Ilkogretim Online - Elementary Education Online, Year; Vol 20 (Issue 4): pp. 975-984
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2021.04.105

A Technology Acceptance Model for E-Learning during COVID-19: Empirical Insight from Pakistan

Sadia Farooq, Assistant Professor, Hailey College of Commerce, University of the Punjab, Lahore, Pakistan, sadia.hcc@pu.edu.pk
Zafar Ahmad, Associate Professor, Hailey College of Commerce, University of the Punjab, Lahore, Pakistan, zafarahmad79@gmail.com
Naveed ul Hassan, Instructor, Department of Business Administration, Virtual University, Lahore. t.haider03@gmail.com
Muhammad Sarfraz Khan, Lecturer, Department of Commerce, University of the Punjab, Gujranwala Campus, Pakistan, sarfraz.khan@pugc.edu.pk

ABSTRACT- Global pandemic of COVID-19 has seriously disrupted education sector of Pakistan. High contagion of the disease have confined students and teachers to their homes, where teaching sifted from physical/on-campus settings to online mode.However, students expressed their discontent for online education modes and resisted online learning. In this background, we studied behavior and attitude of students towards online education system during the pandemic and documented that Technology Acceptance Model (TAM) could be used to improve adoption of online education during uncertain times like COVID-19. We provide implications for developmentof a more inclusive online education system in Pakistan during these uncertain times.

Key words: Online Education, TAM, E-learning, COVID-19

I. INTRODUCTION

Advent of internet and online technologies have revamped educational paradigm in modern societies. Dawn of 21st centaury has established viability of online modes of learning (Harasim, 2000), where it has potential to improve access to education, provide a better learning experience, and minimize cost of education delivery (Protopsaltis & Baum, 2019).The value of online medium of education has exacerbated in recent times due to global pandemic (COVID-19), which severely disrupted traditional mode of physical or in campus teaching based education. Higher contagion of the disease resulted in closure of all educational institutes around the globe and online instructional methods were adopted to proceed with the educational activities. In this context, online mode of education is being considered as an opportunity(Vlachopoulos, 2020) that could be used to mend broken ends during this pandemic and learning from this experience could be utilized in the future to improve remote learning experiences (Basilaia & Kvavadze, 2020). Despite the success of online mode of education in foreign settings (Basilaia & Kvavadze, 2020; Tartavulea et al., 2020), students and teachers in Pakistan have expressed their concerns on its effectiveness (Bari, 2020; Gabol, 2020). In this regard, Adnan and Anwar (2020) argued that online education has technological constraints in developing countries like Pakistan. Such constraints hinder effectives of online education system. Despite the ineffectiveness of online education in the country, it had been the only option to disseminate education during the pandemic. However, electronic modes of learning gave lower acceptance and adoption in Pakistan (Kanwal et al., 2020). Such lower technological adoption has made online education a futile exercise in the country, whereby students have agitated to protest against online education during COVID-19 (Abbasi, 2021). Shortcomings of online education systems are widely acknowledged. However, this pandemic is not over and it is unlikely that wewould return to pre-COVID life any time soon (Gallagher, 2021). Thus, online education might be the only way to keep things moving during these uncertain times.

