

“AN INSIGHT INTO STUDENT’S ACCEPTANCE OF VARIOUS DIGITAL PLATFORMS USING TAM MODEL ACROSS THE INDIAN STATES DURING THE PANDEMIC”

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ABSTRACT

This study employed the technology acceptance model to explore perception of students towards adoption of various digital platforms in the state of Maharashtra and Chhattisgarh. The information was gathered through an online survey of 419 students from Indian Maharashtra and Chhattisgarh from various universities and colleges. Both the measurement and structural models were evaluated using the Partial Least Square-Structural Equation Model (PLS-SEM) method. The findings show that perceived ease of use and perceived usefulness both have a positively impact on behavioural intention, which in turn has an impact on actual usage of various digital platforms. This research aids higher education decision-makers in determining the level of acceptance of the digital technology among students. The study will help higher education decision-makers should recognize the features of digital platforms and construct their infrastructure based on the findings of this study and to put this technology into practice. Higher education institutions should offer students training opportunities so that students’ ability to find the complete and effective features of digital platforms are more evident and extensively used by end-users. Using the TAM model and the PLS-SEM technique, the determines the factors and their interrelationship that influence the adoption of digital platforms utilized in higher education.

INTRODUCTION

With the outbreak of COVID-19, a novel corona virus disease, numerous governments have ordered the closure of all educational institutions. Since they had to protect their students from viral exposures, which are likely in a highly socializing student society, educational institutions have come to a halt. According to UNESCO, 186 countries have imposed nationwide closures in the year 2020, affecting 73.8 percent of all enrolled students (UNESCO, 2020). Due to the indefinite closure of schools and colleges, both educational institutions and students are experimenting with strategies to fulfil their mandated syllabi within the time window set by the academic calendar. These restrictions have undoubtedly caused some discomfort, but they have also sparked fresh examples of educational innovation involving digital inputs. Nevertheless, COVID-19 has prompted educational institutions around the world to investigate innovative techniques in a timely manner to impart education.

Impact of Higher Education

1. Hampered all Educational Activities

Every sector, including education, has been placed on lockdown because to the Covid-19 outbreak. The closure of the schools and the cessation of educational activity presented various difficulties for the stakeholders (Pravat, 2020a). As a result, many activities such as admission, exams, entrance exams, and competitive exams held by different boards, schools, colleges, and institutions have been postponed. Many higher education admission exams were postponed, which presented a significant burden to students. The main difficulty was carrying on the teaching and learning process when students, faculty, and staff could no longer be present on the campuses physically. Online teaching and learning was the institutions' clear choice as a solution. However, HEIs have been able to offer the students help through online channels in a reasonably short period of time. The deployment of digital technology for education delivery has accelerated under Covid-19. It inspired all educators and learners to advance their technological literacy. In order to offer support services to the students, HEIs have begun offering orientation programmes, induction meetings, and counselling sessions using various e-conferencing systems including Google Meet, Skype, Youtube live, Facebook live, WebEx, etc.

2. Blended Impact on Academic Research and Professional Development

Research is impacted by Covid-19 in both good and bad ways. On the downside, it has made it difficult for academics to travel and collaborate with people across national and international borders. Some collaborative research projects or tasks are difficult to execute. It was not possible to undertake some scientific laboratory tests or study. If we use digital tools for online learning (Pravat, 2020a). All final exams were postponed to July 2020. Additionally, UGC has created an revised its entire calendar for the 2020–2021 academic year that includes revised dates considering the shutdown.

In India, the University Grants Commission (UGC), the country's higher education regulator, released a list of MHRD, UGC, and its Inter University Centres (IUCs) - Information and Library Network (INFLIBNET) and Consortium for Educational Communication (CEC) - initiatives that academics can use to pass the time while the country is under lockdown due to the coronavirus outbreak. SWAYAM, MOOCs, SWAYAMPURABHA, CEC-UGC you tube channel, National Digital Library, Shodhganga, e-Sodh Sindhu and other efforts are among them. Providing learners with an online learning system and digital platforms, on the other hand, does not ensure a successful online learning experience. Different factors, such as system components, course creation, and users, should be considered when evaluating successful ICT-based learning (Persico et al., 2014). As a result, while online learning and usage of numerous digital platforms are commonly used, learner-related elements should be researched to apply remote education during catastrophes.

3. Severely Impacted the System of Educational Assessment

Nearly all the internal evaluations have been cancelled, and most of the external exams have been postponed. Assessment cancellation has a detrimental effect on pupils' learning. The postponement of the external examinations would directly affect the educational and professional destiny of students even though many universities have been managing internal evaluations in an online environment utilizing various digital tools. Since they are confined to the same grade or class without advancement, this uncertainty has made students anxious. Similar to this, many students who took final exams would suffer greatly since by the time they received their certificates, it could already be too late for them to apply for the next academic year in other nations due to lockdown.

