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Impact of online learning environment on university students' performance

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Abstract — Online learning is an emerging trend in current education sector. It is a convenient way oflearning for the people who have various constraints regarding traditional education system. The popularity of online learning results in increase of online learning data. Learning analytics is a growing research field to analyze online learning data. The concept of learning analytics and data modeling extends the promising research directions in online learning environment. Although numerous researches have investigated on experience in online education field, limited findings are available for the challenges and the specific strategies that students apply to conquer those challenges. The present research study aims to analyze the impact of online learning environment on student's performance and identify challenges in opting online courses. The goal of the study is to develop a model for the student data using structural equation modeling in Jamovi software that can explain and analyze the impact of online learning environment on students' performance. The hypothesis established for the model is supported by the results. It is observed that established model has acceptable fit indices with significant p-values. The analysis indicated that the challenges in opting online courses for university credits are mostly due to internet, device facility, language comfort and mode of learning. The research study provides the baseline to understand the impact of online learning factors on students' outcome for improving the learning system.

Keywords: Online learning; Learning analytics; Structural Equation Modeling; Learning factors; Student performance.

1. Introduction

Since last two decades online education has become popular in offering continuity in education to all levels of students (Ye, 2021). Online education is now seen as an alternative way of learning that is well suited particularly to learners looking for higher education opportunities (Lockee, 2021). This learning style is gaining popularity because it provides the opportunity to remain in touch remotely with classmates and teachers (Ferri, Grifoni & Guzzo, 2020) and also because of its easy accessibility and reachability in remote and rural areas (Dhawan, 2020). Given today's unpredictability, it is essential to gain a subtle understanding of students' learning experience in online education (Barrot, Llenares & Del Rosario, 2021). This is where the role of learning analytics comes. Learning analytics enables to make decisions and take actions based on online educational data while indicating the importance of understanding and acquiring learning in day-to-day educational practices (Mougiakou, Vinatsella, Sampson, Papamitsiou, Giannakos & Ifenthaler, 2023). The application of learning analytics is increasing among researchers also to provide new methods for standard and measurable decision making processes, for ensuring student success (Kew & Tasir, 2022) and to enable the educational stakeholders understand how to effectively design and deliver online programmes for ensuring engagement and learning gains.

It is important to understand that each student has its own perspective and different set of factors that impact his/her performance in online learning environment. This understanding can help in enhancing the learner's academic achievement as well as making other decisions for online learning trend. The main focus of this study is to analyze the impact of learning factors related to online learning on students' performance using learning analytics and to identify the challenges in choosing online courses by the students as their university credits.

In this paper, a comprehensive model is developed to illustrate the key factors that influence the performance of university students' in online learning systems using structural equation modeling (SEM). SEM is a powerful tool for explaining the dependencies between latent and observed variables. It is not only a mere statistical technique rather it provides an analytical process involving model conceptualization, parameter identification and estimation, data-model fit assessment, and potential model re-specification (Mueller & Hancock, 2018). The developed model will be used to explain the effect and influence of online learning factors on learners' performance. The research questions addressed in this study are:

RQ1: What are the factors that influence student's performance in online learning system?
RQ2: What is the impact of online learning factors on students' performance?
RQ3: What are the challenges due to which students do not opt online courses for university credits?

2. Literature review

2.1 Learning analytics

Several researchers and educators have been motivated to improve the effectiveness and efficiency of online learning due to of its rising popularity. The significance of learning analytics is in assisting students in continuously improving their academic performance using educational technology (Jo, Yu, Lee & Kim, 2015). Learning analytics plays a vital role in designing various technical and methodological strategies from educational data that can be used in decision-making (García-Peñalvo, 2020). Emphasis has been given to analyze data gathered from user interactions with educational and informational technology as a viable strategy to deepen the understanding of the learning process (Vassakis, Petrakis & Kopanakis, 2018; Gasevic, Tsai, Dawson & Pardo, 2019). Toro-Troconis, Alexander, and Frutos-Perez (2019) analyzed student engagement with online content to encourage both high order cognitive skills (like participating in online forums and webinars) and low order cognitive skills (like listening to podcasts, watching videos, and reading materials). Coussement, Phan, De Caigny, Benoit & Raes (2020) analyzed the reasons of student's dropout and outlined the effects of student demographics, classroom features, and academic, cognitive, and behavioral engagement variables. Mukhtar, Javed, Arooj, and Sethi (2020) investigated how teachers and students perceive the benefits, drawbacks, and suggestions of online learning. For learning analytics research and practices Tsai, Whitelock-Wainwright, and Gaevi (2020) identified a number of important consequences that can be used to improve student's performance and also for enhancing the decision making process in educational institutions. Garca-Morales, Garrido-Moreno, and Martn-Rojas (2021) emphasized the need to digitalize educational and training procedures with technology capabilities for online instruction. The expectations of academic personnel towards learning analytics services were examined by Kollom et al. (2021) from both an ideal and a pragmatic standpoint. Rajabalee and Santally (2021) analyzed the connections between first-year university students of various disciplines' performance in an online module and their degrees of engagement and satisfaction. Community, engagement, pedagogy, equity, and design-based research were identified by Greenhow, Graham, and Koehler (2022) as crucial perspectives that could be used by scholars to produce information that has an impact on research and practice in online learning contexts. The impact of tailored metacognitive feedback assistance based on learning analytics in online learning for recommendation and guidance on student engagement was examined by Karaoglan Yilmaz & Yilmaz (2022). To improve students' learning performance, Kew and Tasir (2022) created a Learning Analytics intervention for e-learning. In order to determine the effectiveness of online learning, Sumadi, Hidayat and Agustina (2022) examined studies on the study of learning facilities in elementary schools.