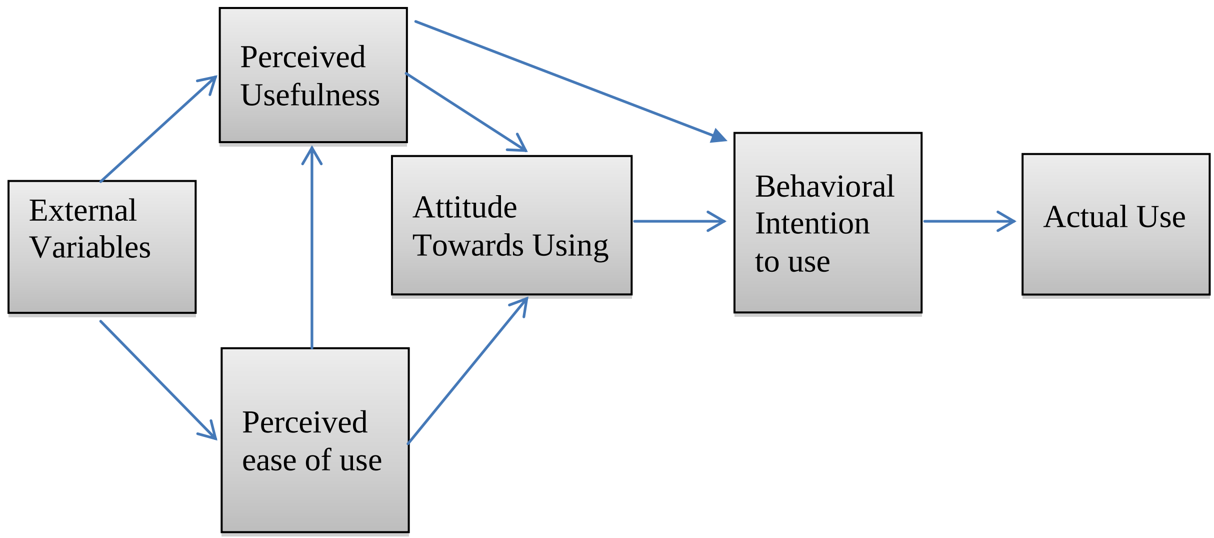
In this paper, we argue that effectiveness of online education could be improved in the country by helping students to accept and adopt technology being utilized in online education systems. Previous research has demonstrated that Technology Adoption Model (TAM) could be effectively used to facilitate adoption of E-learning and other settings of online education (Alone, 2017; Kanwal & Rehman, 2014; Mehta et al., 2019; Rafiq et al., 2020). Davis et al. (1989) argued that technology adoption islinked to personal decision of individual to learn the technology, whereby perceived ease of use and perceived usefulness are important elements of new technology adoption (Davis, 1993). Al-Maroof et al. (2020) demonstrated that TAM could effectively be used to learn online instructional technologies during COVID-19. Considering agitation and reluctance of students for online mode of education in Pakistan, it is imperative that we devise ways to help students to adopt online education. This study uses TAM to assess its usefulness during COVID-19 to provide implication for adoption of online mode of education during uncertain times. Findings of the study are helpful for educational institutes and policy makers, who might be interested to impact education through online technology.

II. LITERATURE REVIEW

It has been widely argued that electronic modes of education cannot substitute on campus based model education. Online education falls short of learning expectations of the students as they are unable to develop understanding of the taught material (Kilmurray, 2003). This has been widely acknowledged in scenario of COVID-19 pandemic as well (Farooq et al., 2020; Adnan & Anwar, 2020). Under suboptimal learning scenarios, educationists need to formulate effective strategies to address the problems faced by the students (Hara, 2000). Despite the short comings of e-modes of education, it allows for time and space flexibility (Concannon et al., 2005), which is need of the era to protect educational interests of the society on the whole (Vlachopoulos, 2020; Dhawan, 2020). Despite the need of the hour, such online modes of education can pose challenges that can have a major impact on the culture and the technological skills and development of targeted audience and staffs (Al-Adwan & Smedley, 2012). Saade et al. (2007) argued that use acceptance of such technology embedded system is considered an imperativecriterion of functional effectives of the system.Thus, participation and acceptance of students in online education along with their satisfaction is an important consideration while proceeding with online education (Žuvić-Butorac et al., 2011).

In order to facilitate technology adoption, Davis (1989)proposed Technology Adoption Model (TAM) arguing that perceived ease of use and perceived usefulness of the technology could help users to accept and adopt new technologies. The model has previously been used in online modes of teaching and learning and has successfully predicted technology adoption and other learning outcomes (Bazelais et al., 2018; Gibson et al., 2008; Legris et al., 2003; Yalcin & Kutlu, 2019; Zhang et al., 2008). Davis et al. (1989) provided extended version of TAM, which is depicted by figure 1.

Figure 1: TAM Model



Source: Davis et al. (1989)

Considering technology adoption of students, TAM has shown a good explanatory power. Base TAM explained about 50% of variation in technology acceptance, while extended version has about 60% explanatory power in this regard (Venkatesh & Davis, 2000).

