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Adoption of E-Learning among Higher Education Students During Post-Pandemic: An Extended Model of UTAUT2

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Abstract

In the era of digitalization, the technology has advanced. This study explored the significant drivers of adoption of e-learning technology among higher education students during post-pandemic era. This work used the extended model based on Unified Theory of Acceptance and Use of Technology-2 (UTAUT2) with external variable of technology anxiety of users. PLS SEM was used to analyse the data collected from the sample of 263 higher education students. Results show that all constructs of UTAUT2 have significant effect on behavioural intentions of students to use e-learnings except effort expectancy and price value. The external variable of technology anxiety has also negative and significant effect. The highest impact was found of performance expectancy. Outcomes of study have several theoretical and practical implications for higher education institutions (HEIs) policy makers, technocrats and service providers.

Key words: e-learning, UTAUT2, technology anxiety, HEIs and PLS SEM.

1. Introduction

We witnessed educational institutions rapidly switch to distant and online learning due to the COVID-19 crisis (Almaiah et al., 2020). In the era of COVID-19, higher education institutions worldwide were compelled to adopt online learning. However, e-learning technologies were not new for the education institutions and stakeholders but it had become mandate during the worldwide health crisis of pandemic. Consequently, Class times and physical locations are no longer barriers to information collecting, dissemination, and acquisition due to prevalence of e-learning during pandemic (Dash et al., 2022).

The role of e-learning technologies in HEIs has grown from that of a supplemental tool during the pandemic to a fundamental one in present time. This is because e-learning technologies provide numerous benefits to users. E-learning aspires to make education more accessible, save time and money, and improve students' academic performance (Konwar, 2017). In times of crisis, these platforms are crucial for keeping education going because of their adaptability, accessibility, and scalability. In post-pandemic era, according to researchers, online and hybrid learning are quickly replacing traditional classroom instruction as the norm in the wake of the epidemic. The two phrases are sometimes used interchangeably, but "e-learning" refers to learning that takes place on the internet and is separate from "distance learning," which is learning that takes place via e-learning (Zacharis & Nikolopoulou, 2022).

Online education has not faded in the post-pandemic age; on the contrary, it has grown into an integral part of the educational process. In adoption of e-learning technologies various models was used by different studies like TAM (Kaakour et al., 2022; Koivisto et al., 2016; Tran, 2017), TPB (Chu & Chen, 2016; Santos & Okazaki, 2013), UTAUT (Twum et al., 2021).Nevertheless, there are a number of psychological, social, and technological variables that impact the rate of student acceptance of e-learning tools, which is not uniform despite its benefits. While UTAUT2 (Venkatesh et al., 2012) is widely applied in technology adoption studies, its relevance in the specific context of post-pandemic e-learning, where students' prior exposure to technology may have altered their perceptions and behaviours, requires further exploration. Additionally, the emotional and psychological factors surrounding technology adoption, such as anxiety related to using technology have not been fully integrated into existing models. Technology anxiety can significantly affect students' willingness to use digital tools, especially in an academic environment where performance pressure is high. This gap highlights the need for extending traditional models to better understand how emotional and psychological barriers impact technology adoption in education.

Consequently, present work focused on the following research concerns to fill these gaps.

RQ1. Which elements have an impact on students' intentions to embrace e-learning technologies during post-pandemic?

RQ2. Do technology anxiety has any influence in the behavioral intentions to use e-learning technologies among higher education students?

This paper continues as follows: Hypothesis creation for this model and an explanation of pertinent literature are provided in the second section. Subsequent section explained research methods used in this study, with outcomes being covered in the fourth. A thorough explanation of the results will be done in the next section. The sixth section will finish with the theoretical and practical consequences, and the final portion will detail about limitations and research direction for future.

