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Student Acceptance and Satisfaction with Machine Learning Applications in Higher Education Institutions

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Abstract

Purpose: The purpose of the study was to identify the factors that influence students' acceptance and satisfaction of machine learning (ML) usage and adoption; to analyse the acceptance rating and satisfaction of the students in higher education institutions on machine learning applications on their educational experiences and to determine the predictors that influence the acceptance and satisfaction of machine learning techniques among students in higher education institutions.

Design/methodology/approach: This study adopted a descriptive research design and a quantitative approach. Primary data was obtained through a survey questionnaire where snowball sampling was employed with a total of 176 students from different HEIs. Chi-square test and regression analysis were employed to assess the association and relationship between students' demographic profiles, specialization, ML acceptance, and satisfaction.

Findings: The results of the study revealed a very high acceptance rating of machine learning among the students and a high level of satisfaction with the ease of use of machine learning techniques. It was also found that there was no significant association between the classification of major/specialization of the field of study and with Acceptance rating of ML and no significant association between the classification of major/specialization and the Ease of use of Machine Learning techniques. It was also found that there was no significant association between Gender with the Satisfaction Rating of ML and there was no significant association between the Gender and the Acceptance Rating of ML. There was no impact of the demographic factors viz. Gender, Nationality, Residence, Age, Classification of Major/Specialization of the study, and the familiarity level on the students' Satisfaction with ML techniques while the socioeconomic factors – Marital Status and the Acceptance Rating of Machine Learning techniques had an impact on the Satisfaction of Machine Learning utilization and adoption in higher education institutions.

Research limitations/implications: The study was focused on students' acceptance and satisfaction with ML utilization and adoption in higher education institutions. This initiative is limited by its sample size and the geographical focus on specific universities.

Social Implications: This study will help policymakers to develop ML applications with intuitive interfaces to ensure accessibility for students to improve user experience and to ensure that ML tools are adaptable to the needs of students avoiding socioeconomic biases to advocate policies that prioritize equitable technology distribution.

Originality / Value: This research explores diverse factors influencing students' acceptance and satisfaction with machine learning technologies utilized in HEIs. It gives further scope to examine the nuanced effects of other personal factors and contexts (e.g., part-time students or working professionals) on technology acceptance and to conduct longitudinal studies to explore how satisfaction with ML evolves over time and across different educational stages.

Keywords: Machine Learning, Higher Education Institutions, HEIs adoption of Machine Learning, Students' Acceptance of ML, Students' Satisfaction on ML Utilization, Students' Satisfaction on ML Adoption.

Introduction

Machine learning (ML) has emerged as a groundbreaking technological advancement, profoundly influencing numerous sectors, including education

In the context of higher education, ML tools are being integrated at an increasing rate to enrich learning experiences, enhance administrative processes, and provide personalized educational opportunities. The adoption of ML in higher education institutions aims to transform traditional teaching methods by fostering innovation, improving engagement, and offering tailored learning pathways for students.

Students' acceptance and satisfaction with ML techniques, when appropriately applied across various specializations, are crucial for maximizing the potential benefits of these technologies. Numerous factors, such as perceived ease of use, perceived usefulness, and technological readiness, have been identified as significant determinants of ML acceptance and satisfaction. Research highlights that ML is one of the most promising technologies for educational development, as it facilitates efficient learning and teaching experiences. According to (Alyoussef, 2021), perceived ease of use and usefulness significantly shape students' attitudes toward ML usage in educational settings.

As higher education institutions continue to invest in ML technologies, understanding their impact on diverse learning environments becomes increasingly important. Machine learning has the potential to bridge educational gaps by enabling data-driven decisions, predicting student outcomes, and identifying personalized strategies to improve learning efficiency. However, realizing these benefits requires thorough research into the experiences and perceptions of students who engage with these technologies.