2.2 Learning analytics and Structural Equation Modeling (SEM)

Learning analytics have been carried out by the researchers using structural equation modeling. Koç (2017) built a theoretical model in a web based distance education course to explain causal linkages between student engagement and academic accomplishment through learning analytics and evaluated it using SEM on an empirical dataset. Abrahim, Mir, Suhara, Mohamed & Sato (2019) designed a SEM and a confirmatory factor analysis method to explain how students can use facebook for educational purposes. Chopra, Madan, Jaisingh and Bhaskar (2019) assessed the efficacy of the online learning environment from the perspective of the students. Fincham, Whitelock-Wainwright, Kovanović, Joksimović, van Staalduinen & Gašević (2019) suggested, measured, and validated a model of engagement based on theoretical literature which could be understood by means of standard metrics taken from the study of learning analytics. To investigate the relationships between latent variables and student results, a SEM was fitted, and MIMIC modelling was used to determine the model's applicability in various course contexts. Kucuk & Richardson (2019) examined the structural connections between the teaching, social, and cognitive presence, engagement, and satisfaction of online learners. The findings showed that major determinants of satisfaction include teaching presence, cognitive presence, emotional engagement, behavioral engagement, and cognitive engagement. The use of self-regulated learning strategies, demographics of MOOC participants, perceived learning, and satisfaction were studied by Li (2019) with a focus on significant links using SEM. The findings had implications not only for educators dealing with increasing these strategy usages, enhancing online learners' satisfaction and cross-cultural teaching; but also for researchers looking at self-directed learning environments and differences in learning of learners from different backgrounds and behaviors. In a web-based distance education course, a theoretical model was put out by Park & Jo (2019) and was tested using SEM to explain causal links between student engagement and academic accomplishment. Submissions to discussion forums and participation in online lectures were discovered to be positively correlated.

Luan, Hong, Cao, Dong & Hou (2020) created a model to illustrate the connections between students' perceived social support and their involvement in online English learning. The links between teacher support and peer support and other forms of student involvement were totally mediated by behavioral engagement, according to the results of the mediational model based on SEM. Abdul Jalil & Wong Ei Leen (2021) determined the relationship between student predictions regarding learning analytics and the personality traits with SEM approach. Student perception of the characteristics of learning analytics tools and their enthusiasm in using them in the classroom was also investigated. Al-Adwan, Albelbisi, Hujran, Al-Rahmi & Alkhalifah (2021) identified a direct correlation between students' pleasure, perceived utility and system use; and the quality of the teacher, technical system, support service, educational systems, and course content. Using SEM, Hizam, Akter, Sentosa & Ahmed (2021) examined a better fit between Moodle use and teaching tasks and investigated its impact on both Moodle use and task performance. This was done by integrating the educators' digital competency and a personal characteristic construct of the task-technology fit theory. On the basis of the acceptance model, Li, He, and Wong (2021) investigated the factors that predicted undergraduates' intention to embrace e-learning for English study. Sanchez, De-Pablos-Heredero, Medina-Merodio, Robina-Ramírez & Fernandez-Sanz (2021) investigated the connection between relational coordination and the effectiveness of institutions' online learning environments with the help of SEM.

According to Ajibade, Adhikari & Ngo-Hoang (2022), perceived usability and convenience of use were factors in students' and teachers' behavioral intents to use social media for e-learning in Nigerian institutions. Based on the reliability analysis, exploratory factor analysis, and confirmatory factor analysis of the data, initial SEM was improved by Liu (2022). According to the SEM based influential order of factors on primary science curriculum blended learning. Nikolaidis, Ismail, Shuib, Khan & Dhiman (2022) developed method to identify students who are likely to attrition in advance through self-evaluation of academic elements influencing their learning progress. The findings showed that the learning progress was mostly influenced by the effectiveness of the teacher and the instructional materials. Sarstedt et al. (2022) demonstrated that performing factor-based SEM was equivalent to estimating models with intricate relationships between observed concepts and their latent variables. The benefit of fit indices in SEM was described by Savalei, Brace & Fouladi (2023) as these allow for some misspecification in the additional restrictions put on the model, which is a more likely outcome. Alamer & Al Khateeb (2023) contributed to a clearer understanding of the benefits and difficulties of applying WhatsApp as a tool for mobile-assisted language learning using SEM in the educational system. İlter (2023) examined how school absences affected the links between various amotivational factors and academic achievement. SEM analysis revealed that the factors, such as ability beliefs, effort beliefs, and task value directly influenced students' academic performance. Using a sample of potential mathematics instructors, Karakose et al. (2023) examined the causal correlations between academic self-efficacy, academic amotivation, attitude toward the teaching profession, and classroom management anxiety. Using SEM Shen, Wang, Yang & Yu (2023) mapped the current state of academic emotions, self-regulated learning technique use, and complex interrelationships among these factors in Chinese university students who were learning English as a foreign language.

On the basis of above review, it can be said that the recent trend is to use SEM for:

(a) examining the influence of an instructor on student engagement,
(b) examining the causal linkages between student engagement and academic accomplishment,
(c) determining structural connection between teaching, engagement and satisfaction of online learners, and
(d) Identifying factors to predict interactions in embracing e-learning for a particular subject.

The attention on the impact of online learning factors on student performance has not been observed yet in a structural manner. Also no study has been found to investigate the challenges that restrict learners from pursuing online courses for university credits. This research study is an effort in this direction. The added value of the present paper for educationists is that they can understand the structural connection between different online learning factors and also how online education is affecting students to further increase the positive impact of the online education system.

3. Methodology

The goal of this paper is to determine the impact of online learning factors on student’s performance and to identify the challenges faced by students in taking online courses for university credits. To achieve the goal of this research study, the data is collected through survey which is first treated statistically. A SEM model is then developed to analyze the impact of learning factors on student performance. The steps of the method are shown in Figure 1.