Reduction in Employee Opportunities

The cancellation of several entrance exams for job openings had a detrimental effect and presented a significant obstacle to higher education students. The loss of their jobs also infuriated the Indians who had been working overseas. Due to the pandemic condition, there are no openings in the government sector in India, and recent graduates are under pressure to accept employment offers from private companies. Many students who work in India and abroad risk losing their employment. Due to several constraints brought on by Covid-19, graduating students may not be able to find employment outside of India. All these factors point to a rise in the unemployment rate as a result of the pandemic. As unemployment rises, people may become less interested in education as they focus more on getting by than on getting an education (Pravat, 2020b).

Covid-19 posed a lot of difficulties. The HEIs have positively responded and implemented several ways to deal with the situation during the pandemic. The Indian government has also

implemented a variety of preventative steps to stop the pandemic COVID-19. For students to continue their education, the MHRD and University Grants Commission (UGC) have established several virtual platforms including online repositories, e-books and other online teaching and learning resources, educational channels through Direct to Home TV, and radios. The incompatibility between educational ideas with the current technical level frequently stymies the progress of online education. Online education is readily impacted by educational ideas, people's comprehension, the external environment, and network technology, all of which are difficult to completely comprehend in a single network setting.

As a result, in online education, the technology acceptance model (TAM) is presented, and its acceptance is examined in detail (Liu and Yang, 2018; Qian et al., 2018). Several elements of innovation are brought up in the current research. To begin with, domestic research on the perception of digital platforms for education platforms has been expanded. Online education is a relatively new idea, and the rapid growth of online education platforms has opened up a new research dimension, which is still in its early stages and focuses on a qualitative examination of the current state and difficulties in this sector (Han, 2020; Racero et al., 2020). Because initially students were hesitant to participate in online education in this context, more subjective influencing variables are presented here to study their acceptance and usage of online digital education platforms. Therefore, the theoretical mechanism of use willingness influence is shown. Second, students' perspectives on the acceptability of digital education platforms are investigated (Siyal et al., 2021). TAM is offered as a novel online education model in this paper, offering a unique viewpoint on the examination of online education issues. Then, using TAM's theory, a questionnaire survey (QS) is created and utilised for quantitative study of the new online education model's influencing elements. The proposal's QS findings suggest that it has some practical value for the nurturing and long-term growth of online education and digital platforms used for it.

In India most institutions have moved to an online method during this COVID-19 times, employing Google classroom, Microsoft Teams, Zoom, Cisco web X or other online platforms. Following the Union Government's decision for nation-wide lock-down beginning March 25, 2020, educational institutions in India have also made the move to an online teaching environment. The main problem, however, is the learning quality, which is intimately tied to how well the content is developed and implemented. Learning effectiveness is partly dependent on how content is chosen for the online environment, as well as identifying and overcoming the limits that students confront. The present study is important because online education has never been undertaken on this scale in India, making it a gigantic social experiment. Secondly, the transition to online mode was abrupt due to an unprecedented lockdown imposed to control the COVID-19, and the institutes did not have time to prepare and implement online course content. Students' experiences and learnings are blended into this environment to make online learning simple, efficient, and productive. Lastly, even when the COVID-19 pandemic is over, life will not be the same, and online learning will continue to exist, albeit in conjunction with traditional offline classes. Because the length of the pandemic and the likelihood of reinfections are unknown, social isolation may become the new normal. This has moved the researcher to investigate the acceptance of various digital platforms by students post transition from off-line mode to online mode of education.

The use of e-learning tools has become a recent trend in higher education. During the current COVID-19 epidemic, each country has used its own digital channels to combat disease transmission, including social media (Budd et al., 2020). With the growth of information and communication technology (ICT), a growing number of individuals are engaging in Internet-based learning activities. Online learning is more flexible than traditional classroom-based learning and widens educational regions without time or location constraints (Cheng, 2012). However, there are also drawbacks to online learning. For example, students may experience a lack of social

presence while studying online, affecting their learning motivation and outcomes (Tang & Hew, 2019). Despite its disadvantages, online learning is considered a viable alternative to traditional classroom-based learning (Liu et al., 2010). Since the onset of COVID-19, online learning has gained fresh importance (Anderson, 2020).

The Technology Acceptance Model (TAM; Davis, 1986, 1989) has been increasingly popular in teaching and learning settings as one of the most important frameworks for exploring concerns of technology acceptance and rejection (Al-Emran et al., 2018). Numerous research have validated TAM's effectiveness, and the model has evolved into the common ground theory for identifying determinants of user intention to utilise a product (Granić & Marangunić, 2019). Despite the fact that the TAM model is extensively used to assess users' willingness to embrace technology, only a few empirical research on Asian learners' technology adoption have been undertaken (Hao et al., 2017; Huang et al., 2019; Teo et al., 2019; Yang et al., 2017). Little is known, in particular, regarding the factors that influence students' use of technology for educational reasons (Zhou, 2016). While different ICT-supported educational methods have gained popularity in Western nations such as the United States, online learning is still in its early stages in many developing countries (Cakr & Solak, 2015).

