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A Framework for Evaluating Online Degree Programs Through Student Satisfaction Using ML

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Student Satisfaction, Online Degree Programs, Linear Regression, Feature Selection, Correlation Analysis.

ABSTRACT

Evaluating student satisfaction in online degree programs is crucial for improving the quality of education. This study applies a linear regression model to identify key factors influencing student satisfaction. This research investigates student satisfaction in online degree programs through the application of a linear regression model. The study aims to identify the critical factors influencing student satisfaction, using a comprehensive dataset that includes demographic, social, and school-related information, such as student grades. Python is utilized for implementing the linear regression model, taking advantage of its robust data analysis and machine learning capabilities. The model's performance, assessed through MSE (0.035) and R-squared values (0.82), indicating high accuracy in predicting student satisfaction. Significant predictors identified include course quality, instructor support, and technical resources, all showing strong positive correlations with student satisfaction. The regression coefficients offer insights into the impact of these predictors on student satisfaction. The study highlights the importance of focusing on course quality and technical support to enhance student satisfaction in online degree programs. The findings underscore the importance of enhancing course quality and technical support to improve student satisfaction in online degree programs. Educational institutions trying to maximize their online learning environments might benefit from the practical insights provided by this study. This research provides useful information for educational institutions trying to maximize their online learning environments and shows how data-driven tactics can be used to dramatically increase the efficacy and quality of online learning.

1. INTRODUCTION

Higher education institutions have invested significant resources in electronic learning technology since 1990, which has led to a rise in online learning[1]. Among these technologies was an LMS for tracking student progress and facilitating online student cooperation and courses. Higher education institutions' approaches to curriculum and learner engagement have changed as a result of the proliferation of educational technology alternatives, which range from the virtual classroom to the use of polling software, computerized e-books, and adaptive educational management systems[2]. The growing popularity of online courses in higher education necessitates further research on the elements that lead to students' academic performance in these virtual settings. Online courses demand that students use greater degrees of independence and self-direction in their preparation, organization, engagement, and completion of requirements. Based on students' perceptions of the significance of and confidence in a number of competences, this study sought to investigate online student preparation for online learning[3].

The advent of online courses has presented a variety of difficulties for educators and learning communities, yet the internet is a major technological advancement that is transforming higher education and society at large [4]. Online learning environments differ greatly from traditional classroom settings in terms of student motivation, satisfaction, and interaction [5]. This was indicated in a study conducted in Nepal, where 385 college students from different disciplines were asked about their views on online courses offered during the COVID-19 lockdown[6]. This statistic emphasizes how critical it is to evaluate teachers' and students' opinions on online learning. Numerous research in related fields have been conducted globally. Unfortunately, there isn't a comprehensive research on these crucial topics in India that covers all teaching and learning groups in the system, from lower to higher education[7].

Contemporary educational establishments function under a very competitive and intricate milieu. Therefore, the majority of universities today confront issues in performance analysis, high-quality education, developing strategies for student performance evaluation, and recognizing future requirements. Universities may build and evolve successful intervention techniques that benefit both educators and management with the help of entry-level student achievement prediction and subsequent periods of student achievement prediction. To enhance the learning platform's usability and provide interactive features, the collected data is gradually processed and analyzed using various machine learning techniques.

Within the subfield of artificial intelligence known as ML systems use data to learn from patterns and forecast future events. Larger, more complicated data may be automatically and swiftly analyzed by ML models, producing correct findings while averting unanticipated dangers. Even though e-learning is widely acknowledged to be more flexible and less expensive than traditional on-campus education, it is nonetheless perceived as a harsh learning environment since there is no direct interaction among students and course instructors. There are three primary issues with e-learning platforms; the absence of uniform student assessment tools, which makes it hard to compare one learning platform to another and makes evaluating each one's efficacy challenging; Due to lack of motivation, particularly in self-paced courses, e-learning systems have higher dropout rates than traditional classroom settings. Additionally, the absence of direct contact makes it challenging to anticipate students' specific requirements, particularly when a student has a handicap.