To ensure the effective integration of ML in higher education, it is imperative for institutions to continuously evaluate the factors influencing students' acceptance and satisfaction. Understanding these dimensions will enable the creation of strategies that align technological adoption with students' educational needs and expectations. This study aims to examine the acceptance and satisfaction levels of students in Oman's higher education institutions concerning ML applications and identify the predictors influencing these factors.

Statement of the Problem

Despite the growing interest and investment in machine learning technologies within higher education institutions, there remains a lack of comprehensive understanding of students' acceptance and satisfaction with these tools. While ML holds promise in enhancing educational experiences, the variability in students' attitudes, technological readiness, and satisfaction poses challenges to its widespread adoption and effectiveness.

Research Questions

This research seeks to address the following questions:

1. What is the Ease of use and acceptance level of students in higher education institutions regarding the application of machine learning to their educational experiences?
2. What demographic factors influence the acceptance rating of students in higher education institutions regarding the application of machine learning to their educational experiences?
3. What predictors (demographic factors & socio-economic factors) influence students' satisfaction with machine learning technologies in higher education institutions?

Addressing these questions is critical for understanding the enablers and barriers to ML adoption, ensuring that higher education institutions can design and implement ML strategies that resonate with students' needs and preferences.

Research Objectives

1. To analyse the Ease of use and the acceptance level of students in higher education institutions regarding the application of machine learning to their educational experiences.
2. To analyse whether the demographic factors Gender and the major/specialization of their study, influence the acceptance rating of students in higher education institutions regarding the application of machine learning to their educational experiences.
3. To determine the predictors (demographic factors & socio-economic factors) that influence students' satisfaction with machine learning technologies in higher education institutions.

The primary aim of the study was to assess student acceptance and satisfaction rating regarding the use of Machine Learning techniques in the Higher Education Institutions of Oman. Understanding various factors that influence their perceptions and how these technologies impact their academic experiences was also determined.

Literature Review

Machine Learning Utilization and Adoption in HEIs

Machine learning (ML) has been transforming higher education by utilizing such technologies in most of its programs and areas of specialization. Jordan and Mitchell (2015) claimed that the adoption of ML is applicable across many walks of life such as healthcare, manufacturing, education, etc. hence, all specializations can have comparable levels of familiarity with the said technologies. Sarker (2021) also suggested machine learning as the key to intelligently analysing data in different forms using various types of algorithms suitable to various domains such as cybersecurity, smart cities, healthcare, e-commerce, agriculture, and others.

The most widely used application of ML in higher education according to the findings was predicting academic performance and employability of students (Pinto et al., 2023). A graduate tracer study was conducted by Al Dhuhli et al. (2022) to derive valuable information to find out the whereabouts and performance of Oman Tourism College graduates in their workplaces. Predicting the employability of tourism graduates in the tourism and hospitality sector was conducted by Crisostomo et al. (2023) utilizing a tree-based classifier, which showed that occupation is the most influential factor for employability followed by the job sector. Other attributes that were used in classifying the employment status of the graduates include occupation, job sector, specialization, degree, age, personality development skills, cultural competency, leadership, interpersonal skills, creativity, and problem-solving skills. The above initiatives showed how ML has emerged as one of the technologies enabling higher education transformation.

Factors Influence Acceptance and Satisfaction on Machine Learning (ML) Usage

Albayati (2024) employed the Technology Acceptance Model (TAM) and identified the factors of privacy, security, social influence, and trust – collectively which influenced undergraduate students' acceptance and utilization of ChatGPT. The students found the tool easy to use, and useful and experienced favourable social impact. Al-Abdullatif (2023) highlighted significant drivers of chatbot acceptance among students, such as perceived usefulness, perceived ease of use, attitude, perceived enjoyment, and perceived value. According to Na et al. (2022), technological factors coupled with external attributes and varied persons' personalities had a positive impact on AI-based technology's perceived usefulness and perceived ease of use. Li (2023) found that perceived usefulness and perceived ease of use of AI-based systems positively influence students' attitudes, intentions, and actual use of these systems. However, college students' attitudes towards AI-based systems indicated an insignificant effect on their learning motivations and in achieving their goals and subjective norms. Velli and Zafiropoulos (2024) revealed perceived usefulness as the most noteworthy factor of teachers' intention to utilize Educational AI Tools. Moreover, trust was likewise found to have a significant influence on usefulness.

