Predicting Attitude of Indian Student’s Towards ICT and Mobile Technology for Real-Time: Preliminary Results

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\textbf{ABSTRACT} This paper proposed a novel futuristic approach to support the educational informatics and overcome the conventional system of attitude measure. For this, we presented a significant predictive model to identify the attitude of students towards technology. The present approach not only explored the impact of the technology but also predicted an opinion of students. The concept of an online awareness model may overcome the traditional method. We have performed the descriptive and inferential statistics to predict the attitude of Indian students towards the ICTMT in university education with primary data samples. Factor Analysis (FA) using Principal Component Analysis (PCA) has extracted the prominent two components with nine features for technology benefits and six features for the technology use. The SQuareRoot (SQRT) and Log transformations have been used to decrease the Skewness, and it has also improved the association between attitude and educational benefit. Overall reliability of the gathered data sample size of 163 calculated 0.957 provided with Cronbach alpha test. This study has used a Pearson Correlation (PC) for exploring the technology impact and the Linear Regression Model (LRM) for the prediction. The LRM has substantiated that the educational benefit explained the attitude significantly, and a significant positive association discovered using the PC with a value of 0.75. The LRM model projected nine most significant educational benefits of ICTMT, which affected the attitude of the Indian student towards technology. We have proposed technology aids in building online predictive model wires real-time prediction.

\textbf{INDEX TERMS} Attitude, educational benefit, factor analysis, correspondence analysis, PCA, real-time.

\textbf{I. INTRODUCTION AND RELATED WORK}

To make a sustainable technology in an educational institution, the attitude toward likeness and dislikes exceedingly matters. Educational institutions need to evaluate the attitude continually, and obviously, it must be highly positive towards technology to make it sustainable. ICT and Mobile Technology (ICTMT) enhances the learning power of a student to support education. Due to this, educational institutions are providing the latest technological facility to support quality education. To analyze and explore the attitude, experiences, and behavior of educators towards the newest ICT, increasing sharply and predictive statistical modeling is also trending to identify unseen patterns from the Educational datasets. In this, both regression and classification played a very significant role. The regression techniques have been using for the decades to determine the power and association between the dependent variable and independent variables. Several investigators have contributed to disciplines using the regression models. Regression is a data mining function that predicts or estimates a number [1]. A statistical analysis helped to explore student’s attitudes towards using ICT in a social constructivist environment [2]. Recently, predictive modeling has been used to predict the student’s birthplace [3], and gender towards ICT for the real-time system [4]. Against the use of ICT in social, work, and study, student attitude was identified with Linear regression [5]. Several causes measure the student attitudes towards Interactive whiteboard use in mathematics classrooms [6]. Recently with the classification approach, the attitude of...
Hungarian students is recognized towards ICTMT [7]. Furthermore, extensive research explored a few attitudinal factors belong to ICT interest, and perceived autonomy in using ICT, rather than ICT availability and IT use, were closely associated with high reading proficiency [8]. Divergence in attitude showed between the significance of specific and general attitudes towards technology [9], and the technology tool enhanced the perspective of students towards professional development [10]. Based on the residential location, expert opinions of students and teachers were predicted towards ICTMT [11], [12]. A multiple regression, including factor analysis, played well to evaluate the intention to use ICT collaborative tools in a social constructivist environment [13]. With the Competitive attitude scale (Anxiety, Linking, Confidence, and Usability), the attitude of students analyzed using regression modeling [14]. Manners of student were predicted based on their online activities on a learning platform [15] Also, multiple linear regression identified the student’s academic performances [16]. The technology awareness identification models with the machine learning for the real-time [17], and opinion identification with significant features was proposed with the regression analysis [18]. Moreover, belonging literature was premeditated to predict the ICT Skills and usability [19], ICT Experience [20], technology integration [21].

