Exploring Factors Affecting E-Learning Adoption among Students in Indian Business Schools: Employing Structural Equation Modelling Technique

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Abstract:

This study aims to investigate features that enable or hinder the utilization of e-learning platforms amongst college students in the Indian higher education system. The researchers in the study have expanded the Technology Acceptance Model (TAM) and the Unified Theory on Acceptance and Use of Technology (UTAUT) by incorporating two additional factors: Challenges (CH) and Social Media Usage (SMU), thus creating a comprehensive conceptual framework. The data was collected via questionnaire-based surveys among post-graduate students enrolled in various colleges across the distinct parts of India. These students had registered on different eLearning platforms for online certificate courses between May 2022 and June 2023. The study's target population comprised 850 students, selected through judgmental sampling from the pool of eLearning users. Data collection was conducted through an online survey using Google Forms, distributed via email and WhatsApp. In this process, the total valid responses received was 620. The analysis of data was conducted utilizing SPSS version 24.0, which involved descriptive analysis. The study’s hypotheses were tested by building the Structural Equation Model (SEM) using the Smart PLS 4. The assessment of the study instrument was done using a five-point Likert scale, based on previous research.

Keywords: e-learning, SPSS, SmartPLS, Structural Equation Modelling (SEM), Technology Acceptance Model (TAM).

1.Introduction:

Learning is a process aimed at improving knowledge, skills, and abilities. With the rise of a global movement for modern learning models in the 21st century, there is a growing belief that formal education needs to be transformed to facilitate the new forms of learning needed necessary to solve complex global problems (Hennessy et al., 2016)

Nowadays, youth acquire knowledge and develop various skills such as communication, leadership, management, and intellectual understanding through interaction on social media platforms. The remarkable growth of the Internet over the past two decades has been one of the main drivers of rapid technological advancement and participation in social media, impacting virtually every aspect of human society,, especially higher education institutions, their professors and students.(Kumari & Singh, 2020)(Elareshi et al., 2022) Recent years have seen an increase in the use of information and communications technology (ICT) in education and the rise of network technology has led to significant developments in online learning practices.(Olufunmilola Ogulande et al., 2016). Online learning is an integral part of the evolving educational landscape of the 21st century, constantly adapting to changes, just like society itself (Albert Sangrà, 2012). (Prasetyo et al., 2021). society itself (Albert Sangrà, 2012). (Prasetyo et al., 2021)

Hence, it is imperative to swiftly brace the new e-learning technology within the education system. E-learning employs modern tools like computers, networks, multimedia, and the internet to provide educational content swiftly and cost-effectively to students. It allows management of the educational process to monitor, measure and evaluate student learning outcomes. (Junne, 2020). Hence, it is imperative to swiftly brace the new e-learning technology within the education system. E-learning employs modern tools like computers, networks, multimedia, and the internet to provide educational content swiftly and cost-effectively to students. It allows management of the educational process to monitor, measure and evaluate student learning outcomes. (Junne, 2020). There arises a question about who the major beneficiaries of the E learning mode would be-carbon footprints and uninterrupted learning could be highlighted as major benefits as digital literacy has become the order of the day for any learner, E learning provides the right direction. The student engagement level, in comparison with offline classes, is still limited. The consistency in classroom deliverables and the assessment methods are tried and evaluated till date.

Many longitudinal studies have focused on how the pupils at various higher education institutions receive online education. However, from the Indian perspective, the various features prompting the adoption of learning in higher education institutions through online platforms are not yet well understood. This study focuses on bringing about a thorough understanding related to the knowledge gaining options provided by the various online platforms to the learners in the higher education sphere. It aims to investigate how the determinants like social media usage impact students' adoption of an online learning system by integrating these variables into technology acceptance model (TAM). Furthermore, the proposed study aims to judge how students' acceptance of an online learning system affects their learning outcome expectations.

Most prior research has focused on various facets of virtual learning, such as the differences in students' attitudes, performance, and satisfaction levels between offline and online courses. Some studies have aimed at developing impactful learning tasks for virtual education. However, only a limited number of studies, such as the one conducted by Tung and Chang (2007), have specifically addressed students' intentions to enroll in online courses. This study seeks to expand the existing literature by contributing further insights into this area.

