Received: 9 July 2020 | Revised: 1 September 2020 | Accepted: 14 September 2020
DOI: 10.1002/pa.2503

ACADEMIC PAPER

WILEY

Factors influencing adoption of online teaching by school teachers: A study during COVID-19 pandemic

Sangeeta[1] | **Urvashi Tandon**[2]

[1]School of Management, Maharaja Agrasen University, Solan, India
[2]Chitkara Business School, Chitkara University, Rajpura, India

Correspondence
Sangeeta, Maharaja Agrasen University, Solan, India.
Email: sangeeta.goele04@gmail.com

The research develops a theoretical model that highlights the determinants of adoption of online teaching at the time of the outbreak of COVID 19. Empirical data was gathered from 643 school teachers by means of an online survey. The proposed conceptual framework was investigated empirically by means of confirmatory factor analysis (CFA) and structural equation modelling (SEM). The findings of the study revealed performance expectancy, and facilitating conditions had a positive impact on behavioural intention as well as attitude. However, effort expectancy failed to drive teachers' adoption to online teaching. On the other hand, social influence had insignificant relationship with attitude but significant relationship with behavioural intention. Attitude had a significant impact on behavioural intention as well as actual use. This study contributes to the literature by presenting and validating a theory-driven framework that accentuates the factors influencing online teaching during outbreak of a pandemic.

1 | INTRODUCTION

The COVID-19 pandemic was declared a national emergency in most of the countries in early 2020. This pandemic forced counties all over the world to adopt a sequence of emergency management mechanisms (Zhang, Wang, Yang, & Wang, 2020). Government of different countries initiated measures such as lockdown of cities, shutting down of educational institutions as well as implementation of strict social distancing measures. Till April 13, 2020, approximately 1.725 billion learners were affected due to closure of schools in response to the pandemic. Consistent with UNESCO monitoring, 192 countries have implemented nationwide closure of academic institutions and 5 have implemented local closures, impacting about 99.9% of the world's student population (UNESCO Report, 2020). A strategic move named as “Suspending Classes without Stopping Learning” was initiated by Chinese Government (Zhang et al., 2020) and later followed by governments of other countries to shift to online teaching while schools were closed. Previous outbreaks of infectious diseases like swine flu have prompted widespread school closings round the world, with varying levels of effectiveness (Barnum, 2020). If school closures occur late relative to a pandemic, they are less effective and should not have any impact in the least (Zumla, Yew, & Hui, 2010). Additionally, in some cases, the re-opening of schools after a period of closure has resulted in increased infection rates. As closures tend to occur concurrently with other interventions like public gathering bans, it is often difficult to live the precise impact of schools closures (Barnum, 2020).

The crisis is usually coupled with opportunities and it's time to understand the complete potential of technology for learning within the wake of this medical emergency and keeping the students' safety in mind alongside their academic concern, different stakeholders within the education space are endorsing online learning in order that the training only grow and do not recede. Online teaching as a response to pandemics and COVID-19, in particular, actually started in China through their “school's out, class's in” response as an initiative to mitigate the academic loss due to the disease (Zhou, Wu, Zhou, & Li, 2020). For schools in India, April is actually the beginning of new session and as a result, schools feared loss of teaching hours. Therefore, schools in India followed by the guidelines of state and union government and initiated virtual classes to bridge the gap. Majority of personal schools and other educational institutions initiated mandatory virtual classes, and thus, teachers are unfailingly sharing their lessons over Skype call, Zoom call, Google hangouts, Microsoft teams or the other virtual class options to stay the training on.

This research is an effort to understand the factors which encourage adoption of online teaching at the time of COVID-19 pandemic induced lockdown.

COVID-19 pandemic motivated the academic institutions and schools to go online. Teachers as well as students are exposed to new platforms such as Microsoft teams, Google hangouts, Zoom and others. In order to conduct classes smoothly, proper protocols and directions were given to the students as well as parents to facilitate adaptation to this novel channel of learning (Saxena, 2020). A number of previous research studies have empirically validated factor leading to online learning but majority of these studies have focussed on higher education (Mei, Brown, & Teo, 2018; Mosunmola, Mayowa, Okuboyejo, & Adeniji, 2018; Tseng, Lin, Wang, & Liu, 2019). There are negligible studies focusing on adoption of online teaching. To the best of the author's understanding, this is the first study in Indian context to understand the factors leading to online teaching due to pandemic emergency.

