Identifying technology features impacted attitude of Indian students using regression modeling for real-time system

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\textbf{A B S T R A C T}

Information, Communications Technology (ICT), and Mobile Technology (MT) are the pillar of the trending educational system. No doubt, without using ICTMT, students might not be able to survive in the present modern world. To achieve the student’s opinion mining, a Linear Regression (LR), and Multiple Linear Regression (MLR) models compared to predict the Attitude about ICTMT in Indian higher education. Therefore, the dependency of student’s attitudes on provided technological benefits explored in IBM SPSS Statistics 25 with 163 primary samples. The Cronbach alpha method provided the outstanding reliability of 0.857. Not only, the square root transformation affected the positive correlation between target variables, but also the impact of educational benefit on the attitude also improved. On the one hand, the LR’s explaining strength ($R^2 = 0.573$) of the Educational Benefit enhanced by adding up two variables Usability and Development Availability in the MLR with ($R^2 = 61.8)$, both models were found significant ($t$ and $F$ values ($P < 0.05$)) and compared with standardized values with equations on the 2-D plane. The findings of the study proved the linear relationship exists between Attitude and Educational Benefit. Due to prediction relevance and significance, we proposed the MLR model to support the real-time system of the demographic identification system.

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1. Introduction and literature

Nowadays, almost every higher education institution is integrating the latest ICTMT in course curriculum not only covert technology-based education but also make learning more ease, revolutionary, attractive, and scientific. No one can expect quality education without embedding the latest technology in teaching-learning. For this, the opinions of educators need to be attracted to ICTMT and must be positive [1]. Educational data mining is a promising approach to support data analytics, and it also named learning analytics [2]. Numerous data mining techniques implemented in research cases for prediction. The success of a student’s in terms of pass or fail predicted with data mining [3–5]. Multinomial regression was used to predict the response of students in the ICTMT survey [6]. A regression technique was applied to explore the ICT Impact factors on Early Adolescents’ Reading Proficiency [7]. The attitude of students towards the Interactive Whiteboard usage in Mathematics Classrooms identified using regression [8]. Binary logistic regression proved influential in the prediction of the development and availability [9] of ICTMT and non-academic factors such as nationality [10]. The investigation was also performed to analyze the student attitude towards the usability of ICT in course study, work, and social activity [11]. In problem-based learning (PBL) with the technology acceptance model, the attitude was investigated [12]. To validate the results of machine learning algorithms, a statistical test used in the prediction of ICTMT awareness level [13]. Regression and machine learning was also compared with academic performance forecasting [14]. Further, the attitude of students towards ICTMT to support university real-time systems was presented [15]. A student’s residential place identification model proposed for two distinct continents (Asia and Europe) [16].

Fig. 1 visualizes the main objective of the paper of research keeping all independents variables pointing (impacting and predicting) to the student’s attitude. We are recommending a regression models to be deployed online web system stores and to query across databases to predict the excepted value. In this paper, we applied regression modeling of ICT factors to predict the attitude,
and also we discovered the relationship and impact of ICTMT on student’s attitudes, assuming four hypotheses. The structure of the paper scattered into five sections. Section 1 briefs the introduction part, and Section 2 discusses the methodology adopted to write. Section 3 performs two main experiments. Section 4 debates on the results of the investigation. Section 5 binds the paper with verdicts.

2. Methodology

2.1. Real-time

Up to now, the author did not explore any real-time or online web prediction of the attitude prediction of educators or students. There is a requirement for online web applications to measure technology development, benefits, uses, and most prominent stakeholder opinions. Using the app, an educational organization might be knowing about technology awareness among its teachers and students. Keeping the idea in mind, we proposed a conceptual approach with the development of a significant regression model. For this, we present and compare two regression models. These models used technology benefits, uses, development, and availability attributes. The online web-based application will be followed by the client–server model and supportive to both desktop and mobile.