In India, the University Grants Commission (UGC), the country's higher education regulator, released a list of MHRD, UGC, and its Inter University Centers (IUCs) - Information and Library Network (INFLIBNET) and Consortium for Educational Communication (CEC) - initiatives that academics can use to pass the time while the country is under lockdown due to the coronavirus outbreak. SWAYAM, MOOCs, SWAYAMPRAKASH, CEC-UGC you tube channel, National Digital Library, Shodhganga, e-Sodh Sindhu and other efforts are among them. Providing learners with an online learning system and digital platforms, on the other hand, does not ensure a successful online learning experience. Different factors, such as system components, course creation, and users, should be considered when evaluating successful ICT-based learning (Persico et al., 2014). As a result, while online learning and usage of numerous digital platforms are commonly used, learner-related elements should be researched to apply remote education during catastrophes.

This study uses the TAM as a framework to achieve this goal, the study intends to investigate elements that may influence students' desire to participate in extracurricular activities. In Indian Universities, employ an online education platform with the goal of extending TAM's original model and uncover probable technology usage antecedents from the learners' point of view. This study's findings might lead to some interesting conclusions. Both practitioners and researchers will benefit from this research in terms of putting online education and usage of various digital platforms into practice. These implications may not only be applicable for situation in India but also other Asian cultures. Meanwhile, the research may offer policymakers with research-based evidence rather of merely finding "what works," instead of finding "why it works" "if it functions" (Teo et al., 2019). Furthermore, the outcomes this study's findings might help improve the design and the creation of online learning systems to increase the number of students who use online learning.

REVIEW OF LITERATURE

During the pandemic phase a peculiar trend have been observed in higher education using different E-learning platforms. TAM has been the subject of several investigations. TAM was utilized by Bhattacharyya et al. (2020) to assess the use of e-learning as a learning medium. The adoption of e-learning as a learning medium was specifically assessed among students majoring in Accounting and Information Engineering. A total of 60 Accounting and Information Engineering students who used e-learning during their academic careers were included in the study. The data was obtained using QS, which included 30 questions, then analyzed using the regression

approach. The test findings revealed that the students were enthusiastic about adopting e-learning as a learning tool. Utility perception influenced students' desire to use e-learning in accounting classes. The model was used by (Dewi and Kharisma, 2020) to investigate the factors influencing public interest in viewing TV sermons over the Internet. The simulation findings demonstrated the viability of the Internet TV application, which had a influence on the actual application and system behaviors. As a result, Internet TV transmission was found to be 90.1 percent feasible. (Handani et al.2020) used five assessment indices to assess the impact of augmented reality technology and game music on players: ease of use, advantages of usage, attitude toward use, willingness of players, and player awareness. All components in shared validation were effective and dependable, according to validation and implementation outcomes. The player had a positive impression of these five indicators, with the highest score of 4.10 indicating ease of use and attitude toward usage. By examining background information, studying the link between variables, and confirming the dependability of the measurement model using search engine marketing, (Liu et al. 2020) used the TAM to investigate customer willingness and usage patterns (SEM). Users' perceived utility had a positive influence on the product's usefulness, their desire to use, their curiosity, and their readiness to use, according to the findings. Users' desire to use a wearable gadget was similarly influenced by social support, although perceived curiosity had no effect on their readiness to use. TAM was combined with social capital theory by Deng and Yuan (2020) to investigate the long-term willingness of passive users. The data was obtained using an online questionnaire to test the hypotheses, and the data was analyzed using a structural equation model. According to the findings, trust and reciprocity played a large and direct beneficial influence in passive users' persistent intentions. Through trust and reciprocity, sharing contributed significantly to passive users' continued intention. Furthermore, via shared vision, trust, and reciprocity, the utility and convenience of use indirectly influence the continued willingness of passive users. In conclusion, the use of TAM is rapidly becoming more widespread (Deng et al., 2021). Many breakthroughs have been made in the sectors of online learning, systems, finance, and health based on the TAM principle. TAM has progressed from corporate systems to mobile enterprises as the Internet has continued to flourish.

TAM and Usage of Digital Platforms for Education

The technology acceptance model was created in the 1980s because of research into the interaction between cognitive, emotional, and technological aspects. In the realm of information technology, the model is frequently utilized. Based on external observation factors, the working premise is to investigate the impact of technology usage on users' beliefs, attitudes, and intentions. TAM is made up of four primary components: (1) user behavior refers to users' actual operation behavior with new technology; (2) behavioral intention refers to users' willingness to try new technologies; (3) perceived usefulness refers to users' subjective understanding of the utility of the newly adopted technology; and (4) perceived ease of use refers to the degree of effort that users put into using new technologies (Tambun et al., 2020). The mathematical model of TAM is expressed in equation (1) to (3) as below:

$$B = W1 A + W2 U \dots \dots \dots (1)$$

$$A = W3 U + W4 E \dots \dots \dots (2)$$

$$U = W5 E \dots \dots \dots (3)$$

In above equation B, A, U and E represents user behavior, behavioral intention, perceived usefulness, and perceived ease of use. In the TAM model, both perceived usefulness and perceived ease of use are subjective notions including numerous elements other than information technology, as shown in Equation (2). As a result, users' intentions are determined by their attitudes toward perceived utility and perceived simplicity of use (Martasubrata and Priyadi, 2020;