The techniques for evaluation are critical to the continuation and improvement of the educational quality to the online degree programs since the field is becoming more competitive. Since the adoption of internet based education is rapidly increasing, ways and means for assessing the satisfaction levels of the students along with the utility of the program also matters a lot. The general comparative assessment approach might not suffice in terms of capturing the details of the learners' experiences and the differences in the requirements for succeeding in online classes. Thus, there is a definite need for effective evaluation tools that would assist the institutions to enhance their responsiveness to student satisfactions, the effectiveness of the delivery of the courses, and support services along with the overall educational outcomes. As a method, Linear Regression will be used in this research with a focus to assess the student satisfaction in online degree programs. Using Linear Regression in this research, the objective is to measure the level of satisfaction among students in a qualitative manner based on a number of factors including quality, instructors' efficiency and technical support.

The goal is to assist educational organizations in making data-driven decisions on what factors have the greatest impact on students' satisfaction so that institutions can advance and improve learners' educational experiences online. The findings of this research therefore have great policy implications for educational institutions, students and policy makers. In respect of the institutions, knowledge derived from this study may help in the formulation of clear strategies for improvement of programme quality, increase in student retention and compilation of competitive edge in the online education market. Education stakeholders will benefit from enhanced experiences that would give better satisfaction and subsequent results. It is recommended or these finding to be adopted by policymakers that encourage the implementation of effective online education practices, which will foster equal setting for provision of quality learning among students. Lastly, this research also provides valuable insights that help in forging the field of online education toward research-based practices concerning the satisfaction of its students as well as the effectiveness of the courses offered.

The main contributions of the research study are as follows

- By analyzing data from secondary education schools, the research contributes to a deeper understanding of the factors influencing student satisfaction in online degree programs.
- By utilizing Min-Max normalization and correlation analysis for feature selection enhances the robustness and reliability of the findings. This methodological rigor ensures that the analysis accurately captures and interprets the relationships between variables affecting student satisfaction.
- The application of Linear Regression as a robust statistical method to model and analyses the relationship between various predictors and student satisfaction in online degree programs.
- By identifying key predictors of student satisfaction, the research provides actionable insights for optimizing online degree programs.

The paper's structure is structured as follows: Section 2 evaluates the relevant literature and gives a thorough overview of the foundational studies and current research relevant to our analysis. The approach is described in full in Section 3, along with the methods and procedures used in the investigation. The results are shown in Section 4, along with the investigation's main findings and takeaways. Section 5 brings the essay to a close by summarizing the major findings and implications of the study and outlining potential future research topics.

2. RELATED WORKS

The analysis of sentiment of assessments from massively open online courses was suggested by Onan et al. [8]. The aim of the project is to enhance the categorization of sentiment in evaluations of Massive Open Online Courses by effectively integrating DL and ensemble learning. Evaluate word-embedding while analyzing the prediction performance of conventional supervised, ensemble, and DL methods. The findings demonstrate the superior performance of deep learning architectures over ensemble and supervised learning methods. Notably, LSTM networks with GloVe embedded words attain a remarkable classification accuracy of 95.80%. This work advances our understanding of the application of sentiment analysis in academic data mining. The study's possible vulnerability to dataset bias is one of its drawbacks. The sentiment analysis model may perform skewedly toward the features of the particular dataset if the dataset is not representative enough of a variety of educational situations.