Almaghrabi et al. (2024) identified usability, privacy, security, and ICT support as the determinants of utilizing AI and ML models predicting users' satisfaction with ICT administrative systems, found that the significant implications of ML utilization enhancing educational institutions' administration and benefiting both decision-makers and developers. Yu et al. (2024) found that the tools' compatibility had a positive effect on users' perceived ease of use and efficiency affected perceived usefulness. Almufarreh (2024) suggested that factors like content quality, emotional well-being, and perceived utility determine student satisfaction with AI tools. Artificial neural network (ANN) outcomes revealed that emotional well-being is the most vital factor in satisfaction equally followed by content quality and perceived utility.

Programs or specializations and ML Familiarity

In recent years, machine learning's progress has been propelled by underlying theory, newly developed algorithms, and the availability of data online. Implementation and adoption of big data and machine learning approaches are found across many walks of life i.e., healthcare, manufacturing, education, financial modelling, policing, and marketing (Jordan & Mitchell, 2015). Sarker (2021) suggested ML as the key to intelligently analysing data in different forms using various types of domains/algorithms such as cybersecurity, smart cities, healthcare, e-commerce, agriculture, and others. Kurshumova (2024) found that the only significant predictor of AI use was technology familiarity. Younger students seemed to have a higher level of familiarity and utilized it for learning requirements and most of them recognized the need for AI skills and literacy for efficient utilization and implementation (Liu & Wu, 2024).

Relationship between Gender and Satisfaction on ML Technologies

In predicting self-regulated learning among students, studies revealed that girls perceive more support than boys. Satisfaction with autonomy and competence is moderated by both gender and AI knowledge, whereas satisfaction with relatedness is only moderated by gender (Xia et al., 2023). Aboudahr et al. (2023) on the

acceptance of augmented reality (AR) among students in Malaysian higher education suggested that male students had higher satisfaction and stronger relationships in using AR than female students. Gender plays a crucial role as a determinant of students' use of AI-based tools in education. (Ofosu-Ampong, 2023). Joseph et al. (2024) claimed that male students had a higher level of awareness and positive perception of AI tools while female students were stronger than male students whereas Perception and awareness directly influenced utilization.

Relationship between Students' acceptance and satisfaction with ML technologies

Pan (2020) revealed that students' acceptance and technological self-efficacy affect their attitude toward self-directed learning. Albayati (2024) emphasized that favourable and positive perceptions of the factors – perceived ease of use, perceived usefulness, privacy concerns, security considerations, social influence, and trust affect acceptance of ChatGPT, and promote positive attitudes toward ChatGPT utilization. It was also indicated that having a user-friendly interface and practical benefits of ChatGPT positively correlate with favourable attitudes and acceptance among students, presenting a compelling case for the tool's integration into educational approaches. Leelavathi and Surendhranatha (2024) and Tiwari (2024) recommended that policymakers and educators require the development of targeted strategies for equitable access assurance to technology and integration of AI in the classroom.

Demographic Factors Influencing Acceptance and Satisfaction of Machine Learning

Rajendran et al. (2024) utilized demographic factors such as age, gender, education level, occupation, and socio-economic status to reveal that younger populations, were more tech-savvy and portrayed higher levels of satisfaction. Atadika et al. (2024) claimed that demographic factors such as gender, academic programs, and academic level influenced the adoption of AI usage, and benefits among students. Pellas (2023) investigated the relationship between AI-generated content and socio-economic demographic factors such as age, devices used, time of usage, and level of revealed that students' participation in AI training had a direct impact on students' ML attitudes as well as their contentment level.