Syarwani and Ermansyah, 2020). Furthermore, the views of users as well as the utility of the technology impact behavioral intention. The intention of users, according to TAM, is the most direct indication of user behavior. TAM also points out that perceived usefulness is directly influenced by perceived ease of use, i.e., if a technology is simpler to use, consumers would perceive it to be more helpful (Korry, 2020; Pibriana, 2020; Ranugalih et al., 2020). In online education, the characteristics of the online teaching system, teaching methods, teachers, and student differences are the factors that lead to an understanding of the technology's utility and simplicity, which then influences users' attitudes and intentions toward information technology use, and, finally, determines the actual use effect of online education (Mardhiyah et al., 2021). The TAM theory can be expressed in figure 1 below:

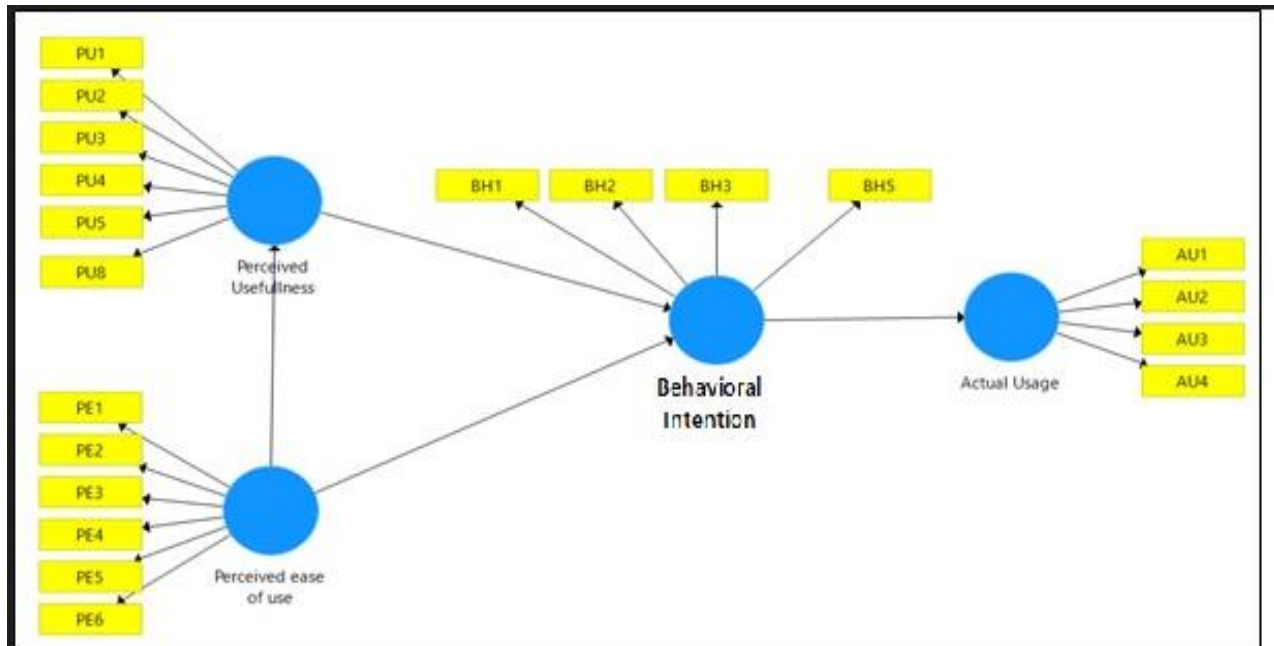


FIGURE 1
THEORETICAL MODEL

According to the TAM model, both the simplicity of use and the utility of technology influence behavioral intention, ultimately influencing the end user experience. Some studies argue that attitude is a reaction to learning and experience, and that learning may enhance the ease of use of technology and the comprehension of its utility, hence influencing users' attitudes (Chen, 2019; Mulyono et al., 2020; Mooya and Phiri, 2021). As a result, psychological elements might transfer the impact of the external environment on new technology, whereas external characteristics do not have a direct impact on usage intention and behavior. The user's inner knowledge and attitudes are the key sources of impact (Sipayung et al., 2020; Sugeng et al., 2020; Liu and Chen, 2021). According to the TAM model, both the ease of use and the utility of technology influence behavioral intention, ultimately influencing the end user experience. Some studies argue that attitude is a reaction to learning and experience, and that learning may enhance the ease of use of technology and the comprehension of its utility, hence influencing users' attitudes (Chen, 2019; Mulyono et al., 2020; Mooya and Phiri, 2021). Online education is a learning approach based on network technology that combines educational reform with network technology. It defies the inflexible teaching paradigm, expands the offline teaching channel, and improves the efficiency of teaching resources (Fanuel, 2020). Online education comes in a variety of formats and platforms, catering to individuals from different walks of life (Mousa et al., 2020; Musyaffi and Kayati, 2020; Wu and Song, 2020). In general, an education model based on

network technology may considerably stimulate learning interests, increase the quality of tailored education, and aid in the development of a wide range of skills (Wu et al., 2020).