We propose that same model can be used to improve student acceptance of online education technology and yield fruitful results. Certain studies have recently embarked on the effectiveness of TAM during COVID-19 pandemic (AlMaroof et al., 2020; Raza et al., 2020; Sangeeta & Tandon, 2020). The model considers behavioural intention to use technology (intention) as main dependent variables, which is predicted by attitude towards using technology (attitude) and perceived usefulness (usefulness), while attitude is predicted by perceived ease of use (ease) and perceived usefulness. Lastly, external factors like subjective norms (norms) and system accessibility (accessibility) were also included in the model as per previous literature (AlMaroof et al., 2020; Musa, 2006; Salloum et al., 2019). We have tested following hypothesis in this study:
H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Subjective norms have a significant impact on perceived ease of use.
H3: Subjective norms have a significant impact on perceived usefulness.
H4: System accessibility have a significant impact on perceived ease of use.
H5: System accessibility have a significant impact on perceived usefulness.
H6: Subjective norms have a significant impact on attitude towards e-learning.
H7: System accessibility have a significant impact on attitude towards e-learning.
H8: Perceived ease of use have a significant impact on attitude towards e-learning.
H9: Perceived usefulness have a significant impact on attitude towards e-learning.
H10: Subjective norms have a significant impact on behavioural intention.
H11: System accessibility has a significant impact on behavioural intention.
H12: Perceived ease of use has a significant impact on behavioural intention.
H13: Perceived usefulness has a significant impact on behavioural intention.
H14: Attitude towards e-learning has a significant impact on behavioural intention.

III. METHODOLOGY

Research design

This study is based on the perceptions and opinions of the students. Thus, survey design was deemed suitable for collection of data, where self-administered questionnaire was floated among students studying online classes during COVID-19.

Sample and Procedure

Students taking online classes during COVID-19 represented population of the study. We delimited our data collection to the city of Lahore, which is largest city of Punjab province of Pakistan and is home to 33 recognized universities out of total 69 in the whole province. We targeted largest university in the city i.e. University of the Punjab. University of the Punjab is among the oldest and largest university in Punjab province and hosts students from heterogeneous backgrounds with representation from rural and urban areas, and from different income classes. Further, it is a general category university, not specializing in any specific discipline and offers education in almost all disciplines and have 73 distant departments. These departments were considered as clusters of students and 7 clusters were randomly chosen from alphabetical list of departments.

Hoyle (1995) opined that a sample of 100-200 is suitable in path modelling, estimating simultaneous relationships. We asked teachers from chosen clusters to share link of questionnaire in student what's app groups with a request to fill the questionnaire. During COVID-19, what's app groups were created and used to communicate with students. Thus, we made sure that questionnaire link reached to as many as students possible. Participation in the survey was explicitly optional and it was clarified that it was not a quiz and students were not obliged to take part in the survey. Initially, we received 548 responses, whereby 495 responses were complete and deemed fit for analysis.

Instrumentation

Self-administered questionnaire was used to collect data from students studying online during COVID-19. Questionnaire had two parts: first part asked questions on the demographics of the students asking them to identify their gender, age, level of degree, and home town area. Second part of the questionnaire contained scales of the variables used in this study. These scales were modified version of scales used by Davis and were adopted Selim (2003) and Salloum et al. (2019). We used Partial Least Square (PLS) based Structural Equation Modelling (SEM)to estimate our model as proposed by Sarstedt et al. (2017). SEM has ability to simultaneously estimate a series of relationships between interrelated constructs being represented by set of multiple variables, while accounting for measurement error (Ali et al., 2018). This makes PLS-SEM an effective tool for the data analysis, which separately provides assessment of measurement model and structural model along with path coefficients to establish relationships between variables (Sarstedt et al., 2017).

IV. RESULTS

Results of the study are divided into four parts. First part provides demographical description of the sample, describing gender, age, degree level, and home town area of respondents. Second part provides evaluation of measurement model considering validity and reliability of the constructs. Third part provides evaluation of structural model assessing collinearity between independent variables and coefficient of determination. Last part of analysis provides path coefficient to assess relationship between variables of the study.

Demographics

Table 1 provides demographical distribution of the sample. Out of total 495 respondents, 258 (52.12%) were male students and remaining 237 (47.88%) were female students. Most of the students in the sample were from age group of less than 20 years (55.56%), while 203 (41.01%) students were aged between 21 to 20 years, and remaining 17 students belong to the age group of 31years and above. Considering degree level, 365 (73.74%) students were studying at undergraduate level, while remaining 130 (26.26%) were from graduate level of study. Lastly, out sample considered both of urban and rural area students, where 60.40% students had urban origin, while remaining 39.60% of the students in sample belonged to rural areas. Thus, our sample has blended demographical characteristics, ensuring better generalizability of the results.