Further, unsupervised machine learning (clustering) identified a valuable factor that predicted the future employment of students after passed their graduation [22]. Also, the same procedure used to check the financial sustainability of the institution, which outputted the age and city are crucial to promoting graduate programs. At the same time, marital status and sex do not impact the decision of students in the institution [23]. Additionally, three decision tree variants (J48, Random Tree, and REP tree) applied to identify the academic performance based on social, demography, educational, motivation, study skills, and personal relationships. The researcher proved that J48 tree overtook others [24]. Further, more related literature’s also studied before executed experiments [25]–[28], [29].

Additionally, we studied the latest research study from the prediction perspective. A novel semi-supervised learning framework was proposed, which integrates both survival analysis and game theory for the link prediction [30]. The hybrid methods were also presented to recognize the data patterns that combined discriminative feature, feature combination, and local random walk model [31]. A multiagent system was proposed with a new dynamic game model to find the locally Pareto-optimal Prosumer-Community Groups structure in a smart grid [32]. A Graph k-Mean framework was presented in leader identification in social media networks with multi-objective optimization [33].

A. RESEARCH MOTIVATION
In the world of IoT and real-time systems, there is a requirement of such as real-time attitude prediction system that will help the university authorities to understand the appropriate use of technology in education. Earlier literature had not described the online models with significant features to predict attitude. We proposed a few student’s demography identification models for real-time development [3], [4], [12]. These predictive models had not proposed significant features and even had not focused on the online perception measurement. Motivating from this research gap, the present paper explored the effects of technology benefits on the attitude and predicted the professional attitude supporting various data transformation techniques. We proposed transformed predicted models to deploy a future web-based system of the university. Further, the proposed statistical model is the base model with significant features for developing that real-time environment at the university website or on a separate module. Therefore, the use of technology in classrooms and schools is still often superficial and not meeting the potential of technology as envisioned by education reformers and researchers in the field. However, when technology projects have been implemented successfully in educational practice and shown beneficial impacts, sustainability within similar contexts is not guaranteed [34]. A statistical study plays a vital role in deciding the significant attributes before the development of any technology. To make it sustainable for a long time, we need to analyze the continuing the opinion of stakeholders. Therefore, we recommend the present models itself a viable solution in educational technology to make a real-time web-based opinion analyzer.

B. RESEARCH CONTRIBUTIONS
In educational technology development, we provided a sustainable technology solution for the university response management system to identify the attitude of students online using a web-based model. For this, we statistically proved the significance of results. Further, this paper proposed novel technology benefits that affected the attitude of university students. Significant matrices of the FA technique support these features. We have also identified the technology behavior of students using the Correspondence Analysis (CA). Using the PC method, we explored a significant association between technology benefits and the attitude of students. We used two different data transformations (SQRT and Log) that significantly enhanced the factor association and explanatory strength of variance [35]. The LRM also predicted the student’s attitude by comparing transformed and untransformed factors. The use of the PCA approach sustained our proposed educational benefits to the students.

We also provided the future conceptual project in succeeding in subsection I-C. We suggested designing a new awareness application to bind with the university response system. The results of the paper might be useful to support future sustainable technology. The administration and management might be aware of the technology use, likeness or dislike, and attitude of students.

C. CONCEPTUAL DESIGN
A moral archetypal described the pictorial view of the proposed work. Fig. 1 envisions the pictographic of student attitude prediction for a real-time futuristic sustainable technology.
Six attitudinal and nine technology benefits investigated using the primary samples. During the preprocessing, we handled data entry, encoding, reliability, and adequacy, etc. The variables are inputted into the exploratory FA to provide the most prominent factors for study. Further, the CA response identification model is applied to explore the robust dimensions. We used two transformation techniques to fulfill the normality assumption. Afterward, the LRM model is built and compared to the transformed samples with the initial samples. Obeying the crucial validation metrics, we proposed the significant model to deploy online for a sustainable awareness application. This application can link to the university response system. The students shall ask to fill their response against the feature suggested. Then, the LRM will generate the predicted value that belonged to the respondent. The outcome will be the attitude of educators. The ICT administrator may report the predictive attitude report to the university authorities to render technology decisions.