2.2. Objectives

To explore the relationship between the student’s attitude and technology in an Indian university. Below-concerned hypotheses are assumed.

\[ RH_0: \rho_{XY} = 0 \] (No relationship between student Attitude and technology in Indian University)

\[ RH_1: \rho_{XY} \neq 0 \] (A relationship between student Attitude and technology in Indian University)

To figure out the impact of technology on the student’s attitude in an Indian university. The following hypotheses are framed.

\[ H_{00}: \text{No Impact of technology on student Attitude in Indian University} \]

\[ H_{11}: \text{An impact of technology on student Attitude in Indian University} \]

2.3. Instrument and sampling

To explore the impact and relationship between the Attitude and ICTMT’s benefits provided in Chandigarh University, we received 163 samples using a Google form, which is designed after discussed with experts. A stratified random sampling method is followed and focused on the participants who are doing a bachelor’s and master’s degree in the university. The Google form designs included 06 questions reflect the attitude, 09 questions relate educational benefit, 06 questions about usability, 16 questions about development availability. The data collection scale was a hybrid type with numeric values. Before applying regression techniques, reliability (Cronbach alpha = 0.857), auto-correlation, Multivariate Normality, and Multicollinearity are checked appropriately and discussed in succeeding sections.

2.4. Transformation and multivariate normality

During preprocessing, we observed the need to transform data samples to get ready for modeling. Tackle skewness problems, several transformations are useful, like Log and Square root, etc., [17]. This study used only a square root transformation in which a square root of each value brings any large value to the center to make a normal curve. For the square root transformation, a reverse transformation must negative skewed values, also named reflective.

Fig. 2 depicts the essential statistics having acceptable skewness and kurtosis in variables and do not exceed between +2 and −2 [18]. Further, average and dispersion are also measured in variables. Higher mean values greater than 3.5 depicts agreement of student with

Fig. 3 shows the normality curves of variables under investigation. We observed that all values fall approximately along the
straight line concerning the concerned variable. It indicates that the observed values are the same as per expectation.

2.5. Multi-collinearity

Multicollinearity is a very high inter-correlation among independent variables, and it implies the presence of predictors representing the same underlying construct [18]. Recommended checking the high inter-correlation among independent variables before applied to the MLR model. The Tolerance (T), which is a direct measure of Multicollinearity calculated with $1 - R^2$ where $R^2$ explained the independent variable. This value should be high, depicts the lowest collinearity in samples. The second approach used the Variance Inflation Factor (VIF), which is the inverse of T (1/T). Thus, instances of a higher degree of Multicollinearity reflected in low T value and high VIF value.

Table 1 shows the acceptable values of the transformed dataset. For three independent variables, T > 0.20 and VIF > 5 depict adequate to perform MLR where T’s threshold is 0.20, and VIF’s thresholds 5. The third approach used the covariance matrix to check individual correlation co-efficient, and none of the variables has more than 0.8 [17].
Table 1: Tolerance and Variance of Inflation Factor.

<table>
<thead>
<tr>
<th>Feature</th>
<th>T</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>SQRT Educational benefit</td>
<td>0.98</td>
<td>1.02</td>
</tr>
<tr>
<td>SQRT Usability</td>
<td>0.99</td>
<td>1</td>
</tr>
<tr>
<td>SQRT Development availability</td>
<td>0.98</td>
<td>1.02</td>
</tr>
</tbody>
</table>

Fig. 4 shows the results of the Pearson Correlation to explore the inter-correlation among sample features at 0.01 significant level. More than 0.30 positive correlations observed. The internet-connected desktops are positively associated with Internet-connected laptops (0.412), digital devices (0.492), and centralized student information systems (0.301). One hand, student responses system has a linear relationship with the automated student attendance system and another hand all digital devices and E-readers have positive bonding with Internet-connected laptops.

3. Experiments

3.1. Experiment 1

This experiment constructs two linear regression models considering one predictor with nine features. The Educational Benefit viewed as a predictor variable (X), and attitude is the target variable (Y). Two different coefficients (β0, β1) of predictors explored to explain the model. This experiment compares the essential parameters of both models (transformed and untransformed). In Eq. (1), Y is Attitude, β0 is an intercept, β1 is slop, and ε is the error term.

\[ Y = \beta_0 + \beta_1 X + \epsilon \]  

Table 2 retains important parameters to justify the significance of the LR model. This model built to predict the attitude using only one feature, i.e., Educational benefit with the data transformation effect. We observed that the residual error reduced using the SQRT transformation. Also, a bit of improvement seen in the correlation value (0.757 > 0.752). The SQRT transformation increased the explaining power of Educational benefit to identify the attitude (0.573 > 0.565). The significance of the LR model justified with the model’s parameters (t = 14.7, df = 03, P = 0.00 < 0.05).