Table 1: Demographical distribution of sample

Demographics	Categories	Frequency	Parentage
Gender	Male	258	52.12%
	Female	237	47.88%
Age	20 years and less	275	55.56%
	21 to 30 years	203	41.01%
	31 years and above	17	3.43%
Degree level	Undergraduate	365	73.74%
	Graduate	130	26.26%
Home town area	Rural	196	39.60%
	Urban	299	60.40%

Evaluation of measurement model

Sarstedt et al. (2017) suggested that evaluation of measurement model should be first step of employing PLS-SEM. Table 2 and table 3 provide evaluation of measurement model of the study assessing reliability and validity of the measurement scheme of the study. Table 2 provides values of Cronbach's Alpha and composite reliability to assess reliability of each construct, while convergent validity is assessed though the value of Average Variance Extracted (AVE). Cronbach's Alpha value exceeding 0.6 represents good reliability of a measurement (Hair et al., 2014). Each of variable included in the study has yielded an alpha's value above this threshold deeming the measurement to be consistent and reliable. For composite reliability, Sarstedt et al. (2017) recommended that values between 0.6 to 0.7 were acceptable, while values between 0.7 to 0.95 represent satisfactory to good composite reliability. All the variables used in this study again yielded values of composite reliability above acceptable threshold, implying a good composite reliability of the measurement.

Table 2: Reliability and composite validity of measurement model

	Cronbach's Alpha	Composite reliability	Convergent Validity - AVE
Attitude towards e-Learning	0.764	0.85	0.588
Behavioral Intention	0.726	0.825	0.542

Perceived Ease of Use	0.754	0.84	0.568
Perceived Usefulness	0.767	0.849	0.586
Subjective Norm	0.807	0.828	0.548
System Accessibility	0.887	0.922	0.748

Lastly, table 2 also provides value of Average Variance Extracted (AVE) to gauge convergent validity of the measurement. AVE value surpassing threshold of 0.5 are representative of acceptable convergent validity. Again all of the variables have yielded AVE values exceeding recommended threshold, implying a good convergent validity of measurement model. Subsequently, table 3 provides hetrotrait-monotrait (HTMT) ratio to assess discriminant validity of variables in relation to each other. HTMT ratio values of below 0.9 is indicative of good discriminant validity (Henseler et al., 2015). All the values of HTMT ration in table 3 are below this threshold indicating a good discriminant validity of the measurement model.

Table 3: Discriminant validity of measurement model – HTMT ratio

		1	2	3	4	5	6
1	Attitude towards e-Learning						
2	Behavioral Intention	0.895					
3	Perceived Ease of Use	0.754	0.767				
4	Perceived Usefulness	0.62	0.661	0.576			
5	Subjective Norm	0.368	0.486	0.302	0.432		
6	System Accessibility	0.856	0.832	0.658	0.405	0.267	0.27

Overall, measurements of variables used in this study i.e. attitude, intention, ease, usefulness, norm, and accessibility were found to be both reliable and valid as per requirements of PLS-SEM. Thus, we could proceed with evaluation of structural model.

Evaluation of Structural model

Structural model takes into account structural relationships between variables included in the study. Sarstedt et al. (2017) recommended evaluation of structural model as a second step of using PLS-SEM. In this regard, table 4 provides multicollinearity diagnostic by means of Variance Inflation Factor (VIF), while table 5 relates to the explanatory power of the predictors in relation to predicted variables. Hair et al. (2011) provided that a VIF value below 5 indicates lack of multicollinearity issues in structural model. VIF values, as provided in table 4 are lower than the threshold value of 5 implying that multicollinearity issues did not exist between predictors of the study.

Table 4: Multicollinearity diagnostic - VIF

		1	2	3	4	5	6
1	Attitude towards e-Learning		3.288				
2	Behavioral Intention						
3	Perceived Ease of Use	1.715	1.781		1.556		
4	Perceived Usefulness	1.494	1.589				
5	Subjective Norm	1.371	1.389	1.125	1.219		
6	System Accessibility	1.472	2.774	1.125	1.467		

After assessing multicollinearity, table 5 provides coefficient of determination, which represents explanatory power of predictors in relevance to the predicted variables. Variables of attitude yielded R-squared of 0.696, variables of intention 0.671, variable of ease 0.357, and variable of usefulness 0.331. This implies that about 70%, 67%, 36%, and 33% of the variance in attitude, intention, ease, and usefulness was explained by the explanatory variables included in the model. Wong (2013) argued that value of R-squared should be at-least 25%. Thus, values of R-squared of our estimated are acceptable.

Table5: Coefficient of determination – R^2

	R-Squared
Attitude towards e-Learning	0.696
Behavioural Intention	0.671
Perceived Ease of Use	0.357
Perceived Usefulness	0.331

Overall, structural model of the study did not show any signs of multicollinearity, while predictors used in the model also had appropriate explanatory power. Thereby, path coefficient calculated and presented in subsequent part of analysis could be interpreted with confidence.