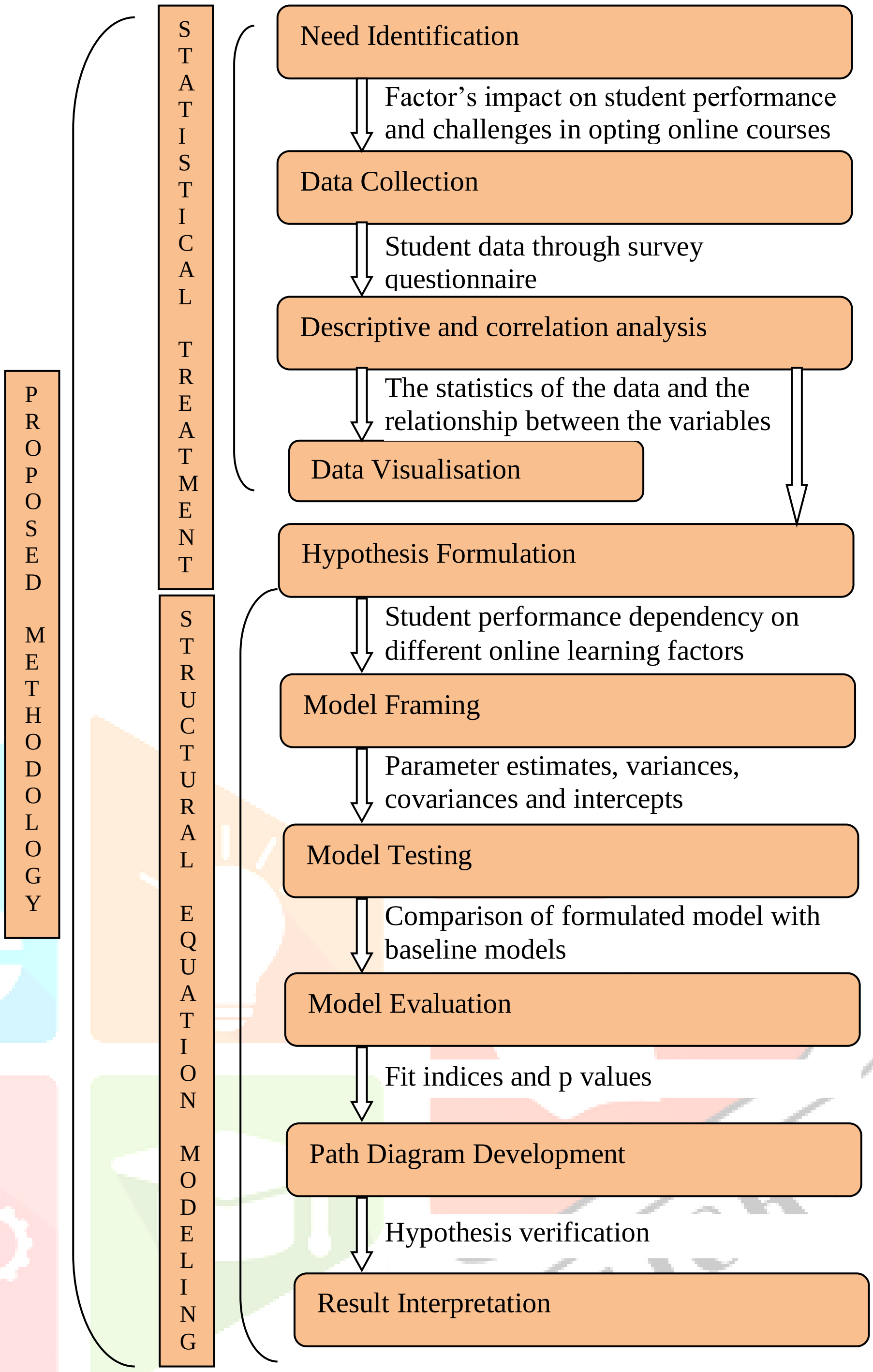


Figure 1: Steps of methodology

3.1 Need identification

The significance of online learning as a potential solution for modern educational need has increased the demand for a more thorough investigation of the factors that influence the results and success of online learning. In this study, the factors related to online learning were determined by reviewing literature and by discussion with experts. These factors were divided into five categories**:**

- Demographic data: It includes the individual characteristics of students.
- Learning program data: This is the data related to program in which the learner is enrolled.
- Mode of learning and assessment: It is the learning methods and assessment techniques used by instructors.
- Internet accessibility: It is mainly related to internet and device facility and accessibility.
- Performance: This is related to the student academic achievement in grades.

Table 1 shows the identified factors with their possible values.

Table 1: Online learning factors and their possible values

Data category	Data variables/label	Possible values
Demographic data	Gender (Gen)/DM1	Male
		Female
	First Language (FL)/DM2	English
		Hindi
		Other
	Age (Age)/DM3	18 – 22
		23 – 27
		28 – 32
		33 or more
	Responsibilities at place of residence (Resp)/DM4	None
		Moderate
		Too many
Learning Program data	Familiarity with English (FEW)/PM1	not at all
		a little
		quite a bit
		a lot
	Year of the course (Yrs)/PM2	1
		2
		3
		4 or more
	Branch (Bch)/PM3	Arts
		Commerce
		Computer Science
		Engineering
		Management
		Science
	Online courses taken for University credit (Cdt)/PM4	0
		1
		2
		3 or more
	Percentage of classes attended (Att)/PM5	<20%
		20-40%
		40-60%
		60-80%
		>80%
Mode of learning and assessment	Preferred learning mode (Mod)/MD1	Face to face interactive classes
		pre recorded video/audio lectures
		lecture notes
		discussion forum
		peer learning
	Assessment technique (AT)/MD2	Essay type questions
		Online viva
		Online quizzes
		Peer evaluation and review
Internet accessibility	Easy access to the Internet (Net)/CON1	Yes
		No
	Device used for online learning (Dev)/CON2	Laptop
		PC
		smart phone
		Tablet
		other device(please name the device)
	Functioning of the device (FD)/CON3	Good
		Sometimes not good
		Not at all

Data category	Data variables/label	Possible values
	Internet connectivity (Con)/CON4	Poor
		Weak
		Average
		Good
		very good
Performance	Grade (Grd)/GRD	A >=85%
		B >=60 & <85
		C >=45 & <60
		D >=30 & <45
		E <30

3.2 Data collection

The data is gathered from 3 different universities of India through survey questionnaire. 202 undergraduate students were taken from different streams like arts, commerce, computer science, engineering, management and science.

3.3 Descriptive and correlation analysis and data visualization

The descriptive analytics is performed to find out the statistics of the collected data. The relation between data variables are found using correlation analysis. Results of analysis are shown through graphs and tables.

3.4 Structural equation modeling

SEM is the statistical analysis approach to construct linear relationship between the observed and latent variable in structural form. It is used to test the hypothesis about variables in the construct. In this analysis, two types of variables endogenous/dependent variable (performance) and exogenous/independent variables (demographic data, learning program data, mode of learning and assessment and internet accessibility) are used. The formulated hypotheses of the model are:

- **H_0:** Student performance is not dependent on four measured variables
- **Ha:** Student performance is dependent on four measured variables

The developed SEM model is tested by comparing user model with the baseline model. The model is evaluated through significant fit indices, p values and chi square values. Chi square values of SEM model show how fit the model is or similarity and discrepancies between implied user model and baseline model for a sample size (df) at significant p value. The hypotheses are verified by the path diagram. The analysis is done on Jamovi software. Jamovi is a powerful open source statistical analytical tool.