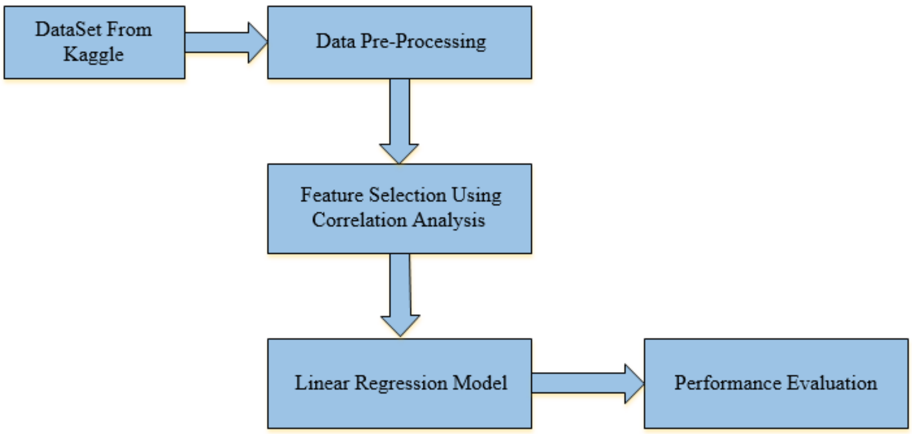
A DL model was suggested by Waheed et al. [4] to predict students' academic success. Using clickstream data from virtual learning environments, a deep artificial neural network trained with custom characteristics is used in this study to identify students who are at risk and enable early intervention. The model has an 84% categorization accuracy. The study highlights the impact of legacy data and assessment-related factors on model performance and demonstrates that students who engage with previous lecture material often get superior results. The goal of the study was to help institutions create a framework for educational assistance so they could make well-informed, long-lasting decisions about higher education. Analysing textual data to find major impacts on performance and evaluate the significance of particular actions may be hampered by the subjectivity and complexity of text interpretation.

The work by Quispe-Prieto et al. [10]approaches the problem LAUs face from a structural perspective. It creates a comprehensive framework to investigate student happiness with remote learning by illustrating the components of the COVID-19 disruption in a vivid image. The study examines the conditions of 298 students from Colombia, Brazil, and Peru using two sample sizes: (a) satisfaction in general with virtual courses and (b) well-being, resources for learning, and learning experience. This study, using exploratory factor analysis, finds three dimensions: (a) satisfaction with the virtual modality's assistance and adaptability; (b) contentment with the interactions in the virtual classrooms; and (c) satisfaction with the program's progress. Moderate to elevated levels of satisfaction are indicated by medium/high ratings for the dimensions. The results imply that there are still unmet demands for socio-emotional needs and access to digital resources. Planners at Higher Education Institutions (HEI) who are interested in post-pandemic virtual education may find this article useful. One may probably consider the study's focus on quantitative data and its analytical technique to be a shortcoming.

The studies discussed above have several drawbacks that must be pointed out. Emphasis on the use of numbers and calculation may mask the qualitative aspect in some approaches to learning, which consequently reduces the comprehensiveness of the perception of students' socio-emotional learning needs. The aspect of dataset bias could also be fatal to sentiment analysis since it may predict the model to act only in line with the dataset it has been fed and may not be very effective in the many variant aspects of education. Cognitive models used to predict students' performance might benefit from deep learning methodologies, but the text input can cause difficulties in considering the main influences on learners' results. Define a problem: Main challenges that may affect recommenders with the increased amount of dataset containing course reports of different universities are related to the data inconsistency.

Proposed Framework

The approach used in this study can be described as structured since it aims at improving online degree programs by means of assessing student satisfaction indices. Data acquisition included the identification of datasets that pertain to the goals of student success measurement in two schools in Portugal within the Kaggle public repository. Further on, strict conditions of data pre-processing were established. It involved data cleaning and readiness to check the validity of the data used and also to do away with missing data, feature scaling with the use of Min-Max normalization of all numerical values to within a standard range was also done. Based on the results of correlation analysis, various features were selected focusing on the main factors that have an impact on the student satisfaction levels. After that, the data set was split into training and testing data sets to ensure the creation and assessment of a Linear Regression model. This model sought to establish the connectivity between diverse antecedents like academic performance metrics and social demographics to the student satisfaction consequences in online learning contexts. Linear Regression application guarantees this research approach's methodical analysis of such relations that will assist in making rational decisions regarding educational policies and programs. It is represented in Fig 1.