Based on the above, review of literature the following hypotheses were defined:

Hypotheses

1. There is a high level of Ease of use and strong acceptance rating of the students in higher education institutions on machine learning applications in their educational experiences.
2. Demographic factors – Gender and Major/Specialization of their study, influence the acceptance rating of students in higher education institutions regarding the application of machine learning to their educational experiences.
3. Demographic factors such as Gender, Age, Nationality, Marital status, Employment Status, and Major/Specialization of their study and Socioeconomic factors such as Residence, Familiarity, and the Acceptance Rating of ML influence the satisfaction of machine learning techniques among students in higher education institutions.

Research Methodology

The research employed a quantitative approach where the survey questionnaire was utilized for data collection. This study adopted a descriptive research design where various factors influencing acceptance and satisfaction of machine learning were identified and students' satisfaction was analyzed. The impact of satisfaction on applied ML techniques on students' acceptance of these technologies was also investigated to enhance learning experiences and provide more customized and personalized education. Students utilizing machine learning technologies and applying techniques/algorithms to their learning experiences were the target population of the study. A sample size of one hundred seventy-six was drawn from the population of students, employing snowball or referral sampling techniques.

Primary and secondary data were utilized in this research. The primary data were collected via questionnaire while the secondary data were collected from published journal articles, websites, books, etc. SPSS software was utilized to analyse collected data. The data obtained were summarized in tables and the appropriate tests were conducted to analyse the objectives and hypotheses validation Descriptive statistics combined with non-parametric tests such as Chi-Squared Test and Regression Analysis were conducted to analyse respondents' acceptance and satisfaction on ML utilization and adoption in higher education institutions.

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Findings

Table 1. Demographic profile

Demographic Profile		Frequency	Percent
Gender	Male	94	53.4
	Female	82	46.6
Nationality	Omani	149	84.7
	Non-Omani	27	15.3
Category	Student	176	100.0
Employment Status	Not Working	176	100.0
Marital Status	Single	139	79.0
	Married	37	21.0
Residence	Muscat	144	81.8
	Others	32	18.2
Age	18-20	65	36.9
	21-23	44	25.0
	24-26	33	18.8
	27-29	6	3.4
	30 years & above	28	15.9
Major/Specialization	Engineering	39	22.2
	IT	90	51.1
	Science	5	2.8
	Humanities	6	3.4
	Business	31	17.6
	Tourism	5	2.8

Source: Questionnaire

Table 1 presents the demographic profile of one hundred and seventy-six students who participated in the survey.

Student Familiarity with ML

Table 2. Familiarity Level

	Frequency	%
Beginner	71	40.3
Intermediate	77	43.8
Advanced	26	14.8
Expert	2	1.1
Total	176	100.0

Table 2 reflects that the majority of the respondents were intermediate in terms of familiarity level followed by beginners. Only two participants were experts on their level of familiarity with machine learning technologies.

Student Level of Acceptance on ML

Table 3. Acceptance rating of ML

Level	Totally Unacceptable	Moderately Acceptable	Acceptable	Totally Acceptable	Chi-Square	p-value
Frequency	1 0.6%	32 18.2%	65 36.9%	78 44.3%	81.591	.000

Table 3 presents that only 0.6% of the respondents did not accept Machine language and the rest were all accepted machine language. Further, the p-value < 0.05 clearly showed that the overall result indicated a very high acceptance rating on machine learning utilization and applicability among respondents, i.e. students accept machine learning techniques applicability on their learning experiences.

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Table 4. Ease of Use

Level	Very Dissatisfied	Dissatisfied	Neutral	Satisfied	Very Satisfied	Chi-Square	p-value
Frequency	1 0.6%	1 0.6%	28 15.9%	81 46.0%	65 36.9%	81.591	.000

Table 4 shows that the dissatisfaction rate among the respondents was only 1.2% whereas the students satisfied consisted of 82.9%. Further, the p-value obtained from the non-parametric tests is less than 0.05 which indicated a high level of satisfaction with the Ease of Use of ML among the students who participated in the survey. i.e. students feel the Ease of Use of machine learning techniques in their educational experiences and program requirements.