3.5 Identify challenges in opting online courses for university credits

The data analytical approach is focused on discovering the coherent association of the factors among students, aiming to identify the challenges that students face in pursuing the online courses for university credits.

4. Data analysis

A) Descriptive Analysis: The descriptive analytics on the data is shown in Table 2.

Table 2: Descriptive analysis for the data

Data Fields	Mean	Std Dev	Sample Variance	Kurtosis	Skewness
Gender	1.366	0.483	0.233	-1.704	0.559
Age	1.099	0.299	0.09	5.371	2.705
Responsibilities at place of residence	1.98	0.555	0.308	0.294	-0.009
Year of the course	1.856	0.927	0.86	-1.57	0.366
Branch	4.158	1.644	2.701	-1.01	-0.27
First Language	1.703	0.469	0.22	-1.049	-0.748
Familiarity with English	2.639	1.038	1.078	-1.247	0.042
No of courses taken for Univ. credit	2.198	1.172	1.374	-1.314	0.432
Percentage of classes attended	3.698	1.211	1.466	-0.46	-0.71
Preferred mode for online learning	1.673	1.028	1.057	2.064	1.606
Assessment technique	2.733	0.69	0.475	1.165	-1.065
Easy access to the Internet	3.653	0.982	0.964	1.147	-1.01
Device used for online learning	2.55	0.946	0.896	-0.019	-0.553
Functioning of the device	2.559	0.581	0.337	-0.126	-0.927
Internet connectivity	3.614	0.982	0.965	0.392	-0.529

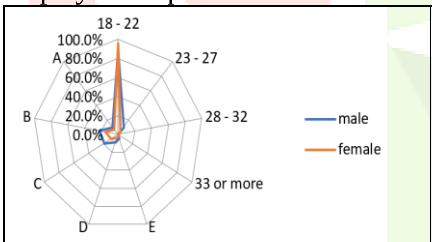
There were 63.7 % male and 36.3 % female in the survey data. The age group of the students is between 18 years to 27 years. Most of the students in this study are in 2nd year of their course. Majority of the students are from science (36.8%) and computer science (32.8%) branch, some are from engineering (16.9%) and arts (9.5%) and very few are from management (3.5%) and commerce (0.5%) branches. In terms of responsibilities at home, 69.2% have moderate, 16.4% have many and 14.4% students have fewer responsibilities at home.

Majority of the students have Hindi as their first language (69.2%), 0.5% have other languages as their first language and rest have English as their first language. 21.9%were fluent in English and 38.8% were not at all comfortable with English.

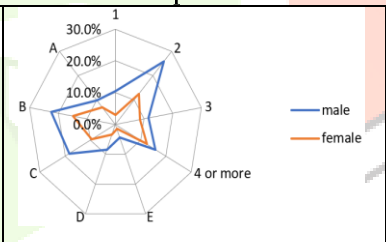
50.2% students did not opt any online course, 15.4% students had 1 subject, 33.3% students had 2 subjects for online course credit and only 1% students have 3 or more subjects for online course credits.

Almost 65% students have easy access to the internet for online learning. The most popular device for online learning is smart phone (70.6%) and then the laptop (24.4%). Devices of 60.2% students worked well for online study, however for 35.5% sometimes did not perform properly for the learning purpose. In terms of internet connectivity, 37.8% students had average whereas 35.3% had good internet connectivity. 18.9% students have very good connectivity and only 8% students have either poor or weak internet connectivity. The preferred mode of learning by the students is face to face interactive classes (61.2%) followed by pre-recorded video/audio lectures (19.4%), lecture notes (13.4%), peer learning (3.5%) and discussion forums (2.5%). According to the students, the preferred assessment technique for online learning is online quizzes (69.7%) followed by online viva (16.4%), essay type subjective questions (8%) and peer evaluation (6%). The attendance of 64.2% students in online classes was more than 60% and only 6.5% students attended very few online classes (20%). The performance of the students in terms of grades was 16.9% students were in grade A, 37.3% were in grade B, 27.9% were in grade C, 11.9% were in grade D and 6% of students were in grade E.

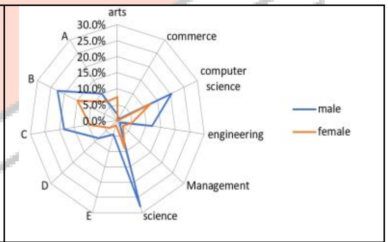
B) Correlation analysis: The correlation analysis between different data variables with the performance of male and female students are shown by radar graphs in Figure 2 and Figure 3. Age vs. performance graph depicts that male and female aged between 18-22 performed average and above average. Year of the course vs. performance graph indicates that as year of the course increases, the performance becomes better for both male and female students. Branch vs. performance graph tells that all the branches show the similar distribution over the male and female student performance in the online courses. Responsibilities of a student vs. performance graph show that no responsibility or moderate responsibility at home well versed with the student's performance. The balance between responsibility at home and learning makes a good combination for better performer in studies than the ones who have a lot of responsibilities at home. The first language vs. performance graph shows that both male and female performed above average with majorly Hindi as their first language. So from this graph it is depicted that the first language is not restricting the performance of the students. Familiarity with English vs. performance graph depicts that fluency in language is not a significant constraint in case of online learning regarding students' performance. Attendance vs. performance graph depicts that the attendance of the student in online learning playsan important role to enhance the student's performance in online classes.