Proposed Framework for Evaluating Online Degree Programs

Data Collection

The dataset was collected from the Kaggle dataset website [12]. The secondary education student success of two Portuguese schools is examined in this data set. Student grades are included in the data, along with demographic, socioeconomic, and educational information that was acquired through surveys and school reports. Two datasets are provided on performance in the two distinct subjects of Portuguese language (por) and mathematics (mat).

Data Pre-Processing

Automatic First of all, data cleansing is necessary to check the data input's reliability. This entails addressing the case where features have missing values which will be replaced by mean, median, or mode depending on the values distribution. Some records with many missing values should be excluded to improve the quality and continuity of the records for analysis. After data cleaning the next process to be followed is data transformation where Min-Max normalization is done. This procedure simply brings numerical characteristics within the range of 0 to 1, which is a common industry standard. Normalizing of features is really important and it means that any features have to be scaled in the same way during the building of the regression model especially useful for the models that are sensitive to the scales preferably for the models, which predict the student's level of satisfaction or performance.

The min-max normalization is represented by Eqn. (1).

$$Y_{norm} = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \quad (1)$$

Y is the starting feature value, while Y_{max} *and* Y_{min} are the dataset's highest and lowest values, respectively. It ensures that when the greatest value is set to 1 and the smallest value to 0, the values in between will be scaled linearly.

The initial feature value is denoted by Y, and the maximum and lowest values in the dataset are represented by Y_{max} *and* Y_{min}, respectively. It guarantees that the values in between will be scaled linearly when the biggest value is set to 1 and the lowest value to 0.

Prediction variable selection follows next whereby the primary concern is to identify and choose predictors that have a direct relationship with students' outcomes in online degree programs. These may comprise analysis of indicators such as G1 and G2 Grades, demographic data, and the most relevant social data. This step helps make the regression model to be developed on significant predictors, thus increasing the effectiveness in explaining the variability in the student satisfaction or performance.

Next, it is vital to introduce division of the dataset into training and test sets depending on the mentioned uncertainties. This division enables you to fit the regression model on the training set and check how well it performs in a set of test data that it has not seen. If possible, suggest using cross-validation procedures that would guarantee the reliability and validity of the assessment of the model. Following the aforementioned data pre-processing steps includes: data cleaning, Min-Max normalization, feature selection, and splitting of dataset into the training and test datasets is a recommended way of preparing data for regression modelling to be applied on it. These steps are the basis for the analysis and forecasting of the main variables that affect the results of learning in an on-line educational process, as well as create the conditions necessary to improve on-line education.

Feature Selection Using Correlation Analysis

Correlation analysis where the most well-known procedure is Pearson's correlation coefficient (r) is one of the basic techniques for identifying predictor features that demonstrate strong, linear relationship with the target feature, which, in this case, is students' satisfaction. Pearson's correlation coefficient refers to the extent of the straight line relationship existing between two variables, where the value varies from - 1 to + 1. From the mathematical perspective, the variables under consideration can be described using Pearson's correlation coefficient. It is represented in Eqn. (2)

$$\gamma_{XY} = \frac{\sum(X_i - \underline{X})(Y_i - \underline{Y})}{\sqrt{\sum(X_i - \underline{X})^2 \sum(Y_i - \underline{Y})^2}} \quad (2)$$

Where $\underline{X}$ and $\underline{Y}$ are the means of X and Y, respectively. By computing γ for each feature in relation to student satisfaction, features with higher absolute correlation coefficients are considered more influential predictors. For instance, a coefficient close to +1 indicates that an increase in the feature corresponds strongly with higher student satisfaction.