Fig. 5 plots both transformed and untransformed Attitude models on 2-D canvas with the regression equations. An identical scale of measurement can be seen for both variables from 1.00 to 5.00. The red line model depicts untransformed data, and the blue line shows the transformed data. We found the lowest coefficient of determinations (R² = 0.565) in the untransformed model, and improvement seen within the coefficient determinations (R² = 0.573).

3.2. Experiment 2

This experiment used multiple linear regression to predict the value of the attitude of students based on significant four Educational Benefits out of a total of nine variables. The impact of Educational Benefit on student Attitude in both countries.

\[ Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon \]  

In Eq. (2), Y is Attitude, β0 is an intercept, β1, β2, β3 and ε are slop, and ε is the error term.

Table 3 shows the three major features (X1, X2, X3) recommended with significant values calculated with the Pearson correlation to explore the linear relationship between Educational Benefit and student’s attitude. The mean values of predictors found near agree statement and responses lie an in-between range of the “undecided to agree” scale because of Std. Deviation.

\[ R = \frac{SP}{(\sqrt{SSX})(\sqrt{SSY})} \]  

In Eq. (3), R is a correlation at (2-tailed at 0.01), SP is the sum of the product of deviation score of X1, X2, X3, SSX is the sum of squared of deviation score of X and SSY is the sum of squared of deviation score of X1, X2, X3. The Durbin Watson test calculated the value of autocorrelation 2.20, which comes under a range of 1.5 to 2.5, and it signifies no auto-correlation among X1, X2, X3.

Table 4 shows the linear positive correlations (0.786) of technology Usability and development-availability with the attitude of students. The explanatory strength of these independent features explained well significant coefficient value R² = 0.618, and adjusted R² = 0.610. The transformation effect of variables improved the correlation with a new value 0.786.
Table 3
Independent variables.

<table>
<thead>
<tr>
<th>Educational Benefit</th>
<th>X</th>
<th>R</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sharing of Resources, expertise, and advice</td>
<td>X₁</td>
<td>0.694**</td>
<td>3.83</td>
<td>0.865</td>
</tr>
<tr>
<td>Enriches Learning</td>
<td>X₂</td>
<td>0.693**</td>
<td>3.89</td>
<td>0.988</td>
</tr>
<tr>
<td>Up-to-date learning materials</td>
<td>X₃</td>
<td>0.666**</td>
<td>3.82</td>
<td>0.848</td>
</tr>
<tr>
<td>Higher Quality Lessons</td>
<td>X₄</td>
<td>0.648**</td>
<td>3.69</td>
<td>0.92</td>
</tr>
<tr>
<td>Improving analytical skills</td>
<td>X₅</td>
<td>0.638**</td>
<td>3.77</td>
<td>0.877</td>
</tr>
<tr>
<td>Encourages self-learning</td>
<td>X₆</td>
<td>0.597**</td>
<td>3.92</td>
<td>0.889</td>
</tr>
<tr>
<td>Learning by doing approach</td>
<td>X₇</td>
<td>0.582**</td>
<td>3.79</td>
<td>0.859</td>
</tr>
<tr>
<td>Learning outside campus</td>
<td>X₈</td>
<td>0.573**</td>
<td>3.90</td>
<td>0.865</td>
</tr>
</tbody>
</table>

Table 4
MLR model based on Usability, Development Availability, and Educational Benefit.

<table>
<thead>
<tr>
<th>R</th>
<th>R²</th>
<th>Adjusted R²</th>
<th>Std. Error of the Estimate</th>
<th>Durbin-Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.786</td>
<td>0.618</td>
<td>0.610</td>
<td>0.184</td>
<td>2.20</td>
</tr>
</tbody>
</table>

Table 5
ANOVA of MLR model.

<table>
<thead>
<tr>
<th></th>
<th>Σ Squares</th>
<th>df</th>
<th>Mean²</th>
<th>F</th>
<th>Sig. (P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>8.731</td>
<td>3</td>
<td>2.91</td>
<td>85.63</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual</td>
<td>5.404</td>
<td>159</td>
<td>0.034</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6
MLR model Coefficient.