2. Literature Review:

2.1 Variables impacting online learning:

The atmosphere in a virtual classroom is different from that of a traditional face-to-face classroom. Challenges and social media usage in online courses are significantly impacted by the design and delivery of these courses (Mudzingiri et al., 2022; Kumar et al., 2023). The study by Fatmasari et al. (2018) examined how the Unified Theory of Acceptance and Use of Technology (UTAUT) influenced the use of M-Learning among bachelor's degree students at Universitas Terbuka (UT) in Jakarta.

A study was conducted to investigate several variables, including self-confidence, social influence, and performance expectations. The findings revealed significant correlations between performance expectations after using mobile learning and the intention to utilize mobile learning among students. Additionally, there were notable correlations between social influence and the intention to adopt the mobile learning approach, as well as between self-confidence and the intention to use mobile learning.

Another study, which explored the variables affecting students' performance and satisfaction in online classes during the COVID-19 pandemic, established the relationships between these variables. The study found that four independent variables—quality of the instructor, course design, prompt feedback, and students' expectations—had a positive effect on students' satisfaction with online courses (Gopal et al., 2021).

Crucial factors of the study based on the Technology Adoption Model (TAM) are discussed in the next section.

2.2 Technology Adoption Model (TAM):

A theoretical framework that describes how people come to accept and use a technology is called the Technology Adoption Model (TAM). The model suggests that perceived usefulness (PU) and perceived ease of use (PEOU) are the two main factors that affect a person's decision to adopt and use new technology. The degree to which the users feel that utilizing a specific system or technology will improve their performance at work is known as Perceived Usefulness (PU). The degree to which a person thinks using a specific system will be effortless is known as Perceived Ease of Use (PEOU). The user's Attitude Toward Using (ATU) of the technology is influenced by these two factors, according to TAM, and this in turn affects their Behavioral Intention to Use (BI). The Actual System Use is ultimately the result of the Behavioral Intention to Use. The model is a useful tool for researchers and practitioners trying to develop and apply technologies that satisfy user needs and increase adoption rates because of its ease of use and solid empirical backing.

The Technology Adoption Model (TAM) has been extensively studied, identifying several crucial factors such as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Actual Usage of eLearning. Various researchers have explored these factors in their studies, providing valuable insights into the adoption and usage of technology in different contexts (Ahmad et al., 2023; Khan et al., 2021; Maheshwari, 2021).

Fatmasari et al. (2018) investigated how the Unified Theory of Acceptance and Use of Technology (UTAUT) affected the use of mobile learning (M-Learning) among bachelor's degree students at Universitas Terbuka (UT) in Jakarta. This study highlighted the significant influence of UTAUT variables on students' adoption of M-Learning.

In a separate study, Shahzad et al. (2022) introduced an enhanced TAM to examine how consumers adopt fintech products and services. This model includes perceived usefulness, perceived ease of use, user innovation, and trust as factors influencing attitudes toward using fintech platforms and behavioral intention to use these platforms.

Al-Rahmi et al. (2015) explored university students' intentions to utilize e-learning, focusing on e-learning material and self-efficacy. The study found that these factors positively affect perceived usefulness and student satisfaction. Despite the growing acceptance of e-learning worldwide, the investigation of e-learning adoption in Malaysia remains largely unexplored. The study utilized TAM to explain Malaysian university students' intentions to use e-learning, revealing positive perceptions and intentions among the students.

During the COVID-19 pandemic, Maheshwari (2021) conducted a study with 145 students enrolled in virtual undergraduate and graduate programs at both state and private colleges in Vietnam. The study aimed to identify the factors influencing students' inclinations to study online, using structural equation modeling (SEM) to analyze the data. The results indicated that perceived satisfaction and institutional support are significant determinants of students' plans to enroll in online courses in the future. Additionally, the study introduced new factors, such as internet accessibility and ICT infrastructure, which indirectly influence students' preferences for online learning.