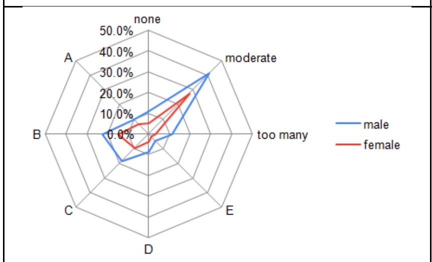
Age vs. performance



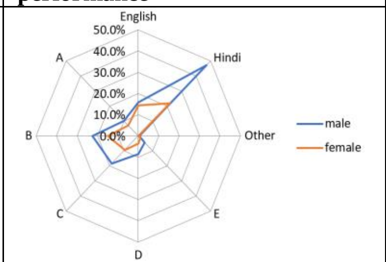
Year of the course vs. performance



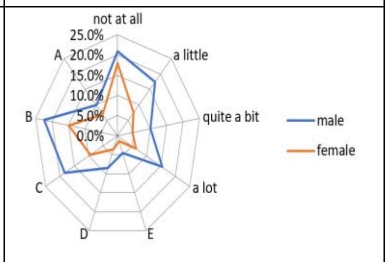
Branch vs. performance



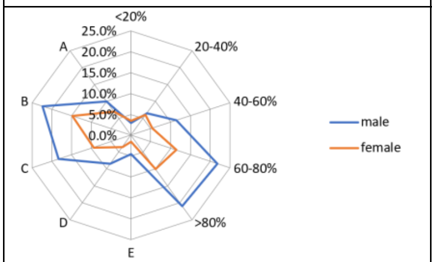
Responsibilities vs. performance



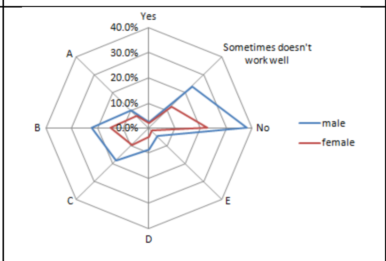
First language vs. performance



Familiarity with Eng vs. performance



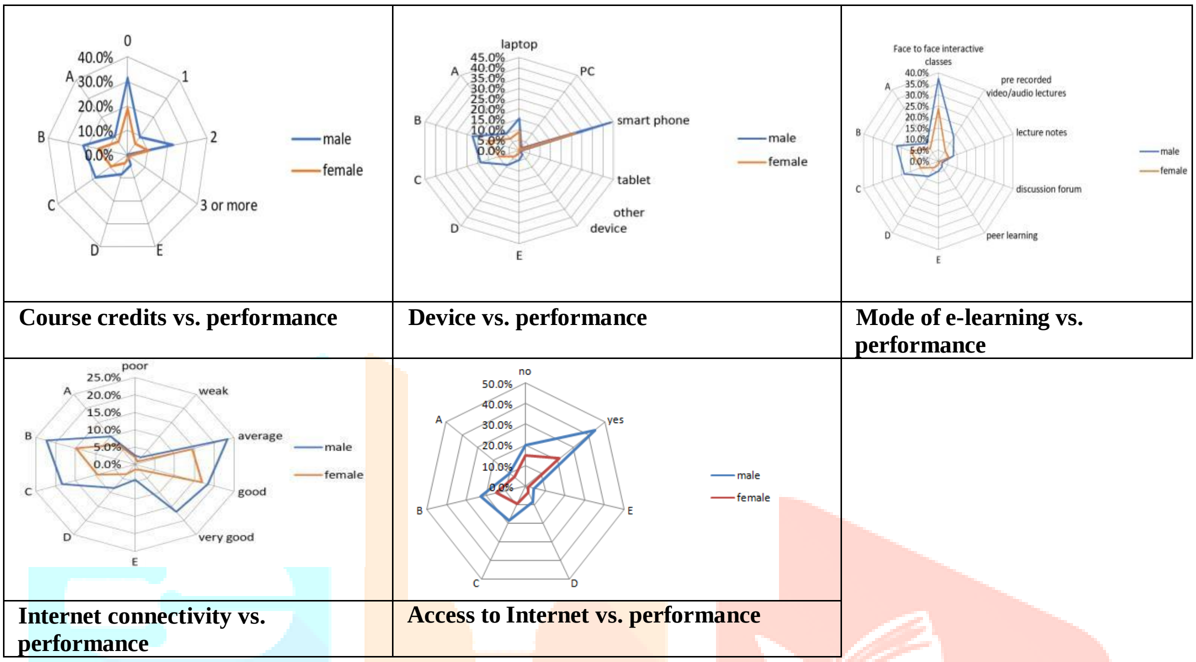
Attendance % vs. performance



Device Functioning vs. performance

Figure 2: Radar Graph for demographic variables

Number of Distance Education or Online Courses that a student has taken for University credit vs. performance graph shows that taking many online courses leads to decrease in performance. Easy access to the Internet vs. performance graph shows that a good access to internet leads to the better performance in online learning. Devices used for online learning vs. performance graph tells that Smart phones are handy and accessible and easy to use for learners, hence leading to better student's performance. The functioning of a device vs. performance graph tells that better conditioned devices for online learning lead to good performers in online learning courses. The connectivity vs. performance graph shows that the internet connectivity has a very high impact on the students' performance. Students' performance and internet connectivity in online learning scenario has the direct relationship. The preferred mode of online learning vs. performance graph shows that face to face interactive classes have the high impact on student's performance as compared to other online learning techniques.



Course credits vs. performance | **Device vs. performance** | **Mode of e-learning vs. performance**

Internet connectivity vs. performance | **Access to Internet vs. performance**

Figure 3: Radar Graph for other variables

C) Structural equation modeling: As there is individual impact of the data variables on the student's performance, so a model is developed using structural equation modeling (SEM) to understand a more clear relationship between the data variables. In this study, demographic data, learning mode and assessment technique are considered as independent variables and performance as dependent variable for structural equation modeling. Each of these latent variables is measured by several questionnaire items or the observed variables. The model information for structural equation modeling is shown in Table 3.

Table 3: Structural Equation Modeling – Models information

Estimation Method	ML
Optimization Method	NLMINB
Number of Observations	202
Free parameters	57
Standard errors	Standard
Scaled test	None
Converged	TRUE
Iterations	231
Model	Demographic=~DM1+DM2+DM3+DM4
	Program=~PM1+PM2+PM3+PM4+PM5
	Mode=~MD1+MD2
	Accessibility=~CON1+CON2+CON3+CON4
	Performance=~GRD
	Performance~Demographic+Program+Mode+Accessibility

The model information table illustrates that estimated method that can be applied for the problem is ML (maximum likelihood). ML process is iterative in nature and it represents the values of the sample covariance matrix which indicates that the values closer to the zero better fits for the model. The estimate maximizes the likelihood of the data drawn from the population. The sample size 202 is pretty good for structural equation modeling.

Table 4: User model and baseline model based on model tests

Label	X²	df	p
User Model	149	95	< .001
Baseline Model	232	120	< .001

Table 5: Fit indices of the model at 95 % confidence intervals

SRMR	RMSEA	Lower	Upper	RMSEA p
0.068	0.053	0.037	0.069	0.058

There is not much difference in chi square values of user model and baseline model with significant p value (<.001) for the sample size 202. So the model is fairly good fit for the data and the sample size. This can also be confirmed by fit indices that should be around 0.06 for acceptable fit model as shown in Table 5.