<table>
<thead>
<tr>
<th></th>
<th>Unstandardized B</th>
<th>Std. Error</th>
<th>Standardized B</th>
<th>t</th>
<th>Sig. (P)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Educational Benefit</td>
<td>0.865</td>
<td>0.056</td>
<td>0.764</td>
<td>15.4</td>
<td>0.000</td>
</tr>
<tr>
<td>Development Availability</td>
<td>-6.13</td>
<td>0.161</td>
<td>-0.187</td>
<td>3.8</td>
<td>0.000</td>
</tr>
<tr>
<td>Usability</td>
<td>-0.117</td>
<td>0.061</td>
<td>-0.086</td>
<td>1.9</td>
<td>0.055</td>
</tr>
</tbody>
</table>

Fig. 6 visualizes an unstandardized observed attitude with the MLR predictive model. The blue line of regression with the line of the equation of Y = 1.47 + 0.23x. We observed the uppermost coefficient of determinants (R² = 0.618). We found that after added up Development Availability and usability features, the predicting power is enhanced.

4. Discussions
This section discussed the performance of both models by suggesting important significant correlated features with the student’s attitude. Also, structured hypotheses are tested based on the experiment results achieved in the preceding section. Fig. 7 depicts the reason to propose specific educational benefits to predict the attitude variable. Pearson Correlation calculates a value for nine independent variables of educational benefit at 0.01 significant level.

All variables are found (**) significant and participated in sound in the prediction task. Enrich Learning, sharing of resource, expertise & advice, improving analytics skills, Reliable and uninterrupted downloading, Up-to-date learning materials, and Higher quality lesson features have the highest correlation (values > 0.60). We observed the lowest correlations value for the variables like learning by doing approach, encourages self-learning, learning outside campus have the weakest values such as 0.582, 0.597, and 0.573, respectively.

Fig. 8 plots the standardized predicted values with both LR and MLR predictive models. The Green regression line shows an equa-
tion of $Y = 1.47 + 0.23x$ provided with MLR model and the highest coefficient of determination ($R^2 = 0.618$). The red line depicts the regression line for the LR model with equation $Y = 1.47 + 0.22x$ and lowest coefficient of determination ($R^2 = 0.573$). Additionally, additive variables usability and development availability significantly improved the coefficient of determination and supported educational benefit to identify a healthier attitude.

The strength of explanatory variables defended with model fit having significant F value 85.63 and P values of regression (*0.000 < 0.05) in the ANOVA Table 5. Based on these values, hypotheses $RH_0$: $\rho_{XY} = 0$ (No relationship between student Attitude and technology in Indian University) is failed to accept and alternative hypothesis $RH_1$: $\rho_{XY} < 0$ (A relationship between student Attitude and technology in Indian University) is failed to reject. Thus, a significant correlation between student attitude and educational Benefit of ICTMT exists in Indian University. Based on substantial values of the educational benefit ($t = 15.4$, *0.000 < 0.05) and development availability ($t = 3.8$, *0.000 < 0.05) instructed to take a decision “failed to accept” for the hypothesis $IH_0$. (No Impact of technology on student Attitude in Indian University). Its alternative hypothesis $IH_1$: (An impact of technology on student Attitude in Indian University) is failed to reject here. Therefore, both influential variables explained the attitude significantly. A noteworthy effect of the technology of ICTMT on the student’s attitude observed.

5. Conclusion

The results of the paper concluded that the application of square root transformation realized correlation enhancement and also increased the impact of educational benefit on the student’s attitude. Comparing the results of LR and MLR models also proved that the MLR model explained the attitude better as compared to the LR model. We proposed educational benefits (enrich Learning, resource sharing for expertise and advice, improving analytics skills, reliable and uninterrupted downloading, up-to-date learning materials, higher quality lessons, learning by doing approach, encourages self-learning, learning outside campus). Every institution in the country needs to focus on providing technology benefits in education, the latest ICTMT for its students and staff. Findings distinct hypotheses testing also proved not only a linear relationship between attitude and educational benefit but also suggested benefits influenced the attitude of students in higher education. The forthcoming task advised to apply more statistical tests to explore the attitude of students accordingly, and the deployment of the presented model might support identifying attitude online supporting the real-time system of the institution.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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