Path coefficients

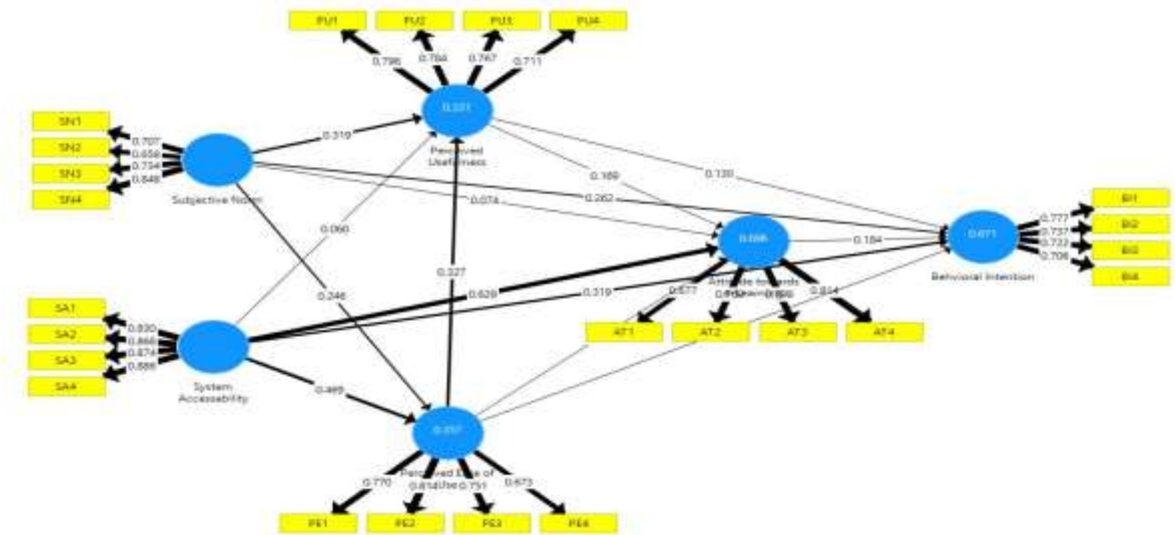
In PLS-SEM, a path relates to a relationship, whereby path coefficients are calculated to depict magnitude of effect, while bootstrapping is used to establish significance of a path coefficient. Table 6 provides path coefficients for the direct relationships of variables. Variables of ease had a positive and significant impact on usefulness (Coefficient = 0.327, p<.01), attitude (coefficient = 0.141, p<.05), and intention (coefficient = 0.164, p<.01). thus, we accept H1, H8, and H12. Subsequently, variable of norm also had a positive and significant impact on ease (coefficient = 0.246, p<.01), usefulness (coefficient = 0.319, p<.01), and intention (0.262, p<.01), while it failed to influence attitude significantly. Thus, we accept H2, H3, and H10, while rejecting H6. Variable of system accessibility yielded a positive impact only on ease (coefficient =0.469, p<.01), attitude (coefficient = 0.629, p<.01), and intention (coefficient = 0.319, p<.01) and not on usefulness. Thus, we accept H4, H7, and H11, while rejecting H5. After that, usefulness also had a positive and significant impact on attitude (coefficient = 0.169, p<.01) and intention (coefficient = 0.13, p<.05), enabling us to accept both H9 and H13. Lastly, attitude also had positive and significant impact on intention (coefficient = 0.184, P<.01), whereby H14 is also accepted.

Table 6: Path coefficients – direct relationships

		Path Coefficient	T-Statistics	P-Value	Decision
H1	Perceived Ease of Use -> Perceived Usefulness	0.327	4.756	0.0000	Accepted
H2	Subjective Norm -> Perceived Ease of Use	0.246	3.98	0.0000	Accepted
H3	Subjective Norm -> Perceived Usefulness	0.319	5.514	0.0000	Accepted
H4	System Accessibility -> Perceived Ease of Use	0.469	6.852	0.0000	Accepted
H5	System Accessibility -> Perceived Usefulness	0.06	0.837	0.4020	Rejected
H6	Subjective Norm -> Attitude towards e-Learning	0.074	1.479	0.1390	Rejected
H7	System Accessibility -> Attitude towards e-Learning	0.629	10.701	0.0000	Accepted
H8	Perceived Ease of Use -> Attitude towards e-Learning	0.141	2.547	0.0110	Accepted
H9	Perceived Usefulness -> Attitude towards e-Learning	0.169	3.331	0.0010	Accepted
H10	Subjective Norm -> Behavioral Intention	0.262	5.319	0.0000	Accepted
H11	System Accessibility -> Behavioral Intention	0.319	4.314	0.0000	Accepted
H12	Perceived Ease of Use -> Behavioral Intention	0.164	2.945	0.0030	Accepted
H13	Perceived Usefulness -> Behavioral Intention	0.13	2.239	0.0250	Accepted
H1	Attitude towards e-Learning -> Behavioral Intention	0.184	2.558	0.011	Accepte