There are a number of challenges from the perspectives of learners and academicians to move from offline to online mode of learning. Engaging students and indulging them in teaching-learning progression is yet another stumbling block in adoption of online teaching. Developing content that not only covers the curriculum but also engages learners is need of the hour. Adoption of online teaching, though laudable during this COVID-19 time, but it is also important to develop and enhance the quality of teaching and courses delivered during pandemic. An operative, competent, and resourceful educational system is mandatory to deliver online delivery of classes. There are end number of technological issues like downloading issues, installing apps, low internet-speed, issues related login ids, inaudible voice, video and so on. Even learners also find e-teaching boring and less interactive. Therefore, the study has been undertaken to comprehend the perception of school teachers so that sufficient efforts could be undertaken to improve delivery, evaluation and interaction among students and teachers. This research thus provides useful information to the school administrators to implement hassle-free online teaching at this phase of lockdown. The study adopts constructs form Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh, Morris, Davis, and Davis (2003) but revised by Dwivedi, Rana, Jeyaraj, Clement, and Williams (2019). Based on the findings, practical insights are provided to school authorities to facilitate adoption, acceptance and use of online teaching during pandemic outbreak.

The rest of this paper is organized as follows: Section 2 reports the theoretical background and hypotheses formulation. Research methodology, measurement items to carry out the survey, sampling and data collection procedures are discussed in Section 3. Section 4 includes the statistical analysis and hypotheses testing followed by Section 5 discussing the empirical findings in detail and excerpts implications, limitations and directions for future research.

2 | THEORETICAL UNDERPINNINGS AND HYPOTHESES FORMULATION

2.1 | Theories on acceptance IT/IS and use

Different models for the introduction and adoption of information technology innovations have been elucidated by previous researchers such as Social Cognitive Theory (SCT) (Bandura, 1986), the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Planned Behavior (Ajzen, 1991), extended TAM (Venkatesh & Davis, 2000), the model combining TAM and the Theory of Planned Behavior (Taylor & Todd, 1995), and the Model of PC Utilization (Thompson, Higgins, & Howell, 1991) and UTAUT and UTAUT2 (Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012).

Among these, UTAUT and UTAUT2 by Venkatesh et al. (2003) and Venkatesh et al. (2012) have been applied widely in various domains to understand users' behaviour concerning different technologies (Appendix A). This research study adopts the modified UTAUT (Dwivedi et al., 2019). Based on the empirical findings (Tandon & Kiran, 2019; Tseng et al., 2019), four moderators were also excluded. Additionally, the user attitude was also included in this research based on revised UTAUT (Dwivedi et al., 2019). The significance of attitude in explaining technology acceptance is also based on previous research studies (Kim et al., 2009; Tandon, Kiran, & Sah, 2016). Previous models like TRA, TPB and DTPB have also validated attitude as a construct in their theory.

The inclusion of attitude in models of IS/IT acceptance is consistent with TRA (Ajzen and Fishbein (1980). The TRA model claims that attitude completely mediates the relationship between beliefs and intention (Taylor and Todd, 1995). TAM hypothesized that the positive attitude is developed when any technology is easy to comprehend (Davis, Bagozzi, & Warshaw, 1989). Attitude has also been validated by previous researchers that used UTAUT also (Aboelmaged, 2010; Alshare & Lane, 2011; Chen & Lu, 2011; Mosunmola et al., 2018; Rana, Dwivedi, Lal, Williams, & Clement, 2017; Tandon et al., 2016). Based on the literature reviewed, direct effect of attitude on behavioural intention is also proposed in this study.

2.2 | Hypotheses development

This research study develops hypotheses based on UTAUT and validates performance expectancy, effort expectancy, facilitating conditions, social influence and attitude.