Table 6: User model versus baseline model

Model	
Comparative Fit Index (CFI)	0.518
Tucker-Lewis Index (TLI)	0.391
Bentler-Bonett Non-normed Fit Index (NNFI)	0.391
Bentler-Bonett Normed Fit Index (NFI)	0.358
Parsimony Normed Fit Index (PNFI)	0.283
Bollen's Relative Fit Index (RFI)	0.189
Bollen's Incremental Fit Index (IFI)	0.606
Relative Noncentrality Index (RNI)	0.518

The values of CFI, TLI, NNFI, NFI, PNFI, RFI, IFI, RNI and TLI also show that the model is a fairly good fit model.

Table 7: Measurement model at 95% confidence intervals

Label	Latent	Observed	Estimate	SE	Lower	Upper	β	Z	P
p1	Demographic	DM1	1.0000	0.0000	1.00000	1.000	0.66903		
p2		DM2	0.2977	0.1526	-0.00141	0.597	0.20518	1.951	0.051
p3		DM3	0.1207	0.0910	-0.05778	0.299	0.13023	1.325	0.185
p4		DM4	0.6012	0.3317	-0.04885	1.251	0.18714	1.813	0.070
p5	Program	PM1	0.2213	0.1686	-0.10919	0.552	0.12882	1.312	0.189
p6		PM2	0.0283	0.2685	-0.49785	0.555	0.00987	0.106	0.916
p7		PM3	1.8686	0.6685	0.55840	3.179	0.36740	2.795	0.005
p8		PM4	0.9487	0.4077	0.14964	1.748	0.26157	2.327	0.020
p9		PM5	0.6345	0.3802	-0.11080	1.380	0.16935	1.669	0.095
p10	Methods	MD1	1.0000	0.0000	1.00000	1.000	0.05454		
p11		MD2	-1.0183	1.0318	-3.04063	1.004	-0.08281	-0.987	0.324
p12	Facility	CON1	1.0000	0.0000	1.00000	1.000	0.25417		
p13		CON2	0.0579	0.2051	-0.34420	0.460	0.01526	0.282	0.778
p14		CON3	0.1564	0.1299	-0.09815	0.411	0.06720	1.204	0.229
p15		CON4	5.0547	6.8193	-8.31087	18.420	1.28430	0.741	0.459
p16	Performance	GRD	1.0000	0.0000	1.00000	1.000	1.00000		

The measurement model in Table 7 shows the statistical statement for defining the relationship among the variables. It shows the differences in estimates for the variables along with the SE, lower and upper bound and beta values for the observed variables with 95% confidence intervals.

Table 8: Parameters estimates at 95% Confidence Intervals

Label	**Dep**	**Pred**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**P**
p17	Performance	Demographic	0.0661	3.03	-5.88	6.01	0.0196	0.0218	0.983
p18	Performance	Program	-0.3622	6.368	-12.84	12.12	-0.0352	-0.0568	0.955
p19	Performance	Methods	1.4565	8.64	-15.48	18.39	0.0750	0.1686	0.866
p20	Performance	Facility	0.4071	1.08	-1.70	2.52	0.0933	0.3780	0.705

Table 8 gives the estimates of the parameters for latent variables in terms of SE, lower bound, upperbound, beta, z and p values. The large p values indicate that model is fairly good.

Table 9: Variances and Covariances

95 % confidence intervals

Label	Variable 1	Variable 2	Estimate	SE	Lower	Upper	β	z	P
p21	DM1	DM1	0.12823	0.03538	0.0589	0.1976	0.552	3.6241	< .001
p22	DM2	DM2	0.20950	0.02161	0.1671	0.2519	0.958	9.6946	< .001
p23	DM3	DM3	0.08769	0.00885	0.0704	0.1050	0.983	9.9144	< .001
p24	DM4	DM4	1.03481	0.10604	0.827	1.2426	0.965	9.7590	< .001
p25	PM1	PM1	0.30145	0.03040	0.2419	0.3610	0.983	9.9174	< .001
p26	PM2	PM2	0.85554	0.08514	0.6887	1.0224	1.000	10.0491	< .001

p27	PM3	PM3	2.32497	0.26971	1.7963	2.8536	0.865	8.6201	< .001
p28	PM4	PM4	1.27322	0.13492	1.0088	1.5377	0.932	9.4366	< .001
p29	PM5	PM5	1.41649	0.14432	1.1336	1.6993	0.971	9.8149	< .001
p30	MD1	MD1	1.04853	0.11500	0.8231	1.2739	0.997	9.118	< .001
p31	MD2	MD2	0.46985	0.06856	0.3355	0.6042	0.993	6.8531	< .001
p32	CON1	CON1	0.89716	0.12070	0.6606	1.1337	0.935	7.4331	< .001
p33	CON2	CON2	0.89091	0.08864	0.7172	1.0646	1.000	10.0508	< .001
p34	CON3	CON3	0.33406	0.03325	0.2689	0.3992	0.995	10.0474	< .001
p35	CON4	CON4	-0.62332	2.08046	-4.7009	3.4543	-0.649	-0.2996	0.764
p36	GRD	GRD	0.00000	0.00000	0.0000	0.0000	0.000		
p37	Demographic	Demographic	0.10390	0.03821	0.029	0.1788	1.000	2.7194	0.007
p38	Program	Program	0.01115	0.02004	-0.02813	0.0504	1.000	0.5563	0.578
p39	Methods	Methods	0.00313	0.04903	-0.093	0.0992	1.000	0.0638	0.949
p40	Facility	Facility	0.06196	0.08796	-0.1104	0.2344	1.000	0.7044	0.481
p41	Performance	Performance	1.16555	0.19896	0.7756	1.5555	0.988	5.8581	< .001
p42	Demographic	Program	0.02941	0.02680	-0.02312	0.0819	0.759	1.0972	0.273
p43	Demographic	Methods	-0.03511	0.03061	-0.0951	0.0249	-1.947	-1.1471	0.251
p44	Demographic	Facility	0.01349	0.01972	-0.0252	0.0521	0.168	0.6842	0.494
p45	Program	Methods	0.00199	0.00930	-0.01625	0.0202	0.312	0.2135	0.831
p46	Program	Facility	0.02116	0.02215	-0.02225	0.0646	0.555	0.9554	0.339
p47	Methods	Facility	0.00270	0.00872	-0.0144	0.0198	0.194	0.3096	0.757

The relationship between the variables is shown in Table 9 by the association method between the variables using variances and covariance. Variances and covariance are significant at level <0.01 level for each variable except con4 (whether the device that students use for online learning work well). Most of the estimates and beta values in variance and covariance table are positive values, whereas very few are negative values at 95% confidence levels. This interpretsthat most of the variables are positively associated with their latent variables.

