 pandemic, has presented challenges for both students and educators, as noted by Hamdan and Amorri (2022). This shift necessitates adaptations in teaching methodologies and technologies, with studies emphasising factors such as technology use, student participation, time management, and workload distribution, all of which significantly impact student performance and success (Nathan, 2020). Kaspar et al. (2023) in their study of online learning during the Covid-19 pandemic found that students’ age was positively related to all online learning perceptions and engagement and that self-regulation skills and academic and digital media self-efficacy were important factors for various online learning experiences. They also found that personality traits and state anxiety were less important for most online learning experiences.

4.4 Impact of online learning on knowledge and success

This study indicates that module failure is relatively uncommon within the student sample. the majority of students (90.26%) have successfully passed all their modules. For educational institutions, a low module failure rate suggests effective teaching methods, student support, and rigorous assessment processes. However, it’s essential to identify the reasons behind the 9.74% failure rate to provide targeted interventions and improve student outcomes. Other studies indicated that the majority of students report increased workloads, particularly in regions like Oceania, Europe, and North America, underscoring the need for ongoing support and adaptation in educational practices to ensure student satisfaction and success (Aristovnik et al., 2020; Hamdan & Amorri, 2022; Nathan, 2020; Sun, 2016). These findings collectively highlight the importance of understanding and addressing students' support needs within the evolving landscape of higher education.

4.5 Limitations of the study

Students who participated in this study were at different levels of study and were experiencing various challenges. Their personal experiences also influenced their overall perception of their experience in the Master's in Public Health program.

5. CONCLUSION

Online learning fosters collaboration among students from diverse backgrounds through virtual discussion forums and group projects. This exposure to different perspectives cultivates critical thinking skills and encourages cross-cultural understanding essential attributes in today's globalised world. The findings underscore the critical role of accessible support structures, such as facilitator assistance and support availability, in facilitating student success and satisfaction within educational programs. Easy access to assistance from module facilitators positively correlates with students' satisfaction with timely completion of activities, comprehension of module content, and overall satisfaction with support availability. The results also highlight the importance of considering sociodemographic factors, such as gender, in understanding and addressing variations in support perceptions among students. Female participants tend to express higher levels of agreement with general support, indicating a gender disparity in support perceptions within academic programs. Lastly, the transition to online learning, accelerated by the COVID-19 pandemic, presents both challenges and benefits. While online learning offers flexibility and accessibility, it also requires adaptation from both educators and students, with factors such as technology use, time management, and workload affecting student performance and satisfaction.

Distance learning also allows students to develop valuable digital literacy skills as they navigate various technological platforms and tools. In an era where digital competency is increasingly sought after by employers, this proficiency gained through online education can significantly enhance career prospects. While traditional face-to-face interactions undoubtedly hold their own value in higher education settings, it is evident that online learning has emerged as a powerful complement rather than a replacement. By harnessing the potential of artificial intelligence alongside distance learning platforms, institutions can create an immersive educational environment that caters to individual needs while preparing students for success in the rapidly evolving job market of the Fourth Industrial Revolution. These findings emphasise the importance of tailored support strategies, ongoing adaptation to online learning environments, and addressing sociodemographic disparities in fostering positive academic experiences and outcomes for students within higher education institutions.

6. ACKNOWLEDGMENTS

The authors also wish to thank the Department of Environmental Health Staff and the Master of Public Health Students for participating in this project.

7. CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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