Mosunmola et al. (2018) re-evaluated UTAUT in adoption of mobile learning and found that model holds good for adoption of mobile learning. The study by Mei et al. (2018) confirmed facilitating conditions as a strongest determinant of intention to adopt Web 2.0 for language learning. Tseng et al. (2019) also corroborated that constructs of UTAUT2 hold equally good for adoption on MOOC programmes by teachers. Nikou and Economides (2019) validated extended TAM and found perceived ease of use, facilitating conditions as determinants of behavioural intention to use mobile-based assessments. The study by Wong (2016) also confirmed facilitating conditions as a vital construct for adoption of educational technology by teachers. Teo and Noyes (2014) validated UTAUT model to comprehend pre-service teachers' intentions to use information technology. Teo et al. (2019) also emphasized that perceived usefulness and facilitating conditions simplify the process of adoption of Web 2.0 for teaching. Pynoo et al. (2011) applied UTAUT to study digital learning by secondary school teachers and found performance expectancy and social influence as significant drivers. The studies by Mosunmola et al. (2018), Tandon and Kiran (2018) and Jairak, Praneetpolgrang, and Mekhabunchakij (2009) validated positive impact of social influence on behavioural intention but the study by Nassuora (2012) reported insignificant impact of social influence. As most of the related literature has led to inconsistent findings concerning the impact of constructs of UTAUT, the model needs to be validated further to understand the comprehensiveness of the model as a theoretical underpinning for examining factors leading to adoption of online teaching by teachers during pandemic outbreak.

Kozma (2011) emphasized that "for smooth learning, the school curriculum should increasingly be interwoven with ICT, and students should be given opportunities to use advanced technological tools and digital resources for creative and innovative problem solving," (p. 115). The study by Basilaia and Kvavadze (2020) confirmed that immediate transition to e-learning by schools due to COVID 19 was successful in Georgia. Bao (2020) presented a case study of Peking University and emphasized upon the contingency plan to deal with the pandemic types situations. König, Jäger-Biela, and Glutsch (2020) studied the impact of school closures in Germany and empirically validated that competence of teachers and opportunities provide to them to acquire digital competence are the significant factors in adoption of online teaching.

On the basis of above discussion, following hypotheses have been posited:

H1 Performance expectancy positively influences behavioural intention.

H2 Effort expectancy positively influences behavioural intention.

H3 Facilitating conditions positively influences behavioural intention.

H4 Social Influence positively influences behavioural intention.

H5 Performance expectancy positively influences attitude towards online teaching.

H6 Effort expectancy positively influences attitude towards online teaching.

H7 Facilitating conditions positively influences attitude towards online teaching.

H8 Social influence positively influences attitude towards online teaching.

H9 Attitude positively influences behavioural intention to adopt only e teaching.

H10 Behaviour intention positively influences actual use of online teaching.

H11 Facilitating conditions positively influences actual use of online teaching.

H12 Attitude positively influences actual use of online teaching.

Figure 1 has been proposed on the basis of above discussion.

3 | MEASUREMENT DEVELOPMENT AND DATA COLLECTION

3.1 | Measurement development

After a thorough literature revision, a survey instrument was elaborated based on established measurement scales. The study adopted the modified UTAUT model validated by Dwivedi et al. (2019). The study adopts

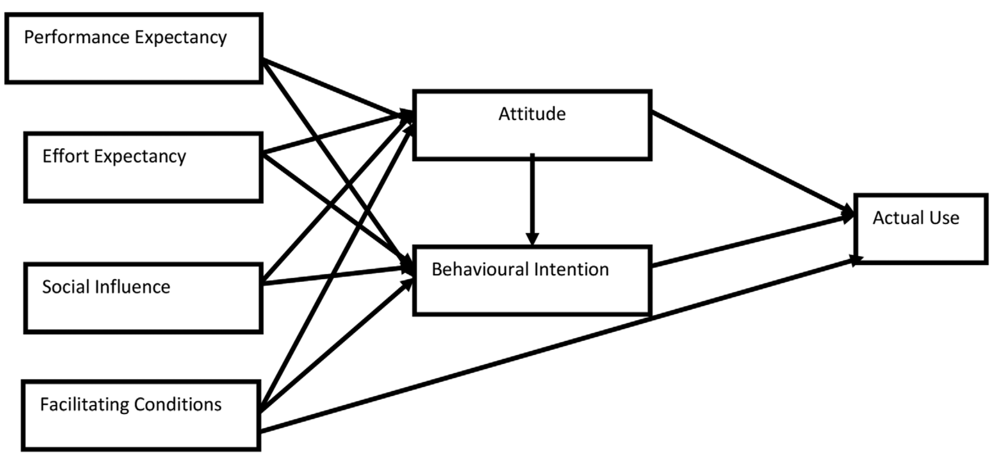

FIGURE 1 Proposed model

the scale items from Venkatesh et al. (2003). The scale items on attitude were adopted from the previous study of Mosunmola et al. (2018). This condensed model help us to understand the perception of school teachers regarding delivery of online classes (Appendix B).