Null Hypothesis 1: There is a statistically significant association between the difference between students' major or specialization and Acceptance Rating on Machine Learning technologies.

Table 5. Crosstabulation between Major and Acceptance Rating of ML

Major /Acceptance	Totally Unacceptable	Moderately Acceptable	Acceptable	Totally Acceptable	Total
Engineering	0	5	14	20	39
IT	1	18	31	40	90
Science	0	2	3	0	5
Humanities	0	3	3	0	6
Business	0	3	12	16	31
Tourism	0	1	2	2	5
	1	32	65	78	176

Chi-square Tests

	Value	df	p-value
Pearson Chi-square	14.523	15	.486
N of Valid Cases	176		

Table 5 revealed that the p-value (0.486) > 0.05 => failed to reject the null hypothesis 1 that there was not enough evidence to conclude that the variables Major/Specialization and Acceptance rating of ML are associated. i.e. there was NO significant association between classification of major/specialization with Acceptance Rating of ML.

Null Hypothesis 2: There is a significant association between students' major or specialization and the Ease of Use of machine learning technologies.

Table 6. Crosstabulation between Major/Specialization and Ease of Use of ML

Major /Ease of Use	Very Dissatisfied	Dissatisfied	Neutral	Satisfied	Very Satisfied	Total
Engineering	0	1	6	16	16	39
IT	1	0	13	42	34	90
Science	0	0	2	3	0	5
Humanities	0	0	1	5	0	6
Business	0	0	4	13	14	31
Tourism	0	0	2	2	1	5
	1	1	28	81	65	176

Chi-square Tests

	Value	df	p-value
Pearson Chi-square	16.035	15	.714
N of Valid Cases	176		

Table 6 revealed that the p-value (0.714) > 0.05 => failed to reject the null hypothesis 2 that there was not enough evidence to conclude that the variables Major/Specialization and Ease of use of ML are associated. i.e. there was no significant association between the classification of major/specialization and the Ease of use of Machine Learning Technologies.

Null Hypothesis 3: There is a significant association between Gender and satisfaction rating on Machine Learning technologies.

Table 7. Crosstabulation of Gender and Satisfaction Rating of ML

Gender / ML Ease of use	Very Dissatisfied	Dissatisfied	Neutral	Satisfied	Very Satisfied	Total
Male	0	0	11	45	38	94
Female	1	1	17	36	27	82
Total	1	1	28	81	65	176

Chi-square Tests

	Value	df	p-value
Pearson Chi-square	5.354	4	.253
N of Valid Cases	176		

Table 7 revealed that the p-value (0.253) > 0.05 => failed to reject the null hypothesis 3 that there was not enough evidence to conclude that the variables Gender and the Satisfaction Rating of ML are associated. i.e. there was NO significant association between Gender with the Satisfaction Rating of ML.

Null Hypothesis 4: There is a significant association between Gender and Acceptance rating of ML on machine learning technologies.

Table 8. Gender vs. Acceptance Rating of ML Crosstabulation

Gender / ML ease of use	Totally Unacceptable	Moderately Acceptable	Acceptable	Totally Acceptable	Total
Male	0	18	35	41	94
Female	1	14	30	37	82
Total	1	32	65	78	176

Chi-square Tests

	Value	df	p-value
Pearson Chi-square	1.278	4	.734
N of Valid Cases	176		

Table 8 revealed that the p-value (0.734) > 0.05 => failed to reject the null hypothesis 4 that there was not enough evidence to conclude that the variables – Gender and the Acceptance Rating of ML are associated. i.e. there was NO significant association between the Gender and the Acceptance Rating of ML.