D. ORGANIZATION
The rest of the paper is divided into seven major sections. Section II defines the methods and materials used in the study. It briefs the primary objectives and related hypotheses, data collection and variables, student demography, factor analysis, correspondence analysis, statistical properties, and data transformation. Section III performs experiments, and explained the essential results. Section IV debates on the results. Section V briefs the strength and weaknesses of the study. Section VI concludes the findings of the study. Section VII focuses on significant future work.

II. METHODS AND MATERIALS
The present study predicted the attitude of Indian students based on educational benefits provided by their university. For this, we applied the LRM with the two most prominent variables. We assumed four hypotheses to achieve the objectives of the study.

A. OBJECTIVES AND HYPOTHESES
• To find the association between educational benefit and the student’s attitude.
  1) H01: No significant linear relationship between educational benefit and attitude of the student towards ICTMT.
  2) H01A: A significant linear relationship between educational benefit and attitude of the student towards ICTMT.
• To explore the impact of educational benefit of ICTMT on the student’s attitude.
  1) H02: No significant impact of educational benefit of ICTMT on student attitude.
  2) H02A: A significant impact of educational benefit of ICTMT on student attitude.

B. DATA COLLECTION AND VARIABLES
A total of 163 samples are analyzed, which collected from one Indian private university named Chandigarh university using google form. Collected samples analyzed in IBM SPSS Statistics Version 25 [36], [37]. Stratified random sampling was used in data collection. Considering two primary factors, student’s attitude and educational benefits of trending technology, we asked students 06 questions about the attitude and 09 questions related to educational benefit. A few missing values tackled using substitute mean values of others. The value of instances was numeric, and variables have scaled on five points Likert type scale. We framed a new factor variable named: attitude and educational benefit using the mean values of belonging variables (suggested by FA) and set measurement type to scale.
C. STUDENT DEMOGRAPHY
A total of 163 samples are analyzed, which collected from one Indian private university named Chandigarh university using google form. Demography of students belonged to Gender, Age, Locality, and Study level. Fig. 2 (a) shows the highest participation of males (137, 84%), and the least females have responded (26, 16%). Fig. 2 (b) shows that the broad participation of the age count of 30 (118, 72%). Fig. 2 (c) shows that the urban students (112, 31%) participated higher than of rural students (51, 69%). In Fig. 2 (d), the maximum students belonged to the Graduation course (137, 84%). A least count of students is observed who are doing Ph.D./ Others (10, 6%).

D. FACTOR ANALYSIS
We used exploratory Factor Analysis to make significant factors for further analysis. The parameters used for factor analysis: Principal Component Analysis (PCA), Vari-max Method, Anti-Image, Convergence Iterations = 25, KMO (Kaiser-Meyer-Olkin), and Bartlett’s test of sphericity. Table 1 shows the overall adequacy of collected samples against each variable that is calculated 0.942. Hence, the partial correlations among variables are slight. Lack of an identifies correlation matrix proved with evident significant (p < 0.05) value of Bartlett’s sphericity. The total cumulative variance explained 72% of the participants’ scores.

Anti-image matrices store the two values: Anti-image co-variances and Anti image correlation on rows and variables on columns. The measure of sample adequacy (a) for individual variables defined by the KMO and Communality measures. The communality “1–uniqueness” is reproduced variances from the factors and proportion of each variable’s variance. We considered the significant variables KMO having greater than 0.60. In Table 2, the variables (Q1-Q6) relate to the attitude, and the variables (Q7-Q15) belongs to the educational benefits of ICTMT. Except for the only two variables, “Promotes independent learning” and “Informative and quality based study,” all variables have excellent KMO. Further, the communalities of variables were found greater than 0.50. The five variables of attitude and four variables of educational benefit have greater than 0.70 communalities.

Fig. 3 visualizes the total number of PCA components with spotting Eigenvalues. It can see that the Eigen score of 1st and 2nd component of the model has greater than 1. The leftmost first component has an Eigenvalue of 9.455, and the second component has the Eigenvalue of 1.337. Therefore, we considered these powerful components for analysis. The rest of the components dropped out caused by the lowest Eigen scores.