3.2 | Sample and data collection

An item screening test was conducted with an expert panel of 12 University Professors, teachers of schools, and researchers to confirm the face validity of the scale items. This panel suggested minor amendments in language and applicability as well as alternatives where applicable, and the scales were modified accordingly. According to Onwuegbuzie and Collins (2007), mixed method sampling is highly imperative where the respondents are unknown and difficult to reach. Therefore, non-probability sampling techniques such as convenience, purposive (also known as judgmental), and snowball sampling methods, were used to contact respondents. An online survey was preferred due to ease in assembling the data and maintaining anonymity with respondents. This technique not only reduces bias (Llieva et al., 2002; Andrews, Nonnecke, & Preece, 2003) but also helps the researcher to get complete responses as respondents answer all the required questions (Andrews et al., 2003). This helps to get complete responses. Further, an online survey saves responses into a data file directly, thereby, reducing the burden of inputting the data and emitting transcription errors (Evans & Mathur, 2005). The questionnaire was composed of two parts. The initial part comprised of demographic details of the respondents followed by second part which comprised of key constructs.

For sample selection, websites of prominent schools located in North India were visited. Those schools who were conducting online classes were considered in this study. An online link covering scale items along with an invitation letter was mailed to school teachers. Simultaneously, an invitation letter as well as link of the questionnaire was also mailed to the Deans/Heads of the schools to circulate the link among those teachers who were conducting online classes.

To control for the social desirability bias, respondents were assured about their response anonymity and motivated to respond sincerely as much as possible (De Leeuw, Hox, & Dillman, 2008; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Since, an online survey was carried out to collect data, common method bias could emerge due to high correlation among constructs. In order to reduce common method bias, all constructs were subjected to a principal component factor analysis with varimax rotation. The results of unrotated factor analysis revealed six factors with each construct accounting for 57% of variation. Thus, no specific factor was noticeable (Podsakoff et al., 2003) indicating the common method bias is acceptable in data set.

Using the above-mentioned methodology, a total of 652 responses were received in the survey. Few responses which had odd figures and incomplete were discarded, resulting in 643 usable responses. Kline (2010) suggested that a sample of 200 responses or larger is suitable for a complicated path model.

TABLE 1 Respondents' characteristics

Category *N* = 643	*N*	%
Male	224	34.83
Female	419	65.17
Age	*N*	%
25–35	190	29.5
36–45	328	51
Above 45	125	19.5
Education	*N*	%
Graduate	186	29
Postgraduate	399	61
Others	58	10
Designation	*N*	%
Primary class teacher (up to class 5)	154	23.96
Secondary class teacher (from class 5 to 10)	358	55.67
Lecturer (class 11 and 12)	131	20.37
Experience of taking online classes	*N*	%
2 weeks	139	21.62
3–6 weeks	284	44.16
More than 6 weeks	220	34.22

In the sample, there is a fair inclusion of respondents across gender—34.83% males and 65.17% females, and good representation of each age group, education level, designation, and experience of conducting online classes. Table 1 reports the characteristics of respondents in more details.

4 | DATA ANALYSIS AND FINDINGS SARCASTIC

The data analysis process was conducted by means of a two-step analytical approach. In the first phase, a confirmatory factor analysis (CFA) assessed the measurement model including reliability, validity and fit. Secondly, a structural equation model (SEM) estimated the structural model to test the hypotheses.

4.1 | Validating the measurement model

A CFA (Amos) was conducted on all the measurement constructs. The results showed that model fit was satisfactory (χ^2/df = 4.688, GFI = 0.899, CFI = 0.881, TLI = 0.895, NFI = 0.902, RMSEA = 0.079) as per Byrne (1994) recommendations. Further, factor loadings were used to assess the indictors' reliability and 0.50 was taken as a minimum threshold for the retention of measurement items (Fornell & Larcker, 1981). As shown in Table 3, all standardized factor loadings were above 0.50 confirming item reliability and factor unidimensionality (Table 2). Further, convergent validity was assessed through item