2. Underpinning theory and formulation of hypotheses

Unified theory of acceptance and use of technology (UTAUT2)

In the literature of technology adoption and behaviour, there are many conceptual models like TAM, TPB, TRA etc. However a new model of UTAUT (Venkatesh et al., 2003) was discovered by combining eight different technology adoption theories. In the initial stage of UTAUT, there were four basic variables namely, 'Performance Expectancy', 'Effort Expectancy', 'Facilitating Conditions' and 'Social Influence'. But later on, this model was extended with three new additional variables called "Price Value", "Habit" and "Hedonic Motivation". This model has been used in various consumer-based technologies like Fintech acceptance (Chan et al., 2022), autonomous cars (Nordhoff et al., 2020) etc. In the area of education technology, this model is also been used in various studies like MOOC adoption (Tseng et al., 2022), mobile learning (Arain et al., 2019), e-learning (El-Masri & Tarhini, 2017). With regard to e-learning technology among higher education students during post-pandemic, this study used the major constructs of UTAUT2 and extended it with an external variable called technology anxiety.

Efforts Expectancy (EE)

EE considered as the convenience for the users to use any technology (Venkatesh et al., 2012). It implies that an individual would like to prefer to use any new technology if it is easy to use and requires less efforts to use it. Previous study (Teng et al., 2022) found the positive and significant effect of EE on behavioural intentions of users. In our case we also assumed that students feel that using e-learning technology is easy and require less efforts. Consequently, we frame the following hypothesis regarding EE:

H1 EE has significant and positive influence on BI of students for using e-learning technologies.

Performance Expectancy (PE)

It's the extent to which a person expects information technology to help them perform well (Venkatesh et al., 2003). It means users will prefer the technology that helps to enhance their performance. PE is one of the major influential predictors for behavioural intentions to use technologies. Most of the studies (Mustafa et al., 2022; Tomić et al., 2022) found the significant effect of PE on BI. In our case, we assume that due to enhanced performance expectancy students want to use the e-learning technologies in their studies. Thus, following hypothesis about PE is developed:

H2 PE has significant and positive influence on BI of students for using e-learning technologies.

Social Influence (SI)

Social influence (SI) shows the impact of someone's belief, thinking and opinion on individual's decision. It is somewhat equal to the subjective norms or social norms used in TPB. Different studies (Twum et al., 2022; Zacharis & Nikolopoulou, 2022) also found the significant effect of SI on BI of users. In our context, we consider that student's perception for using e-learning has also influenced by the belief of their friends, peer-groups and other important persons. Consequently, we frame the following hypothesis regarding SI:

H3 SI has significant and positive influence on BI of students for using e-learning technologies.

Facilitating Conditions (FC)

It pertains customers' beliefs that they have the information, inputs, and all assistance they need to accomplish with certain activity (Venkatesh et al., 2003). Most of the studies (Kamalasena & Sirisena, 2021; Ye et al., 2020) found the significant relations among FC and actual usage of technologies. Facilitating conditions refers to the all assistance and support require for utilization of any technology. In context of e-learning, FC considered as

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availability of all devices like smartphone, laptop, PC and internet services. In context of FC, we frame the hypothesis as mentioned below:

H4 FC has significant and positive influence on BI of students for using e-learning technologies.

Habit (HB)

As per Venkatesh et al. (2012), HB is the belief that an activity will become habitual, meaning it will be executed naturally and without any deliberate effort. Previous studies (Azizi et al., 2020; Kamalasena & Sirisena, 2021) confirmed the significant effect of HB on BI to use technologies. In context of e-learning, we consider HB as prior experience of students during the pre-covid as well as during covid with different platforms of e-learning. It may include online courses, classes, assignments, quizzes or any other learning management system.

H5 HB has significant and positive influence on BI of students for using e-learning technologies.

Hedonic Motivation (HM)

Hedonic motivation might be considered as joy or delight one gets from using cutting-edge technology (Venkatesh et al., 2012). HM is used synonymously to perceived enjoyment (Zacharis & Nikolopoulou, 2022). Within this study's context, HM regards the enjoyment/pleasure that derives when students use eLearning platforms for their studies. It is hypothesized that; Hence, following hypothesis has been designed:

H6 HM has significant and positive influence on BI of students for using e-learning technologies.