2.3 Purpose of the study:

Previous research has extensively explored various facets of virtual learning, focusing on differences in students' attitudes, performance outcomes, and satisfaction levels when comparing offline and online educational modes. While considerable progress has been made in understanding the effectiveness of virtual education and developing impactful learning tasks, there remains a notable gap in research specifically addressing students' intentions to enrol in online courses. Among the few studies that have tackled this issue, Tung and Chang (2007) stand out for their investigation into this area. Despite these contributions, there is still a substantial need for further exploration to enhance our understanding of students' enrolment intentions in the context of online learning.

This study aims to bridge this gap by employing a modified version of the Technology Adoption Model (TAM) to provide deeper insights into students' intentions to engage in online learning. Unlike traditional TAM applications, this study incorporates novel factors, including challenges associated with online learning and the influence of social media usage. To the best of our knowledge, these factors have not been previously integrated into existing models to analyse students' online learning intentions comprehensively.

The primary objective of this research is to advance the knowledge base surrounding technology adoption in education by updating TAM to include contemporary variables relevant to the current digital learning landscape. This objective is driven by the need to enhance the theoretical and practical understanding of technology adoption in educational contexts, specifically focusing on the nuances of online learning.

Specifically, this study investigates how TAM variables, in conjunction with challenges and social media usage, impact students' performance expectations in higher education institutions across various universities in India. By examining these elements, the study seeks to offer valuable insights into the dynamics of online learning adoption and provide actionable recommendations for enhancing the effectiveness and appeal of virtual education.

3. Hypotheses formation:

3.1 Perceived Ease of Use (PEOU) & Perceived Usefulness (PU):

The degree to which a person believes that using a certain system will improve their ability to accomplish their work is what determines how valuable they are in their eyes. (Ahmad et al., 2023). Perceived ease of use and perceived usefulness, both of which may be quantified, are two factors that affect the intention to use a system, according to the Technology Acceptance Model (TAM). (Salloum et al., 2020) Perceived usefulness was described by Davis as the conviction that the modern technology will boost or improve a person's performance. According to Mathwick et al. (Yakubu & Dasuki, 2019) perceived utility is the extent to which a person sees a certain system as beneficial for enhancing their performance at work.

3.2 Challenges (CH):

A circumstance or task that calls for a great amount of work, ability, or imagination to overcome can be referred to as a challenge. It might also pose a challenge or hurdle that prompts the person doing it to look for answers, justifications, or solutions. In Mahyoob's study, (Alghizzawi et al., 2019), the challenges variable played crucial role because it illuminates the difficulties faced by English language learners in a specific environment (Mahyoob, 2020) when they switch to online learning during the COVID-19 pandemic. According to the study's findings, the biggest issues preventing the students from learning EFL during the pandemic were technological, intellectual, and communication difficulties. These issues offer insightful information regarding the problems encountered by pupils in a particular situation.

This study considers technology and communication related issues as the major challenges a student in a e-learning sphere face.The technological challenges encompass *platform usability, the learner's technical skills and the device limitations* and the communication challenges focused on are *lack of learners' engagement or participation, lack of face-to-face interactions and cultural barriers*. Henceforth the term challenges connote the technical and communication trials faced by the learners of the e-learning realm.

Research Hypotheses

H1: There is a correlation between Behavioral Intention (BI) and Perceived Usefulness (PU)
H1A: There is no correlation between Behavioral Intention (BI) and Perceived Usefulness (PU)

H2: There is a correlation between Behavioral Intention (BI) and Perceived Ease of Use (PEOU)
H2A: There is no correlation between Behavioral Intention (BI) and Perceived Ease of Use (PEOU)

H3: There is a correlation between Behavioral Intention (BI) and Challenges (CH)
H3A: There is no correlation between Behavioral Intention (BI) and Challenges (CH)

3.3 Social Media Usage (SMU):

Said A. Salloum's research discusses the inclusion of variable like social media practices in the TAM model and its impact on adoption of eLearning system. The study involved 410 graduate and undergraduate students from the British University located in Dubai, United Arab Emirates. The extended model is analysed using partial least squares structural equation modelling, or PLS-SEM. It was discovered that social media practices, including knowledge sharing, social media features, motivation and uses, and perceived utility and simplicity of use, had a significant positive influence. Both PU and PEOU have a significant impact on the adoption of e-learning technology. Therefore, students' acceptance of e-learning platforms is positively influenced by their use of social media. (Elareshi et al., 2022)