TAM, however, only offers broad data regarding users' willingness to embrace a technology; as a result, other aspects that could influence a user's technology adoption are required for context-based comprehension of how a particular technology is used (Liu et al., 2010; Padilla-Melendez et al., 2013). Despite these drawbacks, TAM has been shown to be one of the best models for analyzing how people adopt and use technology (Grani & Maranguni, 2019). Researchers have increasingly used the Model to forecast whether students would embrace using technology to learn (Al-Emran et al., 2018). These studies include additional factors that largely fall into two categories: external variables and perceived variables, extending and changing the original notions of TAM.

Objectives

The present study focuses on following objectives:

1. To highlight the effect of COVID-19 on higher education in India.
2. To identify key success elements for adoption of various digital platforms used in higher education.

Hypothesis

The TAM is used in this study to assess students' adoption of digital platforms as a technology in their everyday academic lessons. TAM provides a solid foundation for the effectiveness of a new technology in this regard. TAM also claims that when students are introduced to new technology, a variety of circumstances can impact their decision to accept it. The following hypotheses led this investigation, which were based on the status quo of the Technology Acceptance Model (TAM) (Masrom, 2007):

H₁: The actual utilization of digital platform is influenced by the behavioral desire to utilize it.

H₂: The perceived usefulness of digital platforms has a beneficial impact on the behavioral intention to utilize it.

H₃: The behavioral intention to utilize digital platforms is favorably influenced by perceived ease of use.

H₄: The perceived utility of digital platforms is influenced by its perceived simplicity of use.

RESEARCH METHODOLOGY

The literature review, QS, mathematical approach, and statistical analysis are all combined in this study.

Context and Subject

Universities located in states of Maharashtra and Chhattisgarh, in India, served as the study's location. After closure was declared by the government of India different universities in India shifted to online teaching using different digital platforms throughout all its departments. Students from different universities who used digital platforms such as Google Classroom, MS Teams, Cisco web X, zoom etc. for their studies make up the study's sample. A total of 419 valid replies were obtained from 450 administered surveys, yielding a 93.11 percent response rate.

Survey Instrument

For gathering data, an online questionnaire survey was distributed to all enrolled students during the second and fourth semester of the academic year 2020–2021. The method of sampling used was purposive sampling. There are two sections to the survey. The purpose of the first section is to gather demographic data about the pupils. The second section is devoted to gathering information on how various digital platforms were used. This section was devoted to gathering information on the TAM (Technology Acceptance Model) aspects. The perceived utility (PU), perceived ease of use (PEOU), behavioral intention (BI), and actual usage are some of these criteria (AU). The study's items were adapted from (F.D.F. Davis, 1989) and then modified to match the study's objectives. The constructions' items are shown in Appendix A.

Sample Size

The sample size was determined by applying G*Power software 3.1.9.7 version in order to investigate the minimum sample size required for this study (Faul et al., 2007; 2009). The actual power of 0.95 whereas minimum accepted level of power is 0.80 (Cohen, 1988). The sample was duly obtained by a minimum sample size of 262 respondents, whereas the study used a sample size of 419 which satisfies the appropriate sample size requirements.

Method

To evaluate our theoretical model, we used the PLS-SEM method (Lohmoller, 1989; Sarstedt et al., 2017; World, 1982). This multivariate data analysis method is well-established in the social and behavioural sciences (Hair et al., 2019). The goal of confirmatory research is to gather empirical evidence for the description of the operational mechanism to comprehend the causal linkages between theoretical constructs of interest. By testing measurement models and focusing on the explanation of a specific construct in a structural model, confirmatory and explanatory research are frequently combined. PLS-SEM is a suitable approach for analysing mediation effects (Carrion et al., 2017), especially when building more sophisticated models (Nitzl et al., 2016). For the model estimation, we utilize the SmartPLS 3 software (Ringle et al., 2015). Significance testing applies the bootstrapping procedure with 10,000 samples, the percentile approach, and a two-tailed test. The assessment of the results begins with the measurement models and subsequently focuses on the structural model (Hair et al., 2019).

Multivariate Normality Test and Common Method Bias

The decision to choose variance-based structural equation modelling (PLS-SEM) over covariance-based SEM (CB-SEM) was based on several reasons (Bolander, Satornino, Hughes, & Ferris, 2015; Hair et al. 2014). Firstly, the PLS based SEM is appropriate in the exploratory stage for theory building and prediction. Second, through PLS based SEM both formative and reflective relationship can be studied, whereas, with CB based SEM, only reflective relationships are studied (Hair et al., 2011, 2014; Henseler, Ringle, & Sinkovics, 2009). Along with it, multivariate normality of data is also required for CB based SEM whereas for PLS-SEM concept of normality of data is not required. The 'Web power' software was used to test "Mardia's multivariate skewness and kurtosis" (Cain, Zhang, & Yuan, 2016; Mardia, 1970). As the p-value of both skewness and kurtosis was found less than .05 the results indicates that the data was not multivariate normal.