We have found that Subjective norms predict perceived usefulness of the system, perceived ease of use of system, and behavioural intentions to use online education system during COVID-19. Further, system accessibility predicted perceived ease of use of system, attitude towards e-learning, and behavioural intention to use online education during COVID-19. Subsequently, perceived usefulness of the system and perceived ease of use of system predicted both attitude towards e-learning and behavioural intention to use online education during COVID-19. Lastly, attitude towards e-learning also supported behavioural intention to use online education during COVID-19. These relationships are also depicted in figure 2.

Figure 2: Pathdiagram



PLS-SEM is also used to detect mediating channels between variables. Table 7 provides unveils mediating channels between independent and dependent variables of the study. It was found that ease and attitude both mediated the relationship between norms and intention (coefficient = 0.116, p<.05), and between system associability and intention (coefficient = 0.04, p<.05). Subsequently, perceived usefulness and attitude towards e-learning could not mediate the relationship between system accessibility and intention. Lastly, perceived ease of use, perceived usefulness, and attitude towards e-learning mediated the relationship between subjective norm and behavioural intention, and between system accessibility and behavioural intention.

Table 7: Path coefficients – indirect relationships

	Path Coefficient	T-Statistics	P - Values	Decision
Subjective Norm -> Perceived Ease of Use -> Attitude towards e-Learning -> Behavioral Intention	0.116	2.501	0.0120	Mediation
System Accessibility -> Perceived Ease of Use -> Attitude towards e-Learning -> Behavioral Intention	0.04	2.249	0.0250	Mediation
System Accessibility -> Perceived Usefulness -> Attitude towards e-Learning -> Behavioral Intention	0.002	0.676	0.4990	No mediation
Subjective Norm -> Perceived Ease of Use -> Perceived Usefulness -> Attitude towards e-Learning -> Behavioral Intention	0.014	2.064	0.0390	Mediation
System Accessibility -> Perceived Ease of Use -> Perceived Usefulness -> Attitude towards e-Learning -> Behavioral Intention	0.026	2.586	0.0100	Mediation

We found overwhelming support for TAM in students during COVID-19. It could be argued that system accessibility, subjective norms, perceived ease of use, and perceived usefulness of the system are important aspects of attitude towards e-learning and behaviouralintentions to use online education during COVID-19. Previous research is broadly consistent with our findings like Martín-García et al.

(2019) and Rafique et al. (2020) highlighted importance of perceived ease of use and perceived usefulness in context of technology adoption in educational settings. Almaroof et al. (2020) also highlighted that perceived ease of use, perceived usefulness, and subjective norms significantly predicted new technology adoption during COVID-19. Kanwal and Rehman (2014) also proposed TAM for e-learning adoption in Pakistan in post pandemic scenario, while we have demonstrated that this model could be helpful to improve student's willingness to adopt online education system during uncertain times like COVID-19.

V. CONCLUSION

COVID-19 has disrupted educational structure around the globe, where developed nations quickly moved towards online education systems, while developing countries like Pakistan faced considerable difficulties to provide education during these uncertain times. Apart from infrastructural and technological issues, students in the country showed their discontent for online education and staged protests. This study explored implications of technology adoption model in COVID-19 scenario for its usability to improve technology adoption of college and university students in Pakistan. We documented that TAM could effectively be utilized to motivate students to adopt new technologies facilitating online education in the country. We documented that subjective norms, system accessibility, perceived ease of use, and perceived usefulness all contribute to improve student's attitude towards e-learning, which ultimately leads towards behavioural intention to use online education during uncertain times like COVID-19. We argue that instructors and peers can motivate students to adopt online educational technologies (El-Gayar et al., 2011), while system accessibility is another important consideration that must be dealt with at macro level. Policy makers must ensure that students have access to all the technologies and internet to pursue their educational endeavours. Subsidies and special internet packages for educational purposes could be introduced to improve accessibility of students. Further, there is also a need to improve usefulness and ease of use of online education technologies. Both students and teachers in Pakistan are not trained to use these technologies in an effectives manner. Further, different instructors, educational institutes, and students have different preferences for different online instructional technologies and software. Educational institutes need to provide appropriate trainings to teachers and students to improve their ease of use of online educational technologies. Students should also be demonstrated that learning to utilize these online technologies could be a useful skill that might help them in their future professional and personal life. Future studies could be directed to understand the role of support mechanism in online educational adoption. Further, it would be interesting to study longitudinal implications of learning online educational technologies, both for students and teachers.