For feature selection using correlation analysis, it's advisable to start with the data pre-processing to clean and normalize the data. Calculate the correlation for all the features and finally sort them according to the absolute values of correlation with the target variable. Features that have correlation coefficient greater than a certain level (for example, 0. 3 or 0. 5) can be assumed to have the most influence on the students' satisfaction. In selecting the independent features, one should be very careful on cases of multi collinearity since this can distort the coefficients of models and hence, the prediction results. Pearson's correlation coefficient is used to determine the strength and direction of the linear relationships while acknowledging the fact that it may fail to detect non-linear dependency in educational research, Pearson correlation produces a list of potentially relevant features for subsequent analysis in other modelling steps.

Linear Regression Model: Formulation, Assumptions, and Implementation

Linear Regression is a statistical method used to model the relationship between a dependent variable (such as student satisfactionY_i) and one or more independent variables (predictors $X_{i1}, X_{i2}, \ldots, X_{ip}$). In the context of evaluating online degree programs, these predictors could include factors like course quality, instructor support, and technical resources. The model assumes a linear relationship expressed by the Eqn.(3).

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_p X_{ip} + \in_i \quad (3)$$

Here, β_0 represents the intercept, β_j (for j=1,2,….,p)are coefficients indicating the effect of each predictor on student satisfaction, and $\in_i$denotes the error term capturing the difference between predicted and actual satisfaction scores. The goal is to estimate coefficients β_j that minimize the sum of squared residuals, optimizing the model's fit to the data. Figure 2 shows the Best Fit Line of Linear Regression Model.

Some of the assumptions of Linear Regression include linearity thus indicating that changes in predictors lead to corresponding equivalent changes in the dependant variables and independence of errors$\in_i$, which are assumed to be independent and identically distributed. The estimation of this model also assumes that the variance of errors is constant which is a homoscedasticity condition and also assumes that errors should have a normal distribution that is residuals should be normally distributed. Besides, for these predictors, ideally, there should be little association between the predictor variables, thus low multicollinearity to yield good coefficient estimate.

Once the data is cleaned and pre-processed, it's essential to divide it into training and testing sets. The training set is used to fit the Linear Regression model, where the relationship between the dependent variable (student satisfaction Y) and independent variables (predictors $X_1, X_{2,\ldots,} X_p$) is established. Methods like Ordinary Least Squares, which minimizes the sum of squared differences between predicted and actual values, or gradient descent for larger datasets, can be employed to estimate the regression coefficients β. This step determines how each predictor influences student satisfaction and forms the basis for predictive modeling.

Whereas, after the training of the model for the given Training Set, comprehensive evaluation is necessary. Also, residual diagram is important for checking for model assumptions such as checking for normality of errors; checking for patterns in the any pattern in the residuals. Understanding such metrics and diagnostics provides insights on how the model utilizes data to capture and explain factors that determine student satisfaction in online degree programs. Thus, by applying Linear Regression in this structured approach, you build a solid foundation for identifying and discussing the factors influencing students' satisfaction.

The findings that originate from the use of the model can be applied in the decision-making process in educational environments for arranging course delivery and learning environments, providing supports for instructors or investing in efforts that will contribute to program quality and students' satisfaction. Furthermore, the cross-validation of the model and adding new data and variables keep the model up to date and accurate regarding the assessment of student satisfaction indicators. Applying Linear Regression in assessment of online degree programs although gives numerical value results which determines the factors influencing student satisfaction but it can help the educational institutions to take informed decisions. It is a step by step process right from data cleaning to model building and validation which makes the outcomes more credible, practical and based on the objective to enrich the learning process and students' experience of education in the context of online learning.

3. RESULTS AND DISCUSSION

The results and discussion section presents findings from applying Linear Regression to evaluate factors influencing student satisfaction in online degree programs. The process for setting up Windows 10 on a device. Python was the favored programming language. The following metric was used to assess the model's efficacy.