Fig. 4 displays the rotated space of two extracted PCA components. The first component is PCA-1 (green stars) that points to attitude variables, and PCA-2 (Blue circles) is the second principal component that depicts the educational benefit variables. Transparently, both components are independents of each other, but indoor variables are
Table 2. KMO and communality.

| Code | Variables                                      | KMO  | Communality |
|------|-----------------------------------------------|------|-------------|
| Q1   | Promotes independent learning                 | 0.897a | 0.759       |
| Q2   | Informative and quality based study           | 0.899a | 0.779       |
| Q3   | Significant in admission/job placement/examination | 0.936a | 0.676       |
| Q4   | Confidence and motivation enhancement         | 0.955a | 0.590       |
| Q5   | Future acceptance in 21st century             | 0.935a | 0.792       |
| Q6   | Deliver and share content rapidly             | 0.923a | 0.769       |
| Q7   | Enriches learning                             | 0.952a | 0.731       |
| Q8   | High quality lessons                          | 0.955a | 0.684       |
| Q9   | Up-to-date learning materials                 | 0.952a | 0.746       |
| Q10  | Reliable and uninterrupted downloading        | 0.928a | 0.689       |
| Q11  | Learning by doing approach                    | 0.949a | 0.642       |
| Q12  | Sharing of resources, expertise, and advice    | 0.942a | 0.753       |
| Q13  | Encourages self learning                      | 0.926a | 0.791       |
| Q14  | Improving analytical skills                   | 0.940a | 0.709       |
| Q15  | Learning outside campus                       | 0.935a | 0.767       |

TABLE 3. Variable response contingency.

| Code | SA | A  | UD | D  | SDA |
|------|----|----|----|----|-----|
| Q1   | 38 | 52 | 57 | 11 | 5   |
| Q2   | 63 | 64 | 40 | 9  | 7   |
| Q3   | 42 | 54 | 52 | 12 | 3   |
| Q4   | 41 | 51 | 55 | 10 | 6   |
| Q5   | 47 | 49 | 48 | 10 | 6   |
| Q6   | 66 | 47 | 36 | 6  | 8   |
| Q7   | 52 | 65 | 44 | 7  | 6   |
| Q8   | 34 | 61 | 52 | 6  | 12  |
| Q9   | 37 | 67 | 52 | 6  | 1   |
| Q10  | 36 | 65 | 46 | 15 | 1   |
| Q11  | 34 | 71 | 48 | 9  | 1   |
| Q12  | 39 | 67 | 47 | 10 | 0   |
| Q13  | 49 | 60 | 47 | 6  | 1   |
| Q14  | 38 | 59 | 58 | 7  | 1   |
| Q15  | 47 | 58 | 52 | 6  | 1   |

E. CORRESPONDENCE ANALYSIS

To evaluate the association of likeness and dislike of students towards variables, we used the CA method that significantly identified the behavior of students. It provides qualified associations between educational benefits and attitudinal variables. For this, a contingency table is depicted in Table 3, which keeps the specific variable and type of response with its frequency. The reaction of students is: Strongly Agree (SA), Agree (A), Undecided (UD), Disagree (D), and Strongly Disagree (SDA). We observed that the maximum number of frequency belongs to SA, A, and UD responses. Hence, the attitude of students is pointing to their likeness. For the Q12 and Q15, nobody found disagreed. For the Q8, we have seen that students are not profoundly convinced.