Price Value (PV)

When adopting any new technology, consumers often weigh its pragmatic advantages against the associated financial costs. The more the price is worth; the more likely people are to accept new technologies (Venkatesh et al., 2012). Students' behaviour can be positively impacted by the price value of technology if the perceived advantages outweigh the expense. (Osei et al., 2022). Consequently, we develop the following hypothesis for PV:

H7 PV has significant and positive influence on BI of students for using e-learning technologies.

Technology anxiety (TA)

A dread of or discomfort when utilising modern devices is known as technology anxiety (Jeng et al., 2022). In using e-learning technology, students have to use computer and they may suffer also computer anxiety which is also kind of technology anxiety. identified computer anxiety as a state of unease, fear, nervousness, or concern triggered by the prospect of using computers, learning how to use computers, or being in close proximity to computers. In prior works (Jeng et al., 2022; Tsai et al., 2020), technology anxiety had negative significant effect on intentions of users to use new technology. Consequently, following hypothesis is formulated for (TA):

H8 (TA) of consumers has significant impact on (BI) of retail consumers for using 5G technology.

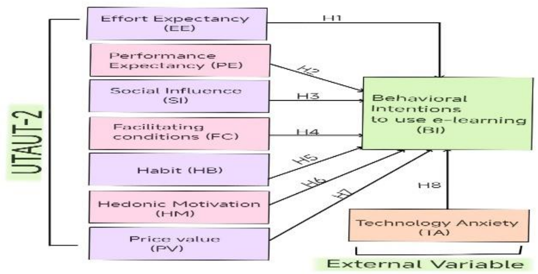

Figure 1. The proposed extended conceptual model of UTAUT2 with external variable of Technology anxiety (TA). **Source.** Authors own.

3. Material and Methods

3.1 Data Collection and measurements

Study used the primary data and were collected the targeted sample through convenience sampling technique from Indian higher education institutions. Study used the overall sample of 263 students from various college and university located at northern area of country. The selected sample was surveyed through online as well as offline though questionnaire. In the questionnaire, two parts were formulated. In first part, the demographic information was targeted. In another part of questionnaire all questions were asked related to selected constructs of UTAUT2 and external variable of technology anxiety. All constructs in the proposed model were of reflective in nature and recorded in seven point of Likert's scale from "1- strongly disagree to 7-stongly agree". The sources of all constructs were reported in Table 1. In the total sample, majority was of male students with 52.4%. In terms of their locations, majority of students were belonged to urban area (63.5%). And in terms of their qualifications, students

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from undergraduate course (48.6%) were highest and followed by post graduates (32.3%) and PhD students (19.1%).

Table 1. Sources of Measurements

Constructs	No. of Items	Source
Effort expectancy (EE)	4	Venkatesh et al. (2003 and 2012)
Performance expectancy (PE)	4	Venkatesh et al. (2003 and 2012)
Social Influence (SI)	5	Alalwan et al. (2018) and Taylor & Todd (1995)
Facilitating conditions (FC)	4	Beza et al. (2018)
Habit (HB)	4	Alam et al. (2021) and Venkatesh et al. (2012)
Hedonic Motivation (HM)	3	Alam et al. (2021) and Venkatesh et al. (2012)
Price Value (PV)	3	Venkatesh et al. (2012)
Technology Anxiety (TA)	4	(Evanschitzky et al., 2015; Meuter et al., 2003)
Behavioural Intentions (BI)	4	Venkatesh et al. (2003)

Source. Authors' creation

3.2 Data analysis procedure

In data analysis, study used the SPSS 24 and PLS SEM 4. PLS SEM is most popular software in social science research studies. In evaluation of direct path relationship of UTAUT2 constructs and external variable with behavioural intentions as shown in figure 1, we performed the bootstrapping process of PLS SEM. Finally, we employed the new PLS SEM feature, PLS predict assessment, to evaluate the predictive relevance of the proposed model (Shmueli et al., 2016).