REFERENCE

1. Abbasi, K. (June 16, 2020). Students protest 'faulty' online system, charging of feeby varsities, DAWN, https://www.dawn.com/news/1563770
2. Adnan, M., & Anwar, K. (2020). Online Learning amid the COVID-19 Pandemic: Students' Perspectives. *Online Submission*, *2*(1), 45-51.
3. Adnan, M., & Anwar, K. (2020). Online Learning amid the COVID-19 Pandemic: Students' Perspectives. *Online Submission*, *2*(1), 45-51.
4. Adnan, M., & Anwar, K. (2020). Online Learning amid the COVID-19 Pandemic: Students' Perspectives. *Online Submission*, *2*(1), 45-51.
5. Al-Adwan, A., & Smedley, J. (2012). Implementing e-Learning in the Jordanian Higher Education System: Factors Affecting Impact. *International Journal of Education and Development using Information and Communication Technology*, *8*(1), 121-135.
6. Al-Maroof, R. S., Salloum, S. A., Hassanien, A. E., & Shaalan, K. (2020). Fear from COVID-19 and technology adoption: the impact of Google Meet during Coronavirus pandemic. *Interactive Learning Environments*, 1-16.
7. Ali, F., Rasoolimanesh, S. M., Sarstedt, M., Ringle, C. M., & Ryu, K. (2018). An assessment of the use of partial least squares structural equation modeling (PLS-SEM) in hospitality research. *International Journal of Contemporary Hospitality Management*, 30(10), 514-538.
8. Alone, K. (2017). Adoption of e-learning technologies in education institutions/organizations: A literature review. *Asian Journal of Educational Research Vol*, *5*(4), 63-71.
9. Bari, F. (September 4, 2020). Online teaching, DAWN, https://www.dawn.com/news/1577831

10. Basilaia, G., & Kvavadze, D. (2020). Transition to online education in schools during a SARS-CoV-2 coronavirus (COVID-19) pandemic in Georgia. *Pedagogical Research*, *5*(4).
11. Bazelais, P., Doleck, T., & Lemay, D. J. (2018). Investigating the predictive power of TAM: A case study of CEGEP students' intentions to use online learning technologies. *Education and Information Technologies*, *23*(1), 93-111.
12. Concannon, F., Flynn, A., & Campbell, M. (2005). What campus‐based students think about the quality and benefits of e‐learning. *British Journal of Educational Technology*, *36*(3), 501-512.
13. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology.MISQuarterly,13(3), 319–340.
14. Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *International Journal of Man-machine Studies*, *38*(3), 475-487.
15. Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, *35*(8), 982-1003.
16. Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, *35*(8), 982-1003.
17. Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. *Journal of Educational Technology Systems*, *49*(1), 5-22.
18. El-Gayar, O., Moran, M., & Hawkes, M. (2011). Students'acceptance of tablet PCs and implications for educational insti-tutions.Journal of Educational Technology & Society,14(2), 58–70.
19. Farooq, F., Rathore, F. A., & Mansoor, S. N. (2020). Challenges of online medical education in Pakistan during COVID-19 pandemic. *J Coll Physicians Surg Pak*, *30*(6), 67-9.
20. Gabol, I. (arch 31, 2020). Students, faculty express reservations over online education system, DAWN, https://www.dawn.com/news/1545094
21. Gallagher, S. (February 16, 2021). Will we ever return to our pre-coronavirus lives?, Independent, https://www.independent.co.uk/life-style/health-and-families/when-coronavirus-lockdown-end-uk-new-normal-b1802829.html
22. Gibson, S. G., Harris, M. L., & Colaric, S. M. (2008). Technology acceptance in an academic context: Faculty acceptance of online education. *Journal of Education for Business*, *83*(6), 355-359.
23. Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2014). Pearson new international edition. In *Multivariate data analysis, Seventh Edition*. Pearson Education Limited Harlow, Essex.
24. Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, *19*(2), 139-152.
25. Hara, N. (2000). Student distress in a web-based distance education course. *Information, Communication & Society*, *3*(4), 557-579
26. Harasim, L. (2000). Shift happens: Online education as a new paradigm in learning. *The Internet and higher education*, *3*(1-2), 41-61.
27. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*(1), 115-135.
28. Hoyle, R. H. (1995). Structural equation modeling: Concepts, issues, and applications. Sage.
29. Kanwal, F., & Rehman, M. (2014). E-learning Adoption Model: A case study of Pakistan. *Life science Journal*, *11*(4s), 78-86.
30. Kanwal, F., Rehman, M., & Asif, M. M. (2020). E-learning adoption and acceptance in Pakistan: moderating effect of gender and experience. *Mehran University Research Journal of Engineering and Technology*, *39*(2), 324-341.
31. Kilmurray, J. (2003). E-learning: It's more than automation. *The Technology Source*.
32. Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & management*, *40*(3), 191-204.
33. Martín-García, A. V., Martínez-Abad, F., & Reyes-González, D. (2019). TAM and stages of adoption of blended learning inhigher education by application of data mining techniques.British Journal of Educational Technology,50(5), 2484–2500.
34. Mehta, A., Morris, N. P., Swinnerton, B., & Homer, M. (2019). The influence of values on E-learning adoption. *Computers & Education*, *141*, 103617.
35. Protopsaltis, S., & Baum, S. (2019). Does online education live up to its promise? A look at the evidence and implications for federal policy. *Center for Educational Policy Evaluation*.
36. Rafiq, F., Hussain, S., & Abbas, Q. (2020). Analyzing Students' Attitude towards E-Learning: A Case Study in Higher Education in Pakistan. *Pakistan Social Sciences Review*, *4*(1), 367-380.