TABLE 2 Measurement model

		Std. estimate	Std. error	Critical ratio	Average variance extracted	Composite reliability
Performance expectancy	PE1	0.689				
Mean = 4.424	PE2	0.795	0.081	17.771	0.574	0.843
SD = 0.821	PE3	0.806	0.066	17.964		
	PE4	0.735	0.066	16.606		
Effort expectancy	EE1	0.733				
Mean = 4.096	EE2	0.806	0.061	18.99	0.544	0.826
SD = 0.895	EE3	0.737	0.056	17.502		
	EE4	0.668	0.055	15.872		
Facilitating conditions	FC1	0.806				
Mean = 4.137	FC2	0.675	0.048	17.154	0.563	0.837
SD = 0.918	FC3	0.756	0.046	19.493		
	FC4	0.759	0.054	19.567		
Social influence	SI1	0.664				
Mean = 4.344	SI2	0.82	0.077	17.866	0.625	0.868
SD = 0.853	SI3	0.899	0.071	18.946		
	SI4	0.761	0.063	16.819		
Attitude	AT1	0.64				
Mean = 4.389	AT2	0.721	0.094	14.146	0.516	0.761
SD = 0.768	AT3	0.787	0.095	14.81		
Behavioural intention	BI1	0.573				
Mean = 4.208	BI2	0.855	0.122	14.894	0.613	0.821
SD = 0.880	BI3	0.883	0.129	14.982		
Actual use	AU1	0.847				
Mean = 4.362	AU2	0.814	0.053	18.871	0.549	0.778
SD = 0.881	AU3	0.518	0.05	12.571		

TABLE 3 Correlations matrix

	Performance expectancy	Effort expectancy	Facilitating conditions	Social influence	Behavioural intention	Attitude	Actual use
Performance expectancy	***.757***						
Effort expectancy	.630**	***.737***					
Facilitating conditions	.522**	.324**	***.750***				
Social influence	.477**	.472**	.504**	***.790***			
Behavioural intention	.441**	.513**	.328**	.476**	***.782***		
Attitude	.461**	.449**	.392**	.398**	.503**	***.718***	
Actual use	.357**	.228**	.509**	.429**	.304**	.418**	***.740***

Correlation is significant at the .01 level (2-tailed).
The italics and bold values represents the average value extracted (AVE). **

loadings, composite reliability (CR), and average variance extracted (AVE) of each construct. Table 3 shows that AVE and CR for each construct is above the minimum suggested cut-off level that is, AVE > 0.50 and CR > 0.70, thereby confirming convergent validity (Bagozzi & Yi, 1991). Further, as can be seen in Table 3, the results also indicated satisfactory discriminant validity since all constructs are more strongly correlated with their own items compared to the other constructs' items (Fornell & Larcker, 1981).

TABLE 4 Structural Model

No	Hypotheses			Std. loading	Std. error	Critical ratio	*p*	Result
H1	Performance expectancy	→	Behavioural intention	0.144	0.093	2.186	.032	Supported
H2	Effort expectancy	→	Behavioural intention	−0.351	0.061	−5.32	***	Not-supported
H3	Facilitating conditions	→	Behavioural intention	0.39	0.048	−6.911	***	Supported
H4	Social influence	→	Behavioural intention	0.21	0.067	3.44	***	Supported
H5	Performance expectancy	→	Attitude	0.145	0.074	1.614	.007	Supported
H6	Effort expectancy	→	Attitude	0.362	0.058	4.277	***	Supported
H7	Facilitating conditions	→	Attitude	0.222	0.04	3.487	***	Supported
H8	Social influence	→	Attitude	0.094	0.046	1.648	.099	Not-supported
H9	Attitude	→	Behavioural intention	0.456	0.078	7.856	***	Supported
H10	Behavioural intention	→	Actual use	0.52	0.063	9.057	***	Supported
H11	Facilitating conditions	→	Actual use	0.41	0.051	8.116	***	Supported
H12	Attitude	→	Actual use	0.28	0.077	4.638	***	Supported

Note: *** Significant at $p < 0.001$.