4. Analysis of Results

4.1 Measurement Model Assessment

The measurement model was assessed through the guidelines suggested by Hair et al. (2019). In this process, initially we calculated the factor loadings of all indicators (shown in Table 2), and all values are more than the threshold value of 0.708. Furthermore, the Cronbach's alpha and composite reliability values are more than 0.70 and thus show the high reliability and validity of our proposed model. In case of convergent validity, we measured the average variance extracted (AVE), which are also more than 0.5, thus showing items were design exactly what for they were intended for. Further, for assessing discriminate validity we utilised the The Fornell-Larcker criterion (see Table 3) and HTMT ratio (see Table 4). All AVE values were higher than the inter-construct correlations squared (Fornell & Larcker, 1981). And in HTMT values, we have all value less than the threshold of 0.85 suggested by Hair et al. (2019). Hence both test justify our discriminate validity.

Table 2. Measurement Reliability and Validity

Construct	Items	Factor Loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)	VIF
Behavioural Intentions	**BI1**	0.901	0.916	0.940	0.798	3.037
	BI2	0.881				2.640
	BI3	0.906				3.182
	BI4	0.884				2.726
Efforts Expectancy	**EE1**	0.832	0.835	0.888	0.665	1.866
	EE2	0.781				1.693

	EE3	0.809				1.794
	EE4	0.838				1.982
Facilitating Conditions	**FC1**	0.867	0.873	0.908	0.711	2.269
	FC2	0.804				1.859
	FC3	0.826				2.004
	FC4	0.874				2.324
Habit	**HB1**	0.866	0.901	0.930	0.770	2.412
	HB2	0.864				2.333
	HB3	0.899				2.900
	HB4	0.880				2.633
Hedonic Motivation	**HM1**	0.895	0.866	0.916	0.784	2.277
	HM2	0.886				2.131
	HM3	0.875				2.205
Performance Expectancy	**PE1**	0.880	0.897	0.926	0.758	2.439
	PE2	0.847				2.193
	PE3	0.869				2.456
	PE4	0.886				2.644
Price Value	**PV1**	0.907	0.884	0.928	0.811	2.594
	PV2	0.896				2.482
	PV3	0.899				2.420
Social Influence	**SI1**	0.859	0.916	0.936	0.744	2.591
	SI2	0.866				2.569
	SI3	0.863				2.721
	SI4	0.842				2.306
	SI5	0.884				2.890
Technology Anxiety	**TA1**	0.839	0.910	0.935	0.784	2.151
	TA2	0.900				3.095
	TA3	0.903				3.199
	TA4	0.897				2.923

Source. Authors' calculations

Table 3. Discriminant Validity: Fornell-Larckers Criterion

	BI	EE	FC	HB	HM	PE	PV	SI	TA
BI	**0.893**								
EE	0.625	**0.815**							
FC	0.684	0.549	**0.843**						
HB	0.619	0.492	0.506	**0.877**					
HM	0.607	0.494	0.438	0.402	**0.885**				
PE	0.731	0.628	0.621	0.575	0.604	**0.871**			
PV	0.629	0.546	0.523	0.590	0.453	0.604	**0.901**		
SI	0.677	0.553	0.532	0.567	0.574	0.639	0.675	**0.863**	
TA	0.561	0.500	0.492	0.449	0.613	0.797	0.513	0.611	**0.885**

Source. Authors' calculations

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Table 4. Discriminant Validity: HTMT ratio

	BI	EE	FC	HB	HM	PE	PV	SI	TA
BI									
EE	0.715								
FC	0.764	0.642							
HB	0.681	0.57	0.569						
HM	0.681	0.578	0.497	0.451					
PE	0.805	0.727	0.701	0.64	0.684				
PV	0.699	0.637	0.598	0.661	0.516	0.677			
SI	0.738	0.633	0.594	0.625	0.643	0.706	0.751		
TA	0.616	0.577	0.552	0.497	0.69	0.803	0.571	0.673	