Regression Analysis

Table 9. (a), (b), (c) & (d) Regression

Model	Variables Entered	Variables Removed	Method
1	Acceptance Rating of ML, Gender, Marital Status, Nationality, Major/Specialisation, Familiarity Level, Age, Residence[b]		Enter

[a] Variables Entered/Removed
[b] All requested variables entered.

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Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.674	.454	.428	1.999

[a] Predictors: (Constant), Acceptance Rating of ML, Gender, Marital Status, Nationality, Major/Specialization, Familiarity Level, Age, Residence

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	555.501	8	69.438	17.371	.000
Residual	667.539	167	3.997		
Total	1223.040	175			

[a] Dependent Variable: MLS
[b] Predictors: (Constant), Acceptance Rating of ML, Gender, Marital Status, Nationality, Major/Specialization, Familiarity Level, Age, Residence

Coefficients

	Unstandardised Coefficients		Standardized Coefficients	t	sig
	B	Std. Error	Beta		
(Constant)	8.350	1.178		7.090	.000
Gender	-.608	.337	-.115	-1.806	.073
Nationality	.180	1.046	.025	.173	.863
Marital Status	-.953	.480	-.147	-1.985	.049
Residence	.216	.982	.032	.220	.826
Age	.120	.139	.064	.861	.390
Major/Specialisation	.088	.112	.049	.789	.431
Familiarity Level	.340	.222	.095	1.532	.127
Acceptance Rating of ML	2.021	.209	.602	9.664	.000

[a] Dependent Variable: MLS

The p-values of the coefficients are > 0 for the variables, Gender (0.073), Nationality (0.863), Residence (0.826), Age (0.390), Major/Specialization (0.431), and familiarity level (0.127). Therefore, eliminating these variables, the regression analysis was carried out again and the obtained regression result was as follows:

Revised Regression Analysis

Table 10. (a), (b), (c) & (d) Revised Regression

Model	Variables Entered	Variables Removed	Method
1	Acceptance Rating of ML, Marital Status[b]		Enter

[a] Dependent Variables: MLS
[b] All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.656[a]	.430	.424	2.007

[a] Predictors: (Constant), Acceptance Rating of ML, Marital Status

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ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	526.274	2	266.137	65.334	.000
Residual	696.766	173	4.028		
Total	1223.040	175			

[a] Dependent Variable: MLS
[b] Predictors: (Constant), Acceptance Rating of ML, Marital Status

Coefficients

	Unstandardised Coefficients		Standardized Coefficients	t	sig
	B	Std. Error	Beta		
(Constant)	8.378	.975		8.592	.000
Marital Status	-.739	.372	-.114	-1.984	.049
Acceptance Rating of ML	2.141	.193	.638	11.086	.000

[a] Dependent Variable: MLS

The R^2 value is 43% i.e. 43% of the samples influenced the regression model.
Therefore, the obtained derived regression equation is as follows:
MLS = 8.378 – 0.739 MS + 2.141 AR
where MLS - Satisfaction of Machine Learning Technologies
MS – Marital Status
AR – Acceptance Rating of Machine Learning

The above results revealed that there was an association between Satisfaction of Machine Learning Technologies, Marital Status, and the Acceptance Rating of Machine Learning. The negative coefficient of MS indicates that this specific variable negatively influenced MLS whereas AR significantly impacts MLS positively.

