A unified perspective on the adoption of online teaching in higher education during the COVID-19 pandemic

Journal:	*Information Discovery and Delivery*
Manuscript ID	IDD-09-2020-0114.R1
Manuscript Type:	Original Article
Keywords