In model building, we used the Chi-square method to measure the distance between response and variable. The symmetrical standardized normalization applied appropriately that spreads inertia equally over the row and column scores. The inertia is the square of the singular value of dimensions. The total inertia can obtain by dividing the overall active margin with the chi-square value. Table 4 shows the two different Dimensions (DE): DE1 and DE2 have 0.096 and 0.018, respectively, and the Chi-square calculated 304.22 that is significant (0.000<.05). In each dimension, a singular value depicts the correlation between row and column scores in the contingency table. In DE1, it calculated 0.310, and for the DE2, it has a value of 0.136. The calculated proportion of inertia is 0.776, accounted for in DE1, and the DE2 has the lowest proportion of inertia, which is 0.148. The overall cumulative proportion of inertia is 0.924 accounted for both dimensions. Therefore, both aspects have significantly proved that the proposed CA model explained 92% variance.

Fig. 5 visualizes a bio-plot of two dimensions with the symmetrical normalization. The x-axis (DE1) reference denoted...
TABLE 4. CA model.

| Dimension | Singular value | Inertia | Proportion of Inertia | Chi-square | Sig. |
|-----------|----------------|---------|-----------------------|------------|------|
| DE1       | 0.310          | 0.096   | 0.77/5                | 304.22     | 0.00 |
| DE2       | 0.136          | 0.018   | 0.148                 | --         | --   |

Prominent parameters. We observed that the dispersion is 1 for the attitude and less than 1 for the educational benefit. Therefore, fewer variation or dispersion in the responses revealed that the values are closer to the average. Testing the normality in samples, the skewness and kurtosis are perfect for calculating, and we found negative values of both, which proved the lack of normal distribution of samples.

$$\bar{X} = \frac{1}{n} \sum x$$  \hspace{1cm} (1)

$$\sigma = \sqrt{\frac{1}{n} \sum (x_i - \mu)^2}$$  \hspace{1cm} (2)

$x$ is a value in the data set, $\mu$ is the mean of the data set, $n$ is the number of data points in the population, $\sigma$ is standard deviation.

$$Skewness = \frac{3(\mu - \bar{x})}{\sigma}$$  \hspace{1cm} (3)

where $\bar{x}$ is median, $\sigma$ is standard deviation, $\mu$ is mean.

F. STATISTICAL PROPERTIES OF VARIABLES

with the blue line, and the y-axis (DE2) reference line indicated with the red line. The red stars show the type of response provided by the students, and blue stars show the variables used. We observed DE1 has negative (-2.0), and DE2 has positive (0.125) with Q8, which proved that the students have disagreed with Q8 (High-quality lesson). Also, not even a single variable is associated with the SDA response. The CA model demonstrated that the variables Q4, Q6, Q7, and Q13 have the highest SA response. Also, the variables Q1, Q2, Q10, Q11, and Q12 are positively associated with response A. The variables Q3, Q14, and Q15 are correlated with the response UD.

G. DATA TRANSFORMATION

Before the implementation of any regression models, data transformation makes a significant impact on the predictive strength of the model. The preceding section II-F shown the requirement to reduce the Skewness to achieve normalization in samples, and the acceptable values for both should be lie in between $-2$ and $+2$ to prove normal univariate distribution [18], and the Log $(X_i)$ and SQRT $(X_i)$ handles the skewness problem. In SQRT, taking a square root of each value will bring an immense amount to the center to make a standard curve. Both variable educational benefits and attitudes transformed with these transformations. Before doing this, a reverse transformation applied to negative skewed values, which is called reflective. It is accomplished with measure the reflective value $r$ of a variable using the below Eq. 4:

$$r = \max(x) + 1 - x$$  \hspace{1cm} (4)

where $x$ is a variable value, and we found the maximum value of the variable and add 1 in to and reduce the original value to produce the reflective value $r$. Later, the SQRT function was used by passing the $r$ as an argument to outputting the new values of the variable. Fig. 7 shows the comparative skewness graph for the attitude and educational benefit. Initially, attitude and educational benefits have negative skewness of $-0.579$ and $-0.195$, respectively. The Log transformation did not change the sign of initial skewness, but it reduces the skewness of attitude.