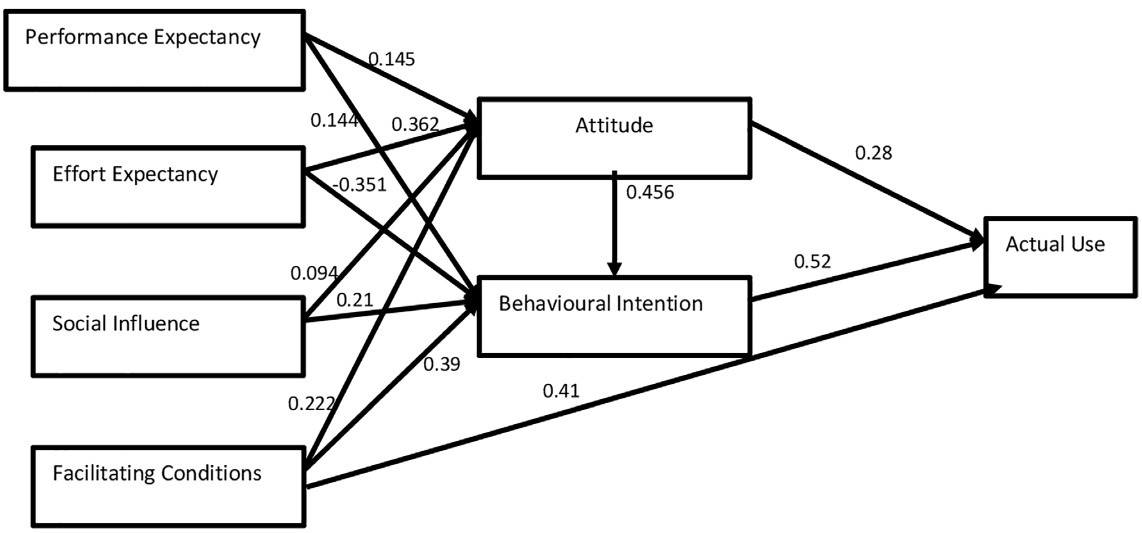

FIGURE 2 Path relationships

4.2 | Structural model

The section examines the structural model. Table 4 also indicates the structural model reporting the theoretical associations between constructs. The results strongly support H1 and H4, H5–H7 and H9–10, but fail to lend support to H2, H3 and H8.

The model fit indices reflect a good fit to the data (χ^2/df = 4.687, GFI = 0.902, CFI = 0.898, TLI = 0.901, IFI = 0.895, RMSEA = 0.077) as per recommended thresholds of Byrne (1994). Thus, it can be concluded that the model fit summary indicates that the hypothesized structural model achieved an acceptable model fit. Thereafter, the potency of direct, indirect and total effect for each path was assessed considering standardized path coefficients (β). Figure 2 and Table 4 concludes the structural model's results by reporting standardized loadings, standard error, critical ratio and significance level for the 12 proposed claims. Overall, analysis has provided support for the acceptance of nine proposed claims, and unsupported three proposed claims.

4.3 | Path analysis showing direct and indirect effects

The results claimed the following significant positive and negative direct effects: (a) from PE to BI (0.14); (b) from EE to BI (−0.351); (c) from FC to BI (0.39); (d) from SI to BI (0.21), (e) PE to ATT (0.145); (f) EE to ATT (0.362); (g) FC to ATT (0.222); (h) SI to ATT (0.094); (i) attitude to BI (0.456); (j) behavioural intention to actual use of online teaching (0.52); (k) FC to actual use of online teaching (0.41) and (l) ATT to actual use of online teaching (0.28) (Table 4). The study findings build an understanding about the intricated relationships among performance expectancy, effort expectancy, social influence, facilitating conditions, attitude, behavioural intention and the actual use of online teaching during pandemic outbreak.

5 | DISCUSSION, IMPLICATIONS AND LIMITATIONS OF THE STUDY

5.1 | Discussion of the results

The adoption of online teaching during pandemic outbreak was a step indeed to exploit the potential of technology for schools by keeping the safety of students and teachers without wasting their academic hours. Majority of schools initiated mandatory virtual classes on a day to day, and thus, teachers are unfailingly sharing their lessons over Skype call, Zoom call or the other virtual class options to stay the training on through the power of digital technology.

Few previous reported studies have validated TAM (Nikou & Economides, 2019) to understand the perception of teachers but the modified UTAUT validating attitude (Dwivedi et al., 2019) has not been explored much in literature. Further, attitude emerged as a significant construct having direct effect in behavioural intention. This finding is vital as it underlines the significance of individual characteristics in adoption of any technology (Dwivedi et al., 2019).