H4: There is correlation between Perceived Usefulness (PU) and Social Media usage (SMU)
H4A: There is no correlation between Perceived Usefulness (PU) and Social Media usage (SMU)

H5: There is correlation between Perceived Ease of Use (PEOU) and usage of social media (SMU)
H5A: There is no correlation between Perceived Ease of Use (PEOU) and usage of social media (SMU)

H6: There is correlation between challenges faced (CH) and usage of social media (SMU)
H6A: There is no correlation between challenges faced (CH) and usage of social media (SMU)

3.4 Behavioural Intentions (BI):

As discussed in numerous studies, there exists a significant & positive correlation between Behavioural Intentions and Actual usage amongst various fields, including technology and health information systems. Therefore, it is observed that Behavioural Intention serves as a robust predictor of technology adoption. (Taylor S, 1995).

Behavioural intentions perform a vital part in the Technology Acceptance Model (TAM) by serving as a direct link between attitudes and behaviour. When a user has a positive attitude towards a technology but lacks the intention to use it, the likelihood of adoption decreases. Conversely, if a user has an optimistic approach and a strong intent to utilise the technology, then adoption is more likely. Behavioural intentions can also be used to predict the likelihood of continued or discontinued use of technology over time. The TAM is a popular theoretical outline used to comprehend the adoption and utilization of technology. The model proposed by Alshurideh and Al Kurdi (Alshurideh & Al Kurdi, 2023) posits that an individual's intention to use a technology is shaped by their perception of its usefulness and ease of use. Alongside these factors, the model incorporates perceived playfulness as a key predictor of technology adoption. The findings showed that the intention to use social networking sites for e-learning was significantly influenced by perceptions of playfulness, usability, and convenience of use.

H7: There is relationship between Behavioural Intentions (BI) of students to practise the e-learning system and the Actual usage (AU) of the eLearning system.
H7A: There is no relationship between Behavioural Intentions (BI) of students to practise the e-learning system and the Actual usage (AU) of the eLearning system.
H8: There is relationship between Student's Social Media Usage (SMU) to use the e-learning system and the Actual usage (AU) of the eLearning system.
H8A: There is no relationship between Student's Social Media Usage (SMU) to use the e-learning system and the Actual usage (AU) of the eLearning system.

3.5 Performance expectations (PE):

Performance expectations are objectives, standards, or both that specify behaviours and outcomes. They are listed on a performance plan to outline the goals to be met as well as the way the work is to be completed. Performance expectation is the likelihood that a person will see a system as helpful to their performance (Garrison.D, 2003). Numerous studies have found several criteria, such as the standard of learning cooperation, the standard of the material offered, and the support for course content, which affect students' effectiveness in e-learning systems. Users' perceived pleasure and actual use of e-learning have both been found to be impacted by these elements, which eventually leads to performance expectations that satisfy stakeholders. (Sewandono et al., 2022).

H9: There is relationship between Actual usage (AU) of eLearning and Performance expectations (PE) of students.
H9A: There is no relationship between Actual usage (AU) of eLearning and Performance expectations (PE) of students.
A crucial factor in determining users' success is the actual usage (AU) of their e-learning certificates. These certificates' apparent value and influence can be diminished if consumers don't use them. Understanding user adoption of e-learning certificates is made easier with the use of the Technology Acceptance Model (TAM). According to TAM, both the variables perceived ease of use (PEOU) and perceived usefulness (PU) have a major impact on actual utilisation. Users' success depends on how they use their e-learning certificates, and the

Technology Acceptance Model (TAM) is a useful outline for comprehending how users utilise their e-learning certifications. Enhance actual usage and performance expectations, developers and providers can focus on improving the perceived usefulness and accessibility of the certificates. This can be finalised by ensuring that the certificates offer relevant and valuable skills and knowledge, are user-friendly, and are widely recognized in the relevant industry or field. Additionally, providers can communicate clearly with users about the expected benefits and outcomes of the certificates, managing their performance expectations and ensuring that they understand the real value of the certificates.