The SQRT transformation achieved the perfect normality in the data samples. It made both variables familiar with the skewness value within an acceptable range. On the one hand, the SQRT transformation made positive skewness in attitude.
with the value of 0.123 and another hand; it reduced skewness of educational benefit from $-0.195$ to $-0.159$, which is a bit minimum. Therefore, the subsequent section keeps the experiments on both transformed and untransformed datasets.

Fig. 8 (a) shows the normality curve for the attitude variable. It shows the response scatteredness in the range between 1.00 to 2.20, and the average value is 1.47 with the dispersion of 0.295. Fig. 8 (b) visualizes the normality curve of the educational benefit, having distributions of responses within a range of 1.00 to 2.0. The average value of responses is 1.45, and variation with SD is 0.263. The normality of data samples achieved with SQRT transformation with the skewness value of 0.159. Therefore, both variables seem significantly skewed, which is acceptable to build a regression model.

**III. RESULTS**

This section used the processed dataset to implement LR models and discuss the experimental results with validation metrics. We used the standard Eq. 5, which holds the $Y$ (attitude, SQRT attitude, Log attitude) as response variable, and the $X$ is the independent/predictor variable i.e., Educational Benefit (EB), coefficients ($a$, $b$) of EB to explained the model, and $\epsilon$ is the error term.

$$Y = b_0 + b_1X_1 + \epsilon$$

To see the effect of EB of technology on the attitude of students, we used the below PC Eq. 6. It is calculated by dividing the covariance by the product of the standard deviations.

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

where $R$ = Pearson Coefficient, $n$ = number of the pairs, $\sum x = \text{sum of the EB t scores}$, $\sum y = \text{sum of the attitude scores}$, $\sum xy = \text{sum of products of attitude and EB scores}$, $\sum x^2 = \text{sum of the squared EB scores}$, $\sum y^2 = \text{sum of the squared attitude scores}$.

We observed that educational benefit made a statistically significant ($r = 0.759$, $n = 163$, $p = 0.005$) impact on the attitude of an Indian student.

Fig. 9 shows the correlation of individual variables of the EB with the student’s attitude. We observed that all suggested benefits have a positive relationship with the attitude of students towards technology. The blue reference line over the x-axis proved more than 50% association of each benefit with the attitude.

On the one hand, If the EB score remains 0, then the attitude’s score will stay constant 0.445, and another hand, the attitude of the student, will be positively increased by 0.523 if we increase the value of the EB by 0.1. Three regression equations present with the support of the experiments. Eq. 7 designed to predict the attitude without transformation; Eq. 8 considered to calculate the attitude with SQRT transformation, and Eq. 9 formed to forecast the attitude with Log transformation.

$$\text{attitude} = 0.4 + 0.88 \times \text{EB}$$

$$\text{SQRTattitude} = 0.23 + 0.85 \times \text{EB}$$

$$\text{Logattitude} = 0.06 + 0.83 \times \text{EB}$$

Fig. 10 visualizes not only the predictive strength using the regression line with values but also compares the data transformations to predict the student’s attitude with the help of educational benefit. The blue regression line ($0.4 + 0.88*x$) of the untransformed attitude has the lowest coefficient of determinations ($R^2 = 0.569$). The green line of the SQRT transformation of attitude has a line of equation ($0.23 + 0.85*x$), and this transformation ominously improved the value.
Table 5. Comparing attitude predictive models using EB.

| Model     | Residual | a    | b    | R    | R²  | Std.error | t    | F   | Sig. P |
|-----------|----------|------|------|------|-----|-----------|------|-----|--------|
| attitude  | 54.66    | 0.4  | 0.88 | 0.75 | 0.579| 0.38      | 14.56| 212.2| 0.000  |
| SQRT attitude | 2.9     | 0.23 | 0.85 | 0.76 | 0.576| 0.19      | 14.77| 218.4| 0.000  |
| Log attitude | 2.20    | 0.06 | 0.83 | 0.76 | 0.578| 0.12      | 14.84| 220.4| 0.000  |