The findings of this research suggest that performance expectancy perceived by school teachers can build positive attitude as well as drive their behavioural intention to adopt online teaching during the pandemic outbreak. This finding is consistent with the previous studies (Dwivedi et al., 2019; Mosunmola et al., 2018). Effort expectancy had negative but significant relationship with behavioural intention (Liao, Shim, & Luo, 2004; Tseng et al., 2019) but a significant and positive relationship with attitude (Mosunmola et al., 2018). A possible of this could be that most of the sample comprised of senior teachers and length of service plays a vital role in shaping the attitude towards the technology (Teo & Noyes, 2014). Additionally, the impact of effort expectancy dilutes with experience (Venkatesh et al., 2003).

Moving further, facilitating conditions has a significant and positive impact on behavioural intentions as well as attitude (Jairak et al., 2009; Tseng et al., 2019; Venkatesh et al., 2003). This finding indicates that in-house training programmes and proper equipment helps in familiarization of faculty members with novel technologies thereby facilitating their adoption.

Further, positive impact of social influence on behavioural intention was observed but surprisingly, social influence had a negative influence on attitude to adopt online teaching. This finding is consistent with previous research studies (Sumak, Polancic, & Hericko, 2010; Tseng et al., 2019; Mosunmola et al., 2018; Dwivedi et al., 2017). This finding indicates that teaching fraternity is influenced with experiences of peers who are performing some activity on a particular technology. Attitude had a direct effect on behavioural intention (Dwivedi et al., 2017) and actual use of online teaching (Dwivedi et al., 2017; Thomas, Singh, & Gaffar, 2013). The inclusion of attitude significantly enhances the explanatory power of the model as the direct impact of four independent variables was stronger on attitude as compared to BI.

5.2 | Implications of the study

The findings of this research provide significant implications to the policy makers of the schools to encourage online teaching at the time of pandemic outbreak. The results of the study indicate that the administrators of schools should improve performance expectancy as it had significant relationship with behavioural intention and attitude to conduct online classes. For performance expectancy, teachers need to be trained about the benefits and usefulness of online teaching. Further, those teachers who do not understand the usefulness of the technology were unable to adopt the technology. Those teachers who are conducting classes online could convince their colleagues to adopt online teaching. A positive incentive could also be linked with those teachers who are promoting as well as motivating their colleagues to adopt online teaching. These teachers can also discuss their experience with those teachers who are reluctant to adopt the technology.

Since facilitating conditions emerge significant, this indicates that infrastructural support is well established in schools to facilitate online teaching, and it can enable behavioural intention as well as actual use. Regular query handling and training sessions for the teachers should be organized by the school administration so that the teachers are able to comprehend the nitty-gritties of the system. School authorities need to instil a positive feeling among teachers about usefulness of the online teaching during pandemic COVID 19.

Finally, the very strong relationship between intentions and actual use suggests that an "intention-behaviour gap" is very unlikely in the specific context of online adoption of classes. This may be explicable by the fact that, unlike other highly involving behaviours where the gap is very acute, the actual behaviour under study (i.e., using online teaching during pandemic) is not so difficult to perform and does not require excessive commitment or motivation. Instead, it fits well in very diverse lifestyles especially since most people use e-learning and e-teaching now for a variety of purposes.

5.3 | Limitations and future directions for research

This study has some limitations. The study draws sample from North Indian schools, future studies may replicate the study in remaining parts of the country as exposure to technology varies in different parts of country. The study excluded moderators validated by UTAUT and UTAUT2 by Venkatesh et al. (2003, 2012). Future studies may validate moderating variables. Since the UTAUT theoretical model is employed to predict the acceptance of all kinds of technology, researchers expect it is conceived too broadly to capture the specifics of the e-teaching environment. To enhance the applicability of the model and make it universally acceptable, constructs relating to education like Regulators' support and Project team capability may also be incorporated in future studies. Nevertheless, it is necessary that the section of population who does not favour new technologies should be included in research during the phase of introducing online or blended learning into teaching staff.

ACKNOWLEDGEMENTS

Authors are thankful to two reviewers for providing valuable insights thereby improving the quality of manuscript. Funding information is not available as authors did not receive any funding for this research.

AUTHOR CONTRIBUTIONS

Sangeeta: Responsible of model development and data collection. Urvashi Tandon: Responsible for data analysis and write up.