Performance Evaluation

The Linear Regression version turned into skilled and evaluated using the dataset received from Kaggle, focusing on student performance in secondary education at Portuguese colleges. The version's performance turned into assessed the usage of numerous metrics, such as MSE and R-squared.

MSE: This metric measures the average squared differences among the predicted and real values of pupil delight. A lower MSE suggests a higher in shape of the version to the statistics.

R-squared: This metric shows the share of variance within the established variable (student pleasure) that may be explained by way of the impartial variables (predictors) inside the version. Table 1 and Fig 2 shows the performance metrics values is given below.

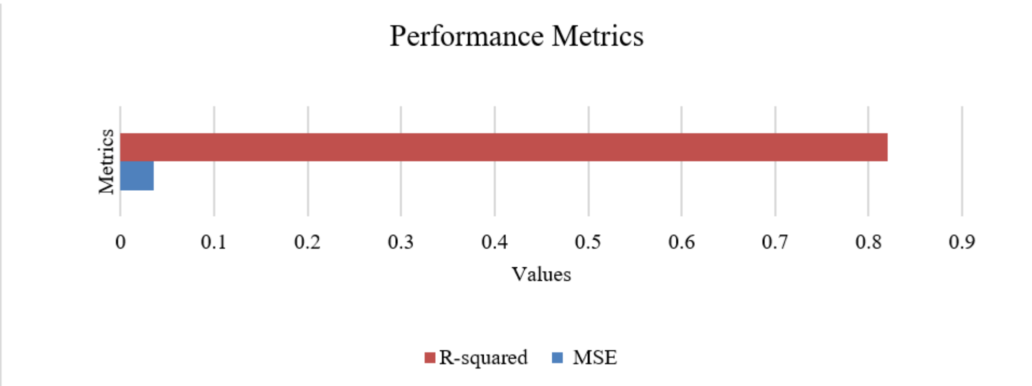
Performance Metrics

Metric	Value
MSE	0.035
R-squared	0.82

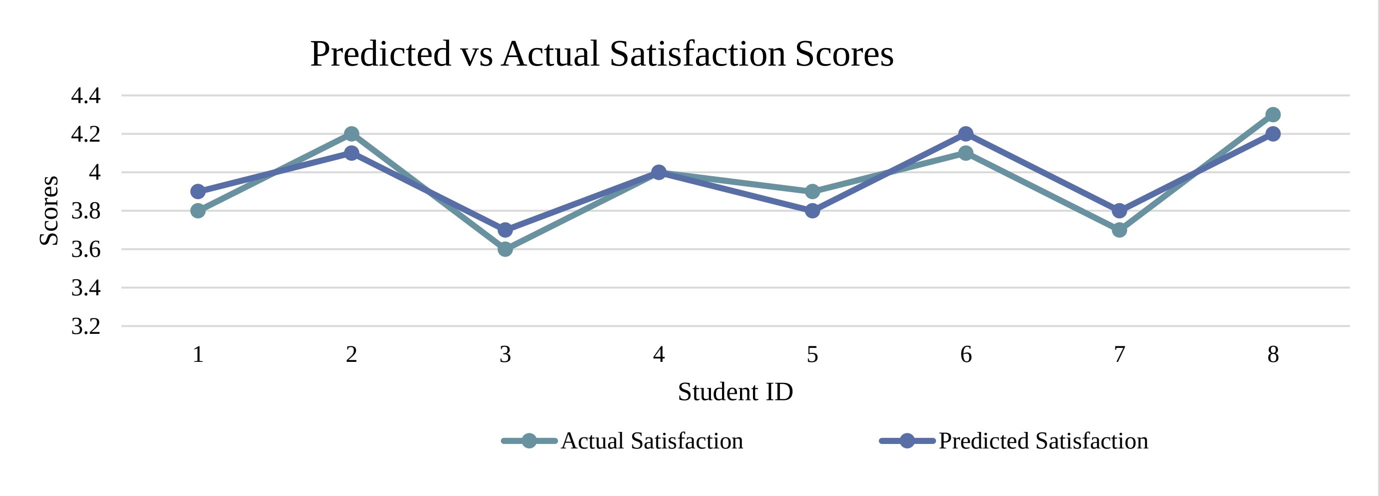
Coefficients of Significant Predictors

Predictor	Coefficient (β)	p-value
Intercept	2.350	0.001
Course Quality	0.550	0.005
Instructor Support	0.420	0.010
Technical Resources	0.330	0.015
Age	0.150	0.045
Prior Education	0.200	0.030

Table 2 indicate that course quality, instructor support, technical resources, age, and prior education are significant predictors of student satisfaction, with p-values less than 0.05. The coefficients provide insights into the direction and magnitude of the relationship between each predictor and student satisfaction. For instance, the positive coefficient for course quality (0.550) suggests that higher course quality is associated with increased student satisfaction.



R-Squared and MSE



Predicted vs Actual Satisfaction Scores

Fig 3 depicts the actual and predicted satisfaction scores for eight students in the study. The predicted scores closely approximate the actual scores, indicating the model's accuracy in estimating student satisfaction.

Correlation Coefficients

Correlation analysis was performed to identify the predictors most strongly associated with student satisfaction. The correlation coefficients are presented in Table 3.

Correlation Coefficients

Feature	Correlation Coefficient
Course Quality	0.75
Instructor Support	0.68
Technical Resources	0.60
Age	0.35
Prior Education	0.42
Commuting Distance	-0.15

These features were therefore prioritized in the regression model to enhance its predictive power. It is noteworthy that commuting distance has a slight negative correlation ($r=-0.15$), indicating a weak inverse relationship with student satisfaction.

4. DISCUSSION