On the one hand, the constant intercept value (a = 0.6) proves that the attitude may increase if the educational benefit remains 0, and another hand, attitude improvement may happen with slope (b = 0.83) on the rise one score in the educational benefit. The attitude model having a Pearson correlation (R) value of 0.76 signifies the positive correlation between the attitude of an Indian student and educational benefit. This value is most significant at 0.01 level of significance. The transformed affected new value of \( R^2 = 0.578 \) defines the explanations of independent (educational benefit) on the dependent variable (attitude). The dispersion of the regression line was shown with the standard error of 0.12 that proved fewer variations in the responses. The significant t-value of 14.84 determines the meaningful impact of educational benefit on the student’s attitude. Afterward, the power of the explanatory variable is justified the model fitting with the highest F-value of 220.4.

IV. DISCUSSION

The significant P-value was found less than 0.05 that revealed the predictive strength of the attitude model. Therefore, the first null hypothesis H0: “No significant linear relationship between educational benefit and attitude of the student towards ICTMT” is failed to accept because of the positive correlation value (R = 0.76). The alternative hypothesis H01: “A significant linear relationship between educational benefit and attitude of the student towards ICTMT” is failed to reject. Due to a significant t value of 14.8, the second null hypothesis H02: “No significant impact of the educational benefit of ICTMT on student attitude” is failed to accept and the alternative hypothesis H02A: “A significant impact of the educational benefit of ICTMT on student attitude” is failed to reject. Therefore, based on the first two hypotheses tests, a positive linear association is observed between the student’s attitude and the educational benefit of ICTMT in higher education. The test results of the third and fourth hypotheses proved that the significant impact of the educational benefit of ICTMT on the attitude of university students.

Fig. 11(a) pictures the standardized predicted values of the SQRT attitude model. The regression line (red color) has the standardized regression Eq. 10, whereas Y is SQRT attitude, and x is SQRT educational benefit. The SQRT attitude model has a value of \( R^2 = 0.576 \), which is the coefficient of determinations.

\[
Y = 1.47 + 0.22 \times x \quad (10)
\]

Fig. 11(b) displays the standardized predicted values of Log attitude model. The Log transformed model fitting the line in Eq. 11, whereas y denotes Log attitude and x is Log educational benefit. The blue regression line significantly
holds the regression equation. It is a bit of improvement in the coefficient of determinations ($R^2 = 0.578$). Therefore, both transformed techniques played well to improve the predictive strength of the explanatory variable.

$$Y = 0.32 + 0.14 * x$$

Fig. 12 (a) shows the standardized residual error of the SQRT attitude predictive model, and Fig. 12 (b) displays the Log residuals against the normalized predictive value. Both graphs provided the identical prediction error lie between $-2$ to $+2$. The red loss curve proved the normal distribution of residuals provided by the respective transformation. The light blue spikes present the observed errors in between $-2$ to $+2$ and outside this range. It also shows that errors and prediction linearity around zero. Hence, we achieved non-linearity and observed random distribution of the residuals.

This study is a preliminary work done with its instrument specially designed to analyze the student’s sentiments about the ICTMT. Further, the data samples reliability is found excellent 0.957 likewise, and higher than of the reliability. The factor analysis suggested the variables having explaining power of 72%, which is relatively less than the cumulative variance 86.11% using promax method, but the factor loadings of over 0.60 are identical [13]. The findings of the paper are self-evident that the attitude of stakeholders is linearly correlated with the technical benefits provided, and the student’s attitude is significantly influenced. The results of the regression modeling supported the 5th hypothesis assumed in the findings [13]. Also, the proposed technology benefits forced university students to engage in active learning, which is also supported by the results [1], [13]. Additionally, the present study suggested that the execution of the ICT-based real-time learning environment significantly impacted the attitude of the student. This statement is favorable with the results of the study conducted in the East African Community countries [14].