ORCID

Sangeeta https://orcid.org/0000-0003-2192-4862

Urvashi Tandon https://orcid.org/0000-0001-6592-101X

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AUTHOR BIOGRAPHIES

Dr. Sangeeta is an assistant professor of Management at Maharaja Agrasen University, Baddi- Himachal Pradesh. She received her Ph.D. from the University School of Management, Kurukshetra University, kurukshetra in 2016. Her current research interests include Stock market volatility, Banking , General Economics and HR practices.

Urvashi Tandon is an Associate Professor at Doctoral Research Centre, Chitkara University, Punjab (India). Her research has been published in several journals like *Electronic Markets*, *Service Science*, *Information Development*, *Nankai Business Review*, *International*, *Information Systems and e-Business Management*, *International Journal of e-Business*. Her research and teaching interests include marketing, e-business, consumer behaviour and technology adoption.

How to cite this article: Sangeeta, Tandon U. Factors influencing adoption of online teaching by school teachers: A study during COVID-19 pandemic. *J Public Affairs*. 2021;21:e2503. https://doi.org/10.1002/pa.2503

APPENDIX A.: DEFINITIONS OF CONSTRUCTS

Performance Expectancy (PE) is defined as "the degree to which an individual believes that using the Information System (IS) will help him to attain in job performance" (Venkatesh et al., 2003 p. 447).
Effort Expectancy (EE) has been explained as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450).
Facilitating Conditions (FC) is described as "the degree to which an individual considers that an organization and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003, p. 453).
Social Influence (SI) has been defined as "the extent to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 450).
Behavioural Intention (BI) refers to "a person's subjective. Probability that he will perform some behavior" (Fishbein and Ajzen, 1975).
Attitude (ATT) An individual's positive or negative feelings about performing the target behaviour (Davis et al., 1989; Taylor and Todd, 1995).

APPENDIX B.: SCALE ITEMS

	Scale items and their source					
	Performance expectancy (Venkatesh et al., 2003)	**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
PE1	I prefer to teach online during the outbreak of contagious diseases because I can have access to students at distant locations.	1	2	3	4	5
PE2	I prefer to teach online during the outbreak of contagious diseases because it helps me to reach students within the shortest time-frame.	1	2	3	4	5
PE3	I prefer to teach online during the outbreak of contagious diseases because it saves time as students can continue participating in discussion sections and lectures without coming to university.	1	2	3	4	5
PE4	I prefer to teach online during the outbreak of contagious diseases because it helps me to utilize the time effectively.	1	2	3	4	5
	Effort expectancy (Venkatesh et al., 2003)					
EE1	It is easy for me to deliver online lectures.	1	2	3	4	5
EE2	The language used by students during online class is easy to understand.	1	2	3	4	5
EE3	I can solve the problems of students easily during an online class.	1	2	3	4	5
EE4	It is easy to customize the lectures online.	1	2	3	4	5
EE5	It is easy to participate in discussions during an online class.	1	2	3	4	5
	Facilitating conditions (Venkatesh et al., 2003)					
FC1	I have been provided with resources necessary to deliver online class by my university.	1	2	3	4	5
FC2	I have the necessary knowledge to deliver online lecture	1	2	3	4	5
FC3	Delivering lectures online is compatible with other technologies I use.	1	2	3	4	5
FC4	I get help from my university when I face difficulties while delivering classes online.	1	2	3	4	5
	Social influence (Venkatesh et al., 2003)					
SI1	People whose opinions I value prefer that I should teach online during epidemic.	1	2	3	4	5
SI2	My colleagues and peers think that I should adopt online mode of teaching during epidemic.	1	2	3	4	5
SI3	People who are important to me think that I should adopt online teaching during epidemic.	1	2	3	4	5
	Behavioural intention (Venkatesh et al., 2003)					
BI1	I intend to teach online teaching during outbreak of an epidemic in the future	1	2	3	4	5
BI2	I intend to adopt online teaching in my daily routine also.	1	2	3	4	5
BI3	I intend to encourage my peers and colleagues to adopt online teaching during spread of contagious disease.	1	2	3	4	5
	Actual use (Venkatesh et al., 2003)					
AU1	I used online teaching frequently during spread of contagious disease.	1	2	3	4	5
AU2	I used online teaching to share my content, and assignments with students.	1	2	3	4	5
AU3	I am used to online teaching now.	1	2	3	4	5