37. Rafique, H., Almagrabi, A. O., Shamim, A., Anwar, F., & Bashir, A. K. (2020). Investigating the acceptance of mobile libraryapplications with an extended technology acceptance model (TAM).Computers & Education,145, 103732.
38. Raza, S. A., Qazi, W., Khan, K. A., & Salam, J. (2020). Social Isolation and Acceptance of the Learning Management System (LMS) in the time of COVID-19 Pandemic: An Expansion of the UTAUT Model. *Journal of Educational Computing Research*, 0735633120960421.
39. Saade, R., Nebebe, F., & Tan, W. (2007). Viability of the" technology acceptance model" in multimedia learning environments: a comparative study. *Interdisciplinary Journal of E-Learning and Learning Objects*, *3*(1), 175-184.
40. Salloum, S. A., Alhamad, A. Q. M., Al-Emran, M., Monem, A. A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE Access*, *7*, 128445-128462.
41. Sangeeta &Tandon, U. (2020). Factors influencing adoption of online teaching by school teachers: A study during COVID-19 pandemic. *Journal of Public Affairs*, e2503.
42. Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial least squares structural equation modeling. *Handbook of market research*, *26*(1), 1-40.
43. Selim, H. M. (2003). An empirical investigation of student acceptance of course websites. *Computers & Education*, *40*(4), 343-360.
44. Tartavulea, C. V., Albu, C. N., Albu, N., Dieaconescu, R. I., & Petre, S. (2020). Online Teaching Practices and the Effectiveness of the Educational Process in the Wake of the COVID-19 Pandemic. *Amfiteatru Economic*, *22*(55), 920-936.
45. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204.
46. Vlachopoulos, D. (2020). COVID-19: threat or opportunity for online education?. *Higher Learning Research Communications*, *10*(1), 2.
47. Vlachopoulos, D. (2020). COVID-19: threat or opportunity for online education?. *Higher Learning Research Communications*, *10*(1), 2.
48. Wong, K. K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin*, *24*(1), 1-32.
49. Yalcin, E. M., & Kutlu, B. (2019). Examination of students' acceptance of and intention to use learning management systems using extended TAM. *British Journal of Educational Technology*, *50*(5), 2414-2432.
50. Zhang, S., Zhao, J., & Tan, W. (2008). Extending TAM for online learning systems: An intrinsic motivation perspective. *Tsinghua science and technology*, *13*(3), 312-317.
51. Žuvić-Butorac, M., Rončević, N., Nemčanin, D., & Nebić, Z. (2011). Blended e-learning in higher education: Research on students' perspective. *Issues in Informing Science and Information Technology*, *8*, 409-429.