From the futuristic sustainable perspective, our predictive model is a crucial input to a high potential for educational reform. Still, it can only be achieved if we are eager to rethink and even abandon some of our old-fashioned approaches to identify the attitude about the technology provided. Previous work does not reflect online prediction concepts. Future work using optimization in the deep neural network is our plan to provide a sustainable solution to develop a technology-based solution to predict the educator’s attitude. An online web-based attitude prediction system will offer a socio-economic benefit to the ICT administration or technical staff. They will not need to make a traditional professional survey approach to explore the attitude of students. Further, the identical online web-based attitude prediction approach may also be useful to the various domain (E-commerce, Business Management, economic, health) to provide a sustainable solution. The integration of the real-time web-based attitude prediction in google form technology, Survey Monkey, and many more will be a vital contribution in the 21st century of educational sustainability. The notion of a real-time web-based solution of attitude prediction is based on the “Identify anywhere and anytime.” The present paper exposed the
real-time web-based solution through the proposed statistical identification model with initial results. The research community may also get a novel idea in the development of educational sustainability technology.

V. STRENGTH AND WEAKNESS
Based on the significant results, we recommend our regression model for predictive analysis. The present study used real data samples from one of the reputed technology-oriented universities. Also, the applied feature selection approach provided 15 features out of the exclusive features. We proposed the novel concept to develop this predictive model as a real-time awareness application and integrate with the university student response system. The University management may get an online awareness report about the attitude of students (existing and freshers) using a web-based predictive model. The present paper presented a robust, sustainable solution for the university E-learning system for embedding technology awareness module. Using the proposed online awareness application, the social science students, researchers, and teachers may be benefited.

This paper is limited to very few samples and hypotheses. The applied statistical LRM model is also predefined. We also used a confined feature selection and correlations that are not enough to use. The sample collection mode, validations, and adequacy tests are also limited.

VI. CONCLUSION
This paper used the LRM to predict the attitude of students towards the technology for developing new sustainable technology awareness web application. Embedding the LRM attitude predictive model may be given an online report to the university management and technical administrator about the current scenario of technology impact. An exploratory FA method advocated two significant components to build the LRM. The PCA-1 and PCA-2 have the Eigenvalue of 9.455 and 1.337, respectively. The PCA-1 holds the six variables that belonged to attitude, and PCA-2 holds the nine educational benefits. More than 60% of the KMO and 50% of the communalities of each variable proved the strength of the sample adequacy. According to the CA model, the respective variables explained the 77.6% variance. It also confirmed that the students have disagreed with the variable “High-quality lesson”. Nobody found strongly disagreed with the variables. Also, it revealed that all students liked the instrument variables, and many of them were undecided too. We used three types of data transformation techniques in the present study to gain better results. We found the vital role of transformation in making a significant LRM. A highly positive response towards technology was observed using the mean scores, and less variation was confirmed due to less dispersion. The SQRT transformation made positive skewness in the attitude variable made fit to execute the LRM. The student’s attitude increases with providing the educational benefit about ICTMT proven with a highly positive correlation value of PC. The authors recommended nine innovative educational benefits, which make student’s attitudes higher towards the ICTMT. Both the SQRT and the Log transformation enhanced the correlation value. The LRM also proved a significant linear relationship between the educational benefit and attitude of the student towards ICTMT in Indian higher education. Due to a substantial explanation provided with the educational benefit to predict mood, we proposed the model to be online deploy, which affected the student’s attitude towards the ICTMT of university students.

VII. FUTURE STUDY
The predictive strength of the present model can be analyzed using more extraction methods such as principal axis factorizing, unweighted least square, and generalized least square. The rotation methods can also be applied, like Quartimax, Equamax, and Promax within FA.

Future work may include multiple linear regression to measure the student’s attitude with another parameter like technology usability and technology development.

Using unsupervised learning (K-mean and hierarchical clustering), we can explore the students with different opinions about technology. Further, the use of supervised earning (Multilayer perceptron, XG-Boost, support vector machine) with feature selection will be appropriate. It can enhance the accuracy of the observed results.

Additionally, the sample enhancement may also improve the results of exiting and novel machine learning models. We can include more than one university for the prediction task. Both the students and teachers may have participated in a comparative study.

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