Source. Authors' calculations

4.4 Structural Model Assessment

In the structural model assessment, initially we check the variance inflation factor (VIF) reported in Table 2. The all values of VIF are less than 5 which confirm that our data has no issue of multi-collinearity. After that, to test the paths of proposed model, we used the consistent bootstrapping prescribed by Hair et al. (2019). In the results (see Table 5 and Figure 2), all direct path of UTAUT-2 constructs show significant effect on BI except EE (β=0.085; t=1.852) and PV (β=0.072; t=1.357), hence H1 and H7 were rejected. The results for PE(β=0.324; t=4.59), SI(β=0.168; t=2.818), FC(β=0.247; t=4.563), HB(β=0.131; t=2.579) and HM(β=0.187; t=3.932) were found significant for behavioural intentions of students to use e-learning technologies. Hence, H2, H3, H4, H5, H6 were supported. In case of external variable, TA (β=-0.173; t=2.776) reported significant but negative effect on BI and thus H8 is accepted. Furthermore, our model has R2 of 71.4% which show the which shows the substantial (Chin et al., 1997). Additionally, we performed the PLS predict to assess the predictive relevancy. Outcomes of PLS predict are reported in Table 6. Results showing that our model has high predictivity as all values generated by PLS SEM RMSE and MAE are less than the values of RMSE and MAE of linear model. Hence, PLS-SEM analysis offers less prediction errors than the LM which shows high predictive relevancy of the proposed model (Shmueli et al., 2016).

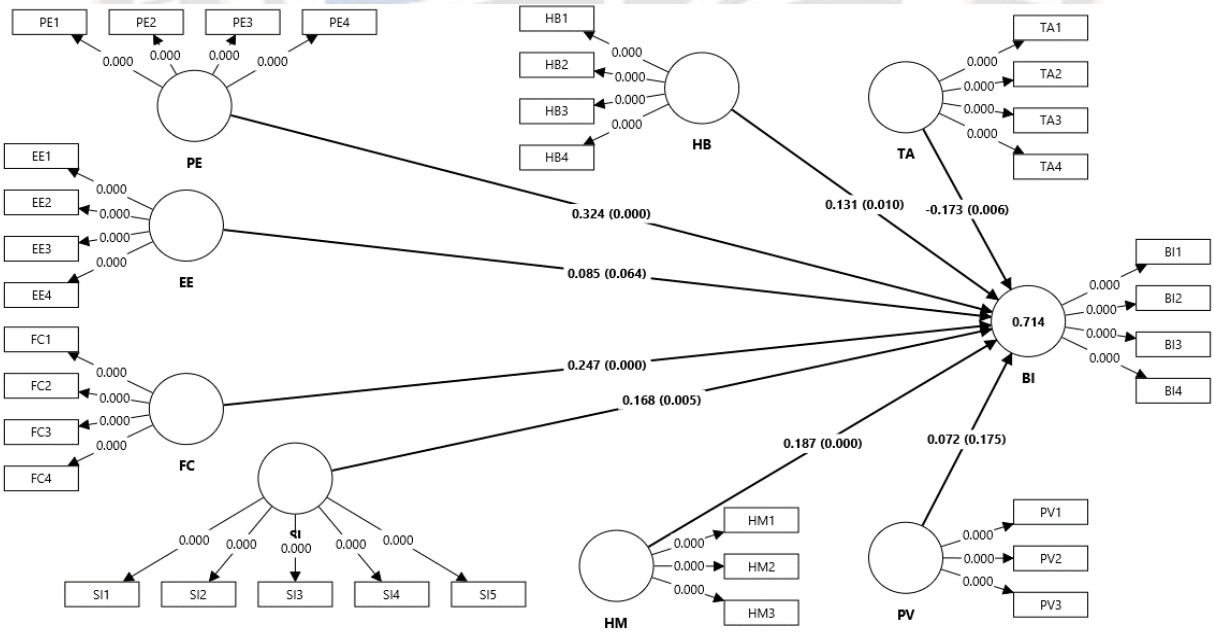

Figure 2. Structural model results. **Source.** Authors own.