III. METHODOLOGY:

Data collection: To evaluate the research model's hypotheses and support its conceptual framework through empirical analysis, the study used a quantitative survey. (Oussous et al., 2023). The population under consideration used for the study consisted of students enrolled in post-graduate programmes at various colleges in India who used the eLearning portal for online certifications. This study employed judgemental sampling, and eLearning users specified the target population. (Akbari, 2021).620 students who are enrolled in post-graduate programmes at various colleges in India make up the study's population. The data was gathered online using a survey built with Google Form. Postgraduate students received the questionnaires via email and a direct WhatsApp link. Eventually, 620 valid surveys were gathered. Version 24.0 of SPSS and SmartPLS 4 were used for the analysis. (Alghizzawi et al., 2019)

4.Theoretical Framework and Hypotheses:

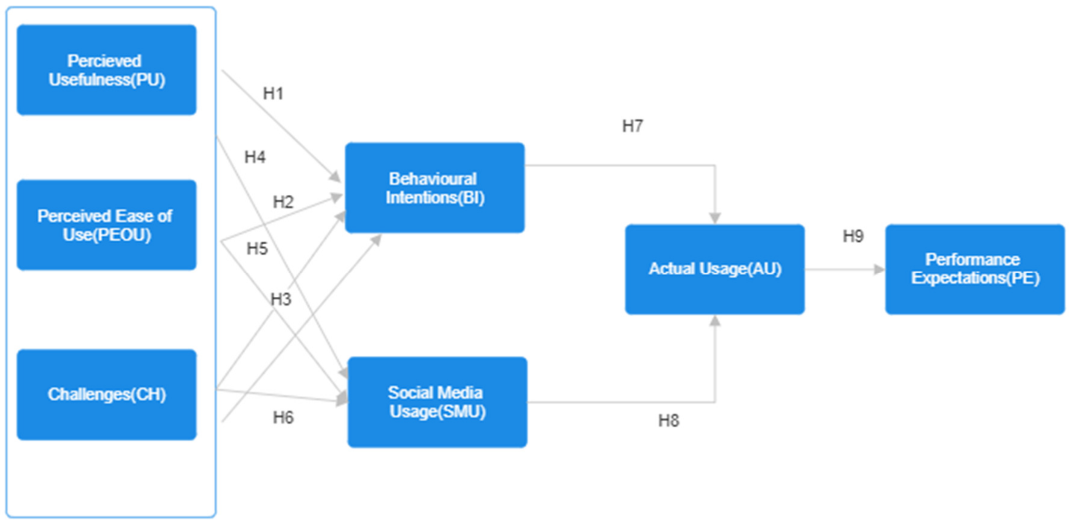

Figure 1. Research model [Source: Researcher]

5. Data Analysis

A. Description of the Demographics:

Features of the participants: -

Table 1. Respondents Demographics Data (n= 620)

Construct	Label	Frequency	Percentage (%)
Gender	Male	364	58.7
	Female	256	41.3
Age (in years)	18-21	166	26.8
	22-25	406	65.5
	26 and above	48	7.7
Region	North India	167	26.9
	West India	255	41.1
	East India	85	13.7
	South India	51	8.2

	Central India	62	10.0
Income of Family(Annual)	**Up to Rs 5 lacs**	208	33.5
	Rs 5 lacs to 10 lacs	227	36.5
	Rs 10 to 20 lacs	121	19.5
	Rs 20 to 30 lacs	28	4.5
	More than 30 lacs	36	5.8
	Total	**620**	**100**

Table 1 shows the findings, which show that 256 women (41.3%) and 354 men (58.7%) made up most of the sample of responders. When the data were examined, it became clear that most respondents (65.5%) fell into the bracket of 22–25 age, succeeded by the 18–21 bracket of age group, which accounted for (26.8%) of all respondents, and finally the 26–and-up age range, which had (4.5%) of respondents. Additionally, it was discovered that students from West India made up the bulk of responses (255, or 41.1%), followed by those from North India (170, or 26.9%), East India (85, or 13.7%), and South India (51, or 8.2%). The analysis also showed that most student families have a yearly income between Rs. 5 lacs to Rs. 10 lacs.

Table 2. States included in data collection.