Discussion

The results of the study indicated a very high acceptance rating on machine learning utilization and applicability among respondents, i.e. students accept machine learning techniques applicability on their learning experiences. Similarly, a high level of satisfaction with the Ease of use of machine learning techniques among the students who participated in the survey. i.e. students feel the Ease of use of machine learning techniques in their educational experiences and program requirements. In other words, Hypothesis 1 is proved positively. The findings of the study are similar to the findings by Albayati (2024) and Yu et al. (2024). Woodruff et al. (2023) revealed that there was an existence of disparities in technology access and ease levels with technology among different regions, genders, and age groups. However, the above results indicated that further to the above results, the development of targeted strategies for equitable access assurance to technology and AI integration in the classroom was suggested to policymakers and educators.
It was also found that there was no significant association between the classification of major/specialization and with Acceptance rating of ML. i.e. Hypothesis 2 is disproved. Similarly, there was no significant association between the classification of major/specialization and the Ease of use of Machine Learning techniques. It was also found that there was no significant association between Gender with the Satisfaction Rating of ML. Similarly, there was no significant association between Gender and the Acceptance Rating of ML.

In short, there is no association between Gender and both the Acceptance Rating of ML and the Satisfaction Rating of ML. i.e. Hypothesis 2 is disproved. Similarly, there is no association between the classification of major/specialization and both the Acceptance Rating of ML and the Satisfaction Rating of ML. The finding is similar to that of (Ofosu-Ampong, 2023), Smerdon (2024), and Yim (2024)that the gender disparity had no impact on the acceptance rating of ML, especially AI usage.

Furthermore, the regression analysis confirmed that there was no association between the socioeconomic factors - Gender, Nationality, Residence, Age, Classification of Major/Specialization, familiarity level, and Satisfaction with ML techniques. In other words, there was no impact of the demographic factors viz. Gender,

Nationality, Residence, Age, Classification of Major/Specialization, and the familiarity level of the students' Satisfaction with ML techniques (i.e. Hypothesis 3 is partially disproved in relates to demographic factors) whereas socio-economic factors – Marital Status and the Acceptance Rating of Machine Learning techniques had an impact on the Satisfaction of Machine Learning Techniques (i.e. Hypothesis 3 is partially proved in relates to socio-economic factors). However, it was noted that Marital Status negatively influenced the satisfaction of ML techniques. The finding is similar to that of Sandu and Gide (2019) who found that there is no relationship between gender, age, or the level of education of the students and the adoption of chatbot technology in higher education.

Conclusion

The findings of this study highlight a high level of acceptance and satisfaction among students regarding the utilization of machine-learning techniques in their educational experiences. Respondents expressed confidence in the ease of use of ML applications, which positively impacted their learning processes and program requirements. These results underline the significance of designing user-friendly and effective ML tools tailored to meet the needs of students across various disciplines.

Interestingly, the study found no significant associations between demographic or socio-economic factors such as gender, age, nationality, or specialization and students' acceptance and satisfaction with ML. This indicates that ML technologies, when appropriately implemented, can cater to a diverse student population without inherent biases linked to these factors. However, marital status was noted to influence satisfaction, albeit with a negative correlation, suggesting the need for further exploration into how personal circumstances might affect perceptions of technology.

The absence of disparities in acceptance and satisfaction ratings across demographic groups is encouraging, as it suggests equitable opportunities for ML integration in education. However, the development of targeted strategies to ensure accessibility and address unique challenges faced by specific student segments remains critical. Policymakers and educators must focus on refining ML applications to enhance inclusivity and foster positive learning outcomes for all students.

Recommendations

Based on the above, the following recommendations were made:

1. Develop ML applications with intuitive interfaces to ensure accessibility for students with varying levels of technical proficiency and conduct regular usability testing to improve user experience.
2. Ensure that ML tools are adaptable to the needs of students from various disciplines, offering customizable features and content-specific applications and avoiding embedding socioeconomic biases.
3. Investigate the influence of personal factors, such as marital status, on technology adoption and provide additional support mechanisms, such as flexible schedules or resources, for students.
4. Deploy ML technologies that are compatible with a wide range of devices, including low-cost and older hardware, to promote accessibility for all students, offering training to students to familiarize themselves.
5. Incorporate analytics within ML tools to establish feedback channels to share their experiences and suggest improvements.
6. Educate faculty on the capabilities and benefits of ML technologies to advocate policies that prioritize equitable technology distribution.

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