RESULTS AND DISCUSSION

The sample shows the replies that were gathered from the 450 students from different universities in Central India. However, after eliminating the outliers and missing numbers, there remain 419

valid replies. Additionally, Table 1 displays the participants' demographic data. We can see from the data gathered, 55 percent are female and only 45 percent were male. Additionally, 65 percent of the sample's participants are students between the ages of 18 and 89 percent of students are from school of commerce and management, followed by 6.2 percent from the school of Biotechnology, 2.86 percent from school of Languages, 1.67 percent form school of fashion technology and 0.71 percent from the school of engineering. Regarding the year of study, it is evident that 69 percent of participants were in their second year, followed by 17 percent in their first year, and 10 percent in their third respectively. As far as usage of digital platform is concerned nearly 39 percent were using MS Teams followed by 36 percent were using Cisco web X, 14 per cent were using Google meet, 10 percent were using Zoom and 1 per cent were using other digital platforms for educational purpose respectively. The demographic profile of the respondents is as below Table 1.

Measure	Items	Frequency	Percent (%)
Gender	Male	190	45.50
	Female	229	54.65
	18-22	274	65.39
	23-28	110	26.25
	> 28	35	8.35
School/Department	Commerce & Management	371	88.54
	Engineering	3	0.71
	Languages	12	2.86
	Law	0	0.00
	Biotechnology	26	6.20
	Architecture	0	0.00
	Fashion Technology	7	1.67
Year of Enrollment	Year 1	73	17.42
	Year 2	289	68.97
	Year 3	42	10.02
	Year 4	4	0.95
	Year 5	5	1.19
	Year 6	6	1.43
Digital Platforms	MS Teams	163	38.90
	Google meet	59	14.08
	Zoom	41	9.79
	Cisco web X	150	35.80
	Others	6	1.43

Measurement Model Assessment

Validity and Reliability: To assess the measurement models, we follow (Hair et al.,2022) and (Hair et al.,2019). The assessment of reflective measurement models includes the analysis of indicator reliability, internal consistency (composite reliability and ρ_A), convergent validity (average variance extracted; AVE) and discriminant validity (Heterotrait-Monotrait ratio of correlations; HTMT). The indicator loadings reflect the amount of variance that is shared between the individual indicator variables and the associated construct, which is used to ensure indicator

reliability. All the indicator loadings in our reflective measurement models exceed the critical value of 0.70; thus, the model provides sufficient indicator reliability (Sarstedt et al., 2017) Furthermore, an analysis of the additional evaluation criteria yielded satisfactory overall results for the data set Table 2 below.

Construct	Item	Indicator Loading	ρ_A	Composite Reliability	Average variance Extracted (AVE)
Perceived Usefulness	PU1	0.838	0.762	0.848	0.583
	PU2	0.851			
	PU3	0.778			
	PU4	0.854			
	PU5	0.728			
	PU8	0.804			
Perceived Ease of Use	PE1	0.806	0.815	0.877	0.642
	PE2	0.798			
	PE3	0.798			
	PE4	0.706			
	PE5	0.807			
	PE6	0.724			
Behavioural Intention	BH1	0.813	0.895	0.919	0.656
	BH2	0.832			
	BH3	0.833			
	BH5	0.723			
Actual Usage	AU1	0.713	0.866	0.900	0.600
	AU2	0.716			
	AU3	0.829			
	AU4	0.788			

The composite reliability and ρ_A support the assessment of the reflective construct's internal consistency reliability. The ρ_A criterion has satisfactory results for our reflective constructs as indicated in above table, which lie between the thresholds of 0.70 and 0.95 (Hair et al., 2019). The AVE enables us to assess the reflective construct's convergent validity. With regards to convergent validity, all reflective constructs' AVE values in our model exceed the critical value of 0.50.

Discriminant Validity

To ensure discriminant validity, the distinctiveness of a construct is measured with the HTMT ratio of correlations (Henseler et al., 2015). Discriminant validity has been established in our model, since all HTMT values are significantly below (one-tailed test, $p < 0.05$) the more conservative cut-off value of 0.85 (Table 3). In this study, the HTMT values were exceeding beyond 0.960 in case of the constructs of behavioural intention & actual system of use for which HTMT inference was applied to establish discriminant validity on liberal side. Similar treatment is provided for the construct perceived usefulness and behavioural intention where HTMT value was 0.921, however the confidence intervals for HTMT inference were well within the limits, thus

establishing the distinctiveness of all the constructs as per the empirical standards as represented in Table 3.