Table 10: Intercepts

95% Confidence Intervals

Label	**Variable**	**Intercept**	**SE**	**Lower**	**Upper**	**Z**	**p**
p48	DM1	1.634	0.034	1.567	1.700	48.191	< .001
p49	DM2	1.703	0.033	1.638	1.767	51.755	< .001
p50	DM3	1.099	0.021	1.058	1.140	52.297	< .001
p51	DM4	2.361	0.073	2.219	2.504	32.409	< .001
p52	PM1	1.980	0.039	1.904	2.057	50.833	< .001
p53	PM2	3.144	0.065	3.016	3.271	48.301	< .001
p54	PM3	4.158	0.115	3.932	4.384	36.05	< .001
p55	PM4	2.198	0.082	2.037	2.359	26.722	< .001
p56	PM5	3.698	0.085	3.531	3.865	43.523	< .001
p57	MD1	4.327	0.072	4.185	4.468	59.965	< .001
p58	MD2	2.267	0.048	2.172	2.362	46.851	< .001
p59	CON1	3.653	0.069	3.518	3.789	53.02	< .001
p60	CON2	2.550	0.066	2.419	2.680	38.385	< .001
p61	CON3	2.559	0.041	2.480	2.639	62.794	< .001
p62	CON4	3.614	0.069	3.479	3.749	52.427	< .001
p63	GRD	3.475	0.076	3.325	3.625	45.468	< .001

The table of intercepts for the variables shows the intercept values along with its SE, lower bound, upper bound, z and p values. The p values are at the significant level for all the observed variables that is less than 0.001. The scale for latent variable is fix first indicator to 1.

5. Results

Descriptive analysis showed that most of the students were science graduates, with very few comfortable with English language. Maximum number of students did not opt for online courses for their university credits and were preferring the offline mode of learning. The correlation chart of different data fields with students' performance (Figure 4) shows that factors like gender, branch, percentage of attendance of students, the device that a student uses and the internet connectivity have a strong positive correlation with student's performance. However, the factors like first language, age, familiarity with English language, responsibilities at home, year of the course, credits of the online course, mode of the learning, assessment techniques, internet accessibility and device condition have a negative correlation with the student's performance which means they are impacting in an inverse way. This interprets that more attendance in the online class and fairly good internet connection leads the student's performance.

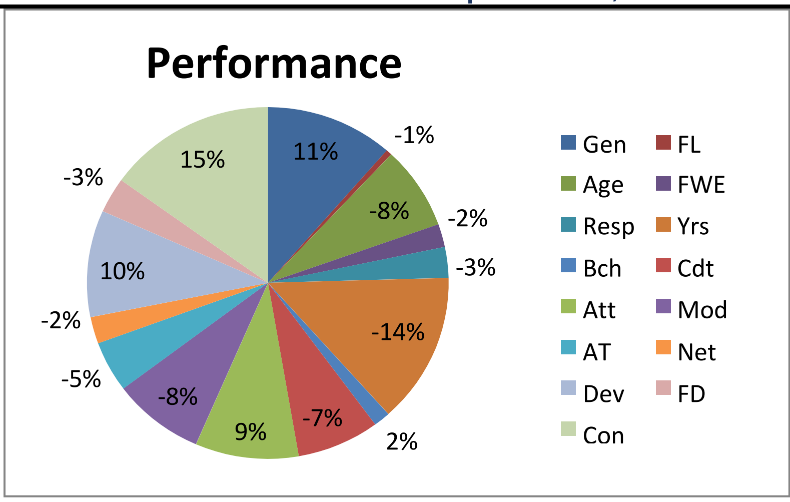


Figure 4: The correlation of different data fields with the students' performance

The pictorial representation of SE model is shown by the path diagram in Figure 5.

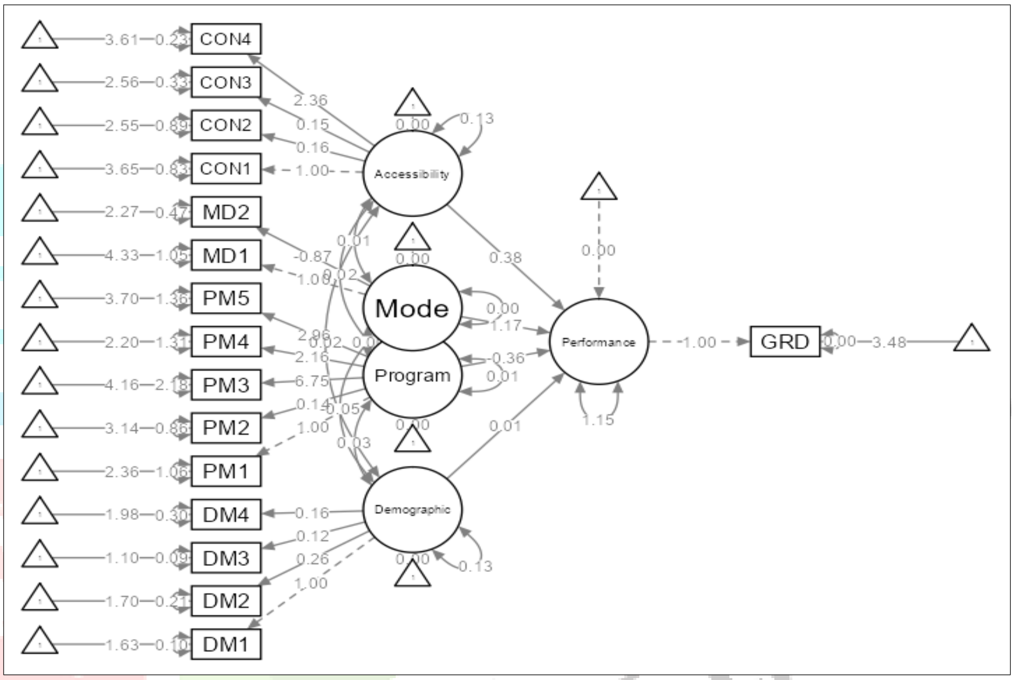


Figure 5: Structural equation modeling - path diagram

The variables incircles are latent variables and observed variables are shown in the rectangular shape. Triangles in the path diagram are the error for latent and observed variables. Two headed arrow are showing the correlation among the variables whereas the one headed arrow is showing the cause effect relationship between the variables that interprets the main cause of variance in observed variables is due to its corresponding latent variable. From the path diagram it is clear that student performance is positively correlated with demographic data, learning program related data, internet accessibility and mode of learning and assessment for the learners which is in line with the hypothesis developed for model. It is observed that