	Frequency	**Percent**
Assam	1	.2
West Bengal	1	.2
Assam	1	.2
Andhra Pradesh	6	1.0
Bihar	12	1.9
Chandigarh	2	.3
Chhattisgarh	3	.5
Delhi	8	1.3
Goa	2	.3
Gujarat	47	7.6
Haryana	7	1.1
Jharkhand	11	1.8
Karnataka	12	1.9
Kerala	5	.8
Madhya Pradesh	51	8.2
Maharashtra	314	50.6

Odisha	15	2.4
Punjab	7	1.1
Rajasthan	23	3.7
Tamil Nadu	11	1.8
Telangana	12	1.9
Tripura	1	.2
Uttar Pradesh	40	4.8
Uttarakhand	4	.6
West Bengal	24	3.9
Total	620	100.0

Measurement Model Assessment:

Various measures were used to assess the questionnaire's reliability and convergent validity like Factor Loadings, Composite Reliability (CR) and Average Variance Extracted (AVE). Higher numbers denote stronger dimensionality. The factor loadings were used to calculate the load and connection of every questionnaire variable. Like previous measures, CR was used to determine the reliability of the questionnaire and factor loadings were used to obtain precise results using a particular formula. AVE was used to illustrate the latent construct and indicate the average variance in each variable. When there is discriminatory validity with more than one factor, it is extremely helpful for determining the convergence of each factor. (K.K., 2013) Evaluate the internal reliability of the observed responses, Cronbach's alpha was used. Cronbach's alpha values more than 0.8 are regarded as excellent by George and Mallery (Mallery, 2003), while values larger than 0.9 are regarded as particularly good. The internal dependability for each construct in this study ranged from good to outstanding based on a standard setup, as indicated below. In PLS-SEM research, both reliability and validity need to be verified while evaluating the measurement model. (Hair Jr., 2016). Cronbach's alpha and composite reliability (CR) are commonly utilized metrics for assessing reliability. The values of these metrics must be equal to or higher than 0.70 to be judged acceptable. (Hair Jr., 2016)

1. Convergent validity:

Numerous indicators, including factor loadings, variance extraction, and reliability, were utilized to predict convergent validity (Hair Jr., 2016). Cronbach’s Alpha, which should be above 0.7, was used to evaluate the internal consistency of the various measurements of a construct, as recommended by Hair (Sarstedt et al., 2020). According to Table 2's findings, the composite reliability (CR) varied from 0.817 to 0.920 with Cronbach's Alpha value higher than 0.7. The average variance extracted (AVE), has also exceeded the benchmark limit of 0.05, (Ansari & Khan, 2020) as it also ranged from 0.606 to 0.752. (Fornell, 1981).

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AU	0.817	0.869	0.861	0.606
BI	0.920	0.921	0.937	0.714
CH	0.888	0.898	0.913	0.638
PE	0.905	0.933	0.928	0.722
PEOU	0.882	0.885	0.914	0.681
PU	0.890	0.891	0.924	0.752
SM1	0.828	0.838	0.885	0.659

Table 2. Construct Reliability & validity findings [Source: Researcher]

2. Discriminant validity:

Discriminant validity is established when the square root of the average variance extracted (AVE) for each construct is greater than the squared correlation between that construct and any other construct in the model (Naveed et al., 2021). This was assessed using the Smart-PLS PLS-SEM software. Table 3 shows the square roots of the AVE scores in the diagonal elements. The AVE score's square root is ranged from 0.654 to 0.867, all surpassing the threshold of 0.5. Additionally, for discriminant validity to be established, each item's loading on its corresponding construct must be greater than its loading on any other construct. (Gefen, (2000)).

	AU	BI	CH	PE	PEOU	PU	SM1
AU	0.654						
BI	0.220	0.845					
CH	0.185	0.136	0.799				
PE	0.250	0.727	0.248	0.850			
PEOU	0.227	0.714	0.104	0.620	0.825		
PU	0.192	0.683	0.126	0.630	0.648	0.867	
SM1	0.242	0.617	0.246	0.618	0.530	0.480	0.812

Table 3. Scales of Fornell Larcker

Table 4 displays that every HTMT quantity less than 0.85, which satisfies the second criterion for discriminant validity. Therefore, complete discriminant validity has been proven. (Naveed et al., 2021)