	Actual Usage	Behavioural Intention	Perceived usefulness
Actual Usage			
Behavioural Intention	0.961 CI.0.95 [0.913-1.011]		
Perceived usefulness	0.858 CI.0.95 [0.791-.0918]	0.923 CI. 0.95 [0.878-0.962]	
Perceived ease of use	0.817 CI.0.95 [0.744-0.878]	0.941 CI. 0.95 [0.896-0.981]	0.864 CI. 0.95 [0.806-0.910]

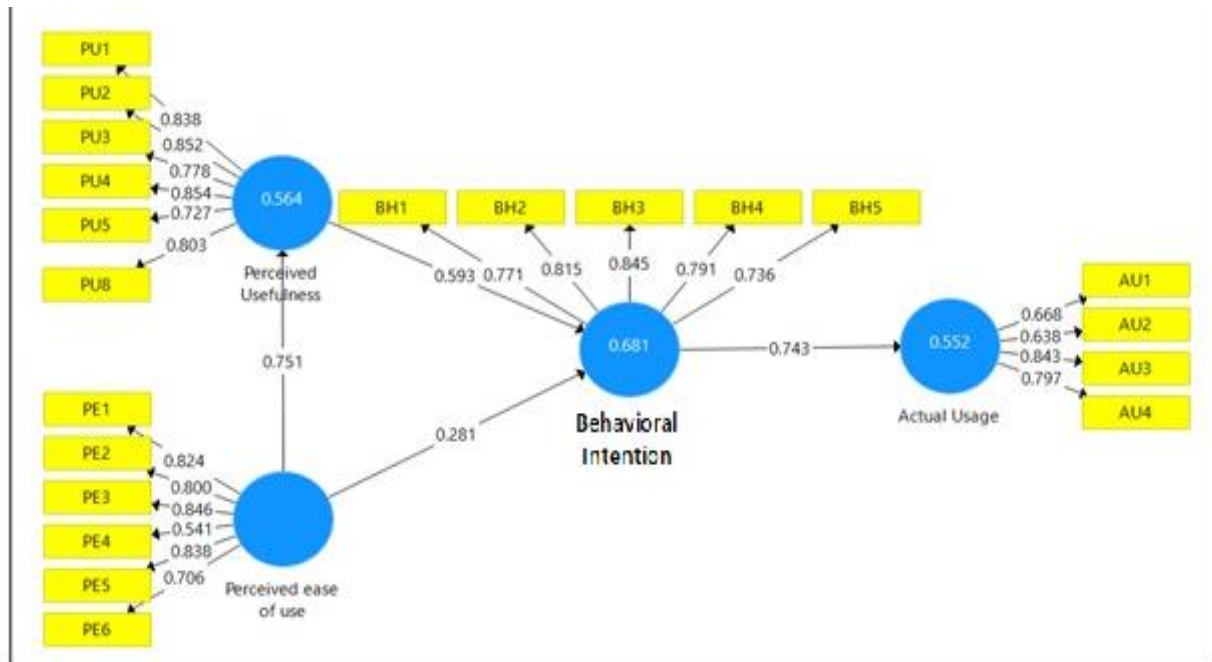
Structural Model Assessment

In structural model evaluations, the link amid the constructs and their predictive usefulness was investigated (Hair et al., 2017). To discover the requisite p-values for the hypotheses framed in the study, the process was undertaken using the bootstrapping process with recommended 10,000 bootstraps without sign change (Hair et al., 2022). Firstly, in the structural inner model, each set of the predictor constructs are assessed separately by considering them as a formative measurement model (Cassel et al., 1999). It is for this purpose, tolerance, and Variance Inflation Factor (VIF) values were calculated, which were found to be below 3.33 (Diamantopoulos et al., 2008). The variance inflation factor (VIF) is frequently used to evaluate collinearity of the formative indicators. VIF values of 5 or above indicate critical collinearity issues among the indicators of formatively measured constructs. However, collinearity issues can also occur at lower VIF values of 3 (Mason and Perreault, 1991; Becker et al., 2015). Ideally, the VIF values should be close to 3 and lower. VIF values are given in Table 4 below.

Construct	VIF values	Construct	VIF values	Construct	VIF values
AU1	1.458	PE1	2.653	PU1	2.469
AU2	1.468	PE2	2.050	PU2	2.685
AU3	2.662	PE3	2.460	PU3	1.944
AU4	2.521	PE4	1.530	PU4	2.742
BH1	1.918	PE5	2.282	PU5	1.647
BH2	1.862	PE6	1.642	PU8	2.088
BH3	1.965				
BH5	1.438				

The table above indicates inner VIF values are below the threshold limits which indicate no collinearity issues were not involved in the study (Hair et al., 2017). Following the bootstrapping procedure using 10,000 subsamples in the PLS Algorithm to rule out any collinearity concerns in the inner model, the next step was to verify the significance and relevance of the path coefficients, which might have ranged from -1 to +1.

The coefficient of determination (R^2) of the endogenous construct actual usage of technology was found be significantly moderate at 55.2 percent. Studies in behavioural sciences shows that any value of $R^2=20.20$ and above is high (Rasoolimanesh et al., 2017), and it is in this study actual usage is significantly determined by behavioural intention. Further, the goodness of fit criterion was studied and explored by the Standardised root mean square residual (SRMR) global fit indices Figure 2.