- Mode of learning and assessment has the highest coefficient (1.17) that means the major impact on student performance is due to learning methods and assessment techniques. This is indicating that a change either in learning method or in assessment technique will have larger impact on student performance.
- Internet accessibility has the second highest coefficient (0.38) meaning that change in facilities regarding online learning will also have impact on student performance.
- Learning program related features has third highest coefficient (0.36) indicating a lesser impact on student's performance.
- Demographic characteristic has the lowest coefficient (0.01) however; a positive coefficient indicating that it has the least impact on student's performance.

Hence the established hypothesis H_0 is rejected and Ha hypothesis for the developed model is clearly supported by the data and verified by the structural equation modeling.

Based on the correlation among data variables and path diagram analysis, it is observed that more than 50% students did not take any online course for university credits. Out of these 68.9% students were not very much comfortable with

English language, 48.7% did not have good internet connectivity, 71.6% used smart phones as learning device and 58.1% liked face to face learning mode. It is inferred from this analysis that these are the challenges that restrict students in taking up online courses for university credits. These challenges are due to:

- Discomfort with English language
- Internet connectivity
- Smart phones as preferred learning device and
- Face to face learning as preferred learning mode

Focusing and working towards mitigating above mentioned challenges can make online learning more successful, easy and effective.

6. Discussion

As per the established hypothesis for the study, the performance of the learner directly depends upon demographic component, the program in which the learner is enrolled, mode of learning and assessment and e- leaning facilities. In this study, grades of the learners are employed as learning analytics for student performance. Demographic factors, program related data, preferred learning mode, assessment techniques and internet facilities are used for analyzing for student academic achievement. The hypothesis is supported by the results obtained through the developed structural model. It is observed that student performance majorly impacted by the mode of learning and assessment followed by internet accessibility, learning program and demographic characteristics. The analysis indicates the challenges in opting online course for university students are majorly due to internet facility, device used for online learning and learning mode, however it is not affected by the demographic factors of the student. These findings are aligned with the previous research investigating that how the factors impact students' online learning experiences (Caskurlu, Richardson, Maeda & Kozan, 2021) and predicting how students perceived their learning outcomes and satisfaction based on the method of teaching and learning online (Su & Guo, 2021). Learning analytics is a trending field for researchers to make predictions and for making decision to improve the quality of education. The area of learning analytics has evolved over the past decade with the intersection of different fields like data science and learning science to inform how data can be collected and analyzed to support proficient learning (Shum, Littlejohn, Kitto & Crick, 2022). It can be considered that learning analytics has abandoned the stage of dispersion and is heading towards a state of maturity that will position it as a fundamental piece in educational practice mediated by technology. However, it cannot be ignored that the power and goodness of these analytics must be channeled to improve learning itself (García-Peñalvo, 2020). For its potential to address some of the key difficulties in the academic sector, learning analytics has drawn a lot of interest from researchers and designers (Cirulli, Caporarello & Milani, 2019). But there is still much to learn about the development of learning analytics interventions in terms of giving students personalized learning materials that fit their needs and improve their learning performance (Kew & Tasir, 2022). The significance of online learning as an answer to educational challenges has grown the need to study more closely the factors that contribute to distance learning outcomes and success rates (Ward-Jackson, & Yu, 2023). The ability to predict a student's performance can be beneficial for actions in modern educational systems (Daud, Aljohani, Abbasi, Lytras, Abbas & Alowibdi, 2017). Previous studies indicated that the available student's and course data can be used to predict and improve student success (Dietz-Uhler & Hurn, 2013). Barrot, Llenares & Del Rosario (2021) gave the observation which is in line with the study that student's greatest challenge was related to their learning environment at home, whereas their least challenge was technological literacy and competency. McKnight, O'Malley, Ruzic, Horsley, Franey & Bassett (2016) claimed that a strategy is required to be developed for higher education if willing to move from traditional to online learning and for this purpose, the observation of student performance on an e-learning platform, and the satisfaction of students need to be considered.

7. Conclusion, limitations and future research

The aim of this study was to develop a structural model to explain the impact of online learning factors on learner's performance. The study is for university students of different streams. A model is established using structural equation modeling which is a fairly good fit model for the data gathered. The study data is collected from Indian universities where English is not the first language of the students unlike most of the countries across the world not having English as their mother tongue. The analysis and established model is for Indian University students that can be generalized with slight modification including the understanding levels of students worldwide. The analysis on the surveyed data identified the factors impacting students' performance. Regarding RQ1, the study discovered that factors like gender, branch of the course, percentage of student attendance, device that a student use and the internet connection have positive correlation with student's performance. The model is developed with a sufficient data size (n=202) including students from three different universities in India. The developed model is useful in understanding the effect of these factors on student's performance for the success of online learning environment ultimately improving students' academic achievements. For RQ2, the model depicts that demographic characteristics like gender or language or age does not much impact student's learning however good internet and device quality and facility plays an important role in online learning environment. The analysis shows the correlation and covariance among the variables for clear understanding. The design and hypothesis of developed model is also supported by the path diagram. Almost all the items under latent variables are at a significant p level which is good for a fit model. The comparison between the user and baseline model is done to verify the model. Regarding RQ3, the analysis also indicated the challenges restricting students in taking up online courses for university credits are due to familiarity with English language, internet connectivity, teacher student face to face interaction and device used for online learning. Ferri, Grifoni & Guzzo (2020) also indicated that technological challenges in online learning are mainly related to the unreliability of Internet connections and many students' lack of necessary electronic devices. Mitigating these challenges will enhance the usefulness of online learning. Hence the developed model is useful in making the online learning an effective and efficient platform for the learners. This model can further be used for applying methodologies to improve students' retention. Optimization techniques can also be applied on this model to enhance the students' performance.

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