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Table 5. Estimated Path Relationship

Hypothesis	Path	Beta	Standard deviation	T-Value	P values	Supported
H1	EE → BI	0.085	0.046	1.852	0.064 ^{NS}	NO
H2	PE → BI	0.324	0.071	4.59	0.000*	YES
H3	SI → BI	0.168	0.060	2.818	0.005*	YES
H4	FC → BI	0.247	0.054	4.563	0.000*	YES
H5	HB → BI	0.131	0.051	2.579	0.010*	YES
H6	HM → BI	0.187	0.047	3.932	0.000*	YES
H7	PV → BI	0.072	0.053	1.357	0.175 ^{NS}	NO
H8	TA → BI	-0.173	0.062	2.776	0.006*	YES
	R^2	0.714	0.036	20.104	0.000*	
	Adjusted R^2	0.705	0.037	19.244	0.000*	

*Note: *Significant (P-value<0.05) NS=Not Significant, S= Significant*

Source. Authors' calculations

Table 6. PLS Predict

	Q^2predict	PLS-SEM_RMSE	LM_RMSE	Difference RMSE (PLS SEM-LM)	PLS-SEM_MAE	LM_MAE	Difference MAE (PLS SEM-LM)
BI1	0.566	1.088	1.135	**-0.047**	0.867	0.913	**-0.046**
BI2	0.55	1.109	1.198	**-0.089**	0.889	0.969	**-0.080**
BI3	0.557	1.097	1.155	**-0.058**	0.88	0.909	**-0.029**
BI4	0.529	1.152	1.214	**-0.062**	0.901	0.972	**-0.071**
BI	**0.693**	**0.559**			**0.443**		

Source. Authors' calculations

5. Discussion

Current work focused on the factors influencing the behavioural intentions of higher education students for adopting e-learning technology in their studies especially during post-pandemic period. To do so, this study used the UTAUT-2 and extended it with an external variable of technology anxiety (TA). Results of the study showed that majority of hypotheses were supported (H2, H3, H4, H5, H6 and H8) except H1 and H7. In our findings, contrary to the expectations, EE (H1) was not found significant for BI which is consistent with results of Zacharis & Nikolopoulou (2022). The reason for this finding could be that students have already developed the digital and computer literacy due to high utilization and exposure of online educations platforms during pandemic. So, students are now more experienced in e-learnings technologies and hence the easiness or difficulty related to use of such technology has not significant for BI of students. In case of PE (H2), results revealed that PE was found as major predictor for BI. These findings are corroborated with the outcomes of previous studies (Azizi et al., 2020; El-Masri & Tarhini, 2017). It implies that e-learning technologies are becoming crucial even in the post-pandemic era as this technology are continue to meet the students' academic need. In H3, SI was also found significant for BI. This is consistent with findings of Azizi et al. (2020) but inconsistent with previous study (Kamalasena & Sirisena, 2021). It indicates that during the post-pandemic era, recommendations from teachers, classmates, and administrative encouragement play a vital role in shaping students' attitudes toward these platforms, reinforcing the social element of technology acceptance. Next, H4 related to FC was also confirmed the significant hypotheses which is consistent with the prior study (Kamalasena & Sirisena, 2021). It implies that students perception for availability of sound internet connection, devices and other technical support have significant for adoption of e-learning