**FIGURE 2
MODEL USED**

In today's research with PLS-SEM models, a global model fit index like SRMR is critical for evaluating the model's quality (Hair et al., 2020). The study model has an SRMR value of 0.068, which is considerably below the threshold value of 0.08, indicating that the model has high explanatory power (Henseler et al., 2016; Hu and Bentler, 1999).

Hypothesis	Path Relationship	Std. Beta	t-values	CI 2.5%	CI 97.5%	p Values	Decision
H1	Behavioural Intention -> Actual Usage	0.753	32.443	0.701	0.794	0.000	Supported
H2	Perceived Usefulness -> Behavioural Intention	0.421	9.828	0.339	0.507	0.000	Supported
H3	Perceived ease of use -> Behavioural Intention	0.476	11.104	0.390	0.557	0.000	Supported
H4	Perceived ease of use -> Perceived Usefulness	0.770	28.041	0.708	0.817	0.000	Supported

Source: Author's calculations; Path Co-efficient (*p<0.01, **p <0.05, *** p<0.001).

Results shown in Table 5 results indicates that perceived usefulness, perceived ease of use and behavioural are the most significant factors which positively influence behavioural intention ($\beta_1=0.421, 0.476$ & 0.770 respectively, $p<0.01$) thereby supporting hypothesis H2, H3 and H4. And behavioural intention determines actual usage and adoption of technology ($\beta=0.753, p<0.05$) thus support hypothesis H1 respectively. Similar to this, research by (I. N. M. Shaharane et al, 2016) discovered that PEOU and PU have a beneficial impact on students' happiness with using digital platforms Classrooms for learning. The behavioural intention to utilise digital platform is

enhanced by PEOU and PU, it may be said. Additionally, while making future decisions on building digital platform infrastructure, higher education institutions' decision-makers should take these data into account.

Based on factor loadings above 0.50 that were retained in the study perceived usefulness, perceived ease of use and behavioural are the most significant factors which positively influence behavioural intention which in turn determines possibility to adopt new technology. The Covid-19 pandemic leaves students with little alternative but to accept and improve online learning, even though there are too many difficulties with it at home. But there's no denying that technology has made remote learning simpler (McBrien et al., 2009). Compared to lectures that are recorded, synchronous learning or virtual live learning offers a lot more opportunity for social engagement (McBrien et al., 2009). All the components of a physical class can now be found online in platforms such as; (1) the ability to hold a video conference with 40–50 students at once; (2) the ability to engage in real-time two-way communication and discussion; (3) accessibility through devices such as mobile phones, tablets, computers, and laptops; and (4) the ability to distribute assignments and receive immediate feedback from students (Basilaia, et al., 2020). The university has been driven by the health issue to accommodate online learning and to give teachers plenty of tools and opportunities for communicating with students (Dhawan, 2020). The university must deliver high-quality instruction and conduct online learning in such a massive way to adapt to the changing environment (Carey, 2020).

The effect size (f^2) and (Q^2) of the suggested model were used to test the predictive value and relevance. The proposed limits of investigating the change in R^2 due to the impact of exogenous constructs on endogenous constructs are 0.02 (small effects), 0.15 (moderate effects) and 0.35 (large effects) (Cohen, 1988). Perceived usefulness (0.250) and perceived ease of use (0.321) disclosed weak effect size behavioural intention. Whereas actual usage (1.313) and perceived ease of use (1.459) disclosed high effect size.

CONCLUSION

Using the TAM, this study examines the impact of COVID 19 on higher education in central India and also the factors that influence various digital platforms acceptance undergraduate students. The PLS-SEM approach is used to assess measurement and structural model.

The findings show that all the factors have a significant impact on both behavioral intention and actual use of Google classes both in terms of behavioral intention and actual usage of digital platforms. The importance of digital platform's familiarity in terms of utility and convenience of use is emphasized. These two characteristics have a substantial impact on the intention of the selected sample since various digital platforms serves as a facilitator for the development of their learning activities.

The fact that students who rely on digital platforms will be able to use it as a new device for leveraging their educational system is one of the exceptional results that might be of considerable relevance to any decision makers in academic institutions. This conclusion is backed up by students' significant reliance on technology because of the previously mentioned aspects of simplicity of use and utility. As a result, higher education decision-makers should recognize the features of digital platforms and construct their infrastructure based on the findings of this study. To put this technology into practice, higher education institutions should offer students training opportunities so that students' ability to find the complete and effective features of digital platforms are more evident and extensively used by end-users.

Limitations

Each study has its own limitations which are summarized below: First, the adopts TAM model with further no extensions. Hence the further research should explore other factors that may

influence adoption of various digital platforms. Second, the data is collected from Maharashtra and Chhattisgarh region hence the results could not be generalized. Therefore, further research is required to collect data across various universities and institutions in India. Thirdly the collection of data was confined to students only hence faculty members should also be included to identify factors affecting acceptance of various digital platforms.

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