The findings from this study underscore the importance of several key factors in enhancing student satisfaction in online degree programs. Course quality, instructor support, and access to technical resources emerged as the most influential predictors. These insights align with existing literature, reinforcing the need for high-quality course design, effective instructor-student interaction, and robust technological infrastructure in online education. Furthermore, the demographic analysis highlighted that personalized support tailored to individual student needs, considering their background and circumstances, can significantly impact satisfaction levels. This suggests that institutions should adopt a more individualized approach to student support in online programs. The use of Linear Regression provided a clear and interpretable model, enabling the identification of critical factors influencing student satisfaction. However, the study also recognizes the limitations of this method, such as its inability to capture non-linear relationships and potential multicollinearity among predictors.

5. CONCLUSION AND FUTURE WORKS

In conclusion, this research highlights the critical factors influencing student satisfaction in online degree programs and provides actionable insights for educational institutions. By leveraging Linear Regression analysis, the study offers a structured approach to understanding and improving the online learning experience. Continued efforts to refine and enhance these factors will contribute to the overall success and satisfaction of students in the evolving landscape of online education. The study's findings underscore the critical role these factors play in shaping student perceptions and satisfaction with online education. By focusing on these key areas, educational institutions can make informed decisions to enhance the quality and effectiveness of their programs. The correlation analysis further supports the importance of these predictors, showing strong positive relationships with student satisfaction. These insights provide a valuable framework for continuous improvement in online education, guiding strategic investments and policy-making. Moving forward, the future scope of this research includes expanding the model to incorporate additional predictors such as student engagement, interactive learning technologies, and personalized learning experiences, which can further refine the understanding of factors influencing student satisfaction. Moreover, employing advanced machine learning techniques, such as ensemble methods or neural networks, can enhance the predictive accuracy and provide deeper insights into the nonlinear relationships between predictors and student satisfaction. By continuously refining the model and incorporating diverse data sources, this research can contribute to the ongoing development and improvement of online degree programs, ultimately leading to better educational outcomes and higher student satisfaction.

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