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technologies. Same finding was found for H5 related to HB. The prolonged use of these platforms during the pandemic may have fostered a reliance on e-learning, which persists in the post-pandemic context. In case of H6, study revealed that HM is also significant predicator for using e-learning technologies among students. This finding is similar with prior work (Arain et al., 2019). It suggests that as students increasingly seek out interactive and engaging learning experiences, the entertainment value of e-learning platforms has become an important factor in adoption during post pandemic. In case of H7, study found insignificant effect of PV for BI to use e-learning technologies which is consistent with prior studies (El-Masri & Tarhini, 2017; Raman & Thannimalai, 2021). It suggests that students' perceptions of cost-benefit trade-offs for e-learning platforms do not have a significant impact on their decision to use these technologies. This may be due to many e-learning platforms and resources being provided at little or no additional cost to students by institutions during the pandemic, minimizing cost concerns. In case of external variable of TA (H8), study found negative and significant effect for using e-learning technologies. This result is consistent with the outcome of Jeng et al. (2022). It implies that technology-related anxiety can deter students from engaging with e-learning platforms. This finding shows the need of technical support and proper mentoring of students through training sessions by HEIs to build the students' faith in using such technologies.

6. Conclusion

Present study explored the behavioural intention of the higher education students for using e-learning technologies during post-pandemic era. Study used the extended model of UTAUT-2 with external variable of technology anxiety. Results of PLS SEM reported the significant effect of all construct of UTAUT2 except effort expectancy and price value. Among significant variables, study revealed the performance expectancy as most influential predictor for effecting behavioural intents of students to use e-learning technologies. Additionally, external variable of TA was also found negative and significant for BI to use these technologies. These finding have several theoretical and managerial implications which are discussed below in detail.

6.1 Theoretical Implication

This study has several theoretical contributions. First, it contributes in the literature of technology adoption by extending the UTAUT-2 model with technology anxiety. The significant and negative impact of TA on BI provides the new insights especially in post-pandemic era where technology is must to use in education. Consequently, this study contributes in the existing literature by adding motivation and phycological factor in technology acceptance related model. Further, the findings of insignificant effect of EE and PV contributes to the literature of technology adoption that in post-pandemic era the easy use of technology and cost factor are not primary among students and thus revealed the new research related to specific-context for students' adoption of e-learning technology.

6.2 Managerial Implication

For HEIs: From the significant effect of FC on BI, findings provide the practical suggestion to HEIs for providing all technical and other support to the students in availing e-learning services. They should ensure students have proper access to the required technology and all kind of organisational assistance for continuing use of e-learning platform in post-pandemic era. Secondly, the negative and significant effect of TA on BI, also offers the managerial implications for HEIs to ensure the reduced anxiety among students for using e-learning technology. To achieve this, HEIs may provide the mentoring programs, workshop, training session and digital literacy courses to build confidence of students in using e-learning technology.

For Policymakers: Policymakers may utilize the findings of the study and may frame the policy related to digitalization in higher education. Policymaker may ensure to proposed the policy that aim to creation of robust digital infrastructure in higher education and minimize the barrier of technology anxiety for better adoption of e-learning technologies.

For Marketer: Significant effect of SI on BI, offers the managerial implications for marketers. They can leverage the benefit of social influence by making campaigns including educators, peer-groups and other influencing bodies or celebrity that attract the students for wider adoption of e-learning technologies in their studies.

For Technocrats: High impact of PE on BI offers the practical implication for technocrats, software developer to focus on creative and ease to use interface with aim to reduce the effect of technology anxiety. Further technocrats may also utilize the significant effect of HM on BI by introducing more enjoyable and engaging features like interactive videos, gamifications etc.

7. Limitations and Future Directions

Present work is also not free from some limitations. First, the sample size of the study is quite small, which could have impact on generalization of findings. Secondly, study used the cross-sectional design and only target the post-pandemic era. So, in future studies, it is suggested to apply the longitudinal studies to measure the significant difference in the utilization of e-learning technologies among students during pre-pandemic and post-pandemic period. Another limitation is the study only used one external variable of TA, in further study it is recommended to study the impact of more new variables like technology readiness, task technology fit etc. Lastly study was conducted only in emerging country of India, so further studies are suggested to incorporate the cross country analysis for gaining more insights.

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