	Heterotrait-monotrait ratio (HTMT)
BI <-> AU	0.511
CH <-> AU	0.622
CH <-> BI	0.141
PE <-> AU	0.207
PE <-> BI	0.791
PE <-> CH	0.257
PEOU <-> AU	0.222
PEOU <-> BI	0.791
PEOU <-> CH	0.113
PEOU <-> PE	0.690
PU <-> AU	0.169
PU <-> BI	0.755
PU <-> CH	0.132
PU <-> PE	0.699
PU <-> PEOU	0.731
SM1 <-> AU	0.232
SM1 <-> BI	0.698
SM1 <-> CH	0.273
SM1 <-> PE	0.700
SM1 <-> PEOU	0.612
SM1 <-> PU	0.547

Table 4. Calculated values of HTMT (Heterotrait-monotrait ratio)

4. Structural Model Assessment:

It was found that all the hypotheses were accepted and are significant & positive except hypothesis H3 and H7.

In this, Perceived usefulness (PU) and perceived ease of use (PEOU) exert a positive influence on the Behavioural intentions (BI) (i.e., value= 0.00 <0.05), but Challenges don't impact behavioural intentions of eLearning users (p value =0.118 >0.05) thus H1, H2 are accepted but H3 is rejected.

Additionally, data also show positive influence of Perceived usefulness (PU), challenges (CH) and Perceived Ease of use (PEOU) while using eLearning portals ($p<0.05$) on social media usage (SMU), therefore hypothesis H4, H5, H6 are accepted.

Furthermore, it is worth mentioning that the study found there is no correlation between Behavioural Intentions (BI) and actual usage of eLearning portals (p=0.069> 0.05), hence hypothesis H7 is rejected.

However, significant influence of social media usage (SMU) was demonstrated upon actual usage of the eLearning portals (p=0.002 < 0.05). Hence, the study supported hypothesis H8.

The findings of the study indicated that Actual usage of the system has a positive influence on performance expectations of the students(p=0.000<0.005), hence we accept the H9 hypothesis.

Summarise:

The results of the study suggest that PU, PEOU, and SMU are all important considerations in influencing the use of eLearning portals and students' performance expectations.

Hypothesis H		Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
H9	AU -> PE	0.250	0.256	0.053	4.685	0.000	Supported
H7	BI -> AU	0.115	0.123	0.063	1.816	0.069	Not Supported
H3	CH -> BI	0.040	0.042	0.026	1.564	0.118	Not Supported
H6	CH -> SM1	0.180	0.184	0.036	5.039	0.000	Supported
H2	PEOU -> BI	0.466	0.466	0.044	10.521	0.000	Supported
H5	PEOU -> SM1	0.372	0.371	0.049	7.633	0.000	Supported
H1	PU -> BI	0.376	0.376	0.040	9.327	0.000	Supported
H4	PU -> SM1	0.216	0.217	0.043	4.987	0.000	Supported
H8	SM1 -> AU	0.171	0.171	0.056	3.052	0.002	Supported

Table 5. Testing results-Hypothesis

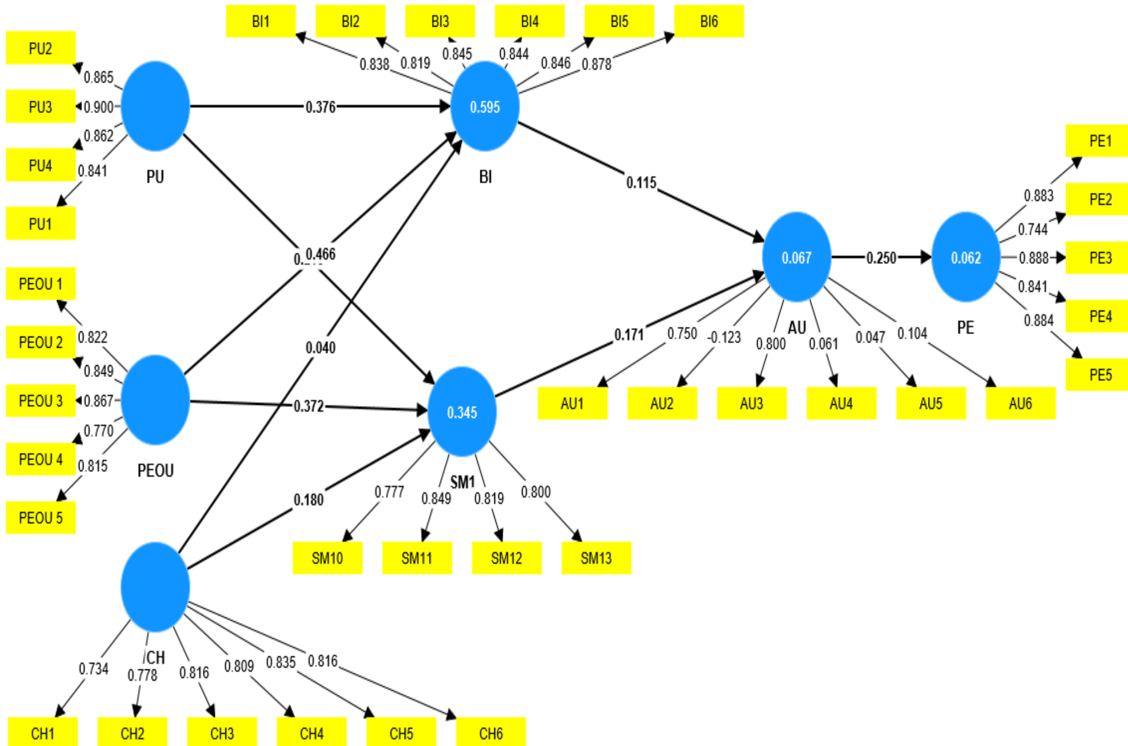

Figure 2. Result of eLearning Bootstrapping

5. Discussion, implications, limitations, and ideas for additional research

5.1 Discussion:

5.1 Conclusion:

In conclusion, the study revealed that several hypotheses were accepted and demonstrated a significant and positive relationship. The hypotheses that were supported include H1 and H2, which suggest that Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) have a positive effect on student's Behavioural Intentions (BI) to adopt eLearning. Additionally, H4, H5, and H6 were accepted, indicating that PU, PEOU, and the challenges faced while using eLearning portals have a positive effect on Social Media Usage (SMU).

However, the study rejected H3, which proposed that Challenges do not impact behavioural intentions of eLearning users. Furthermore, H7, which suggested a correlation between Behavioural Intentions (BI) and actual usage of eLearning portals, was also rejected. On the other hand, H8, which proposed a significant impact of SMU on the actual usage of eLearning portals, was supported.

Notably, the findings of the study demonstrated a substantial influence of actual usage of the system on students' performance expectations, supporting H9. Overall, the study features the scale of PU, PEOU, SMU, along with actual system usage in influencing the use of eLearning portals and shaping students' performance expectations.

5.2 Theoretical implications:

For students enrolled in higher education, eLearning may have the following effects:

a. Flexibility to learn at their own speed: Students who choose to learn online can do it at their own speed and at a time and place that works for them. This can help students who have jobs or families because it gives them the opportunity to balance their education and other commitments.

b. Resource accessibility: Students who use eLearning have admittance to a wide range of assets, such as digital collections, electronic textbooks, and collaborative multimedia content. This can aid students in completing their education and gaining a deeper comprehension of the material.

***c.* Customized learning**: eLearning platforms have the capability to deliver customized learning experiences, catering to the unique requirements of individual students. This can include adaptive learning technologies that use data to provide targeted feedback and recommendations to students.

In general, eLearning can provide higher education students several advantages, such as more flexibility, resources at their fingertips, personalized instruction, enhanced communication, cost efficiency, and the development of new skills. But it's crucial to remember that e-learning has its drawbacks as well.

5.3 Limitations and future work:

Even though research data indicate that the researcher's methodology is successful in various Indian states, it is essential to use caution when projecting the findings to other countries. Future studies may use a variety of methodology (interviews, qualitative techniques, longitudinal research, etc.) to understand the adoption and acceptance of technology. It would also be appropriate to investigate whether our developed model is applicable to a range of nationalities and geographically diverse countries, including both developed and less developed nations, given that our study's discoveries are specific to the framework of India and user behaviour may diverge built on issues such as ethnicity, context, religious beliefs, along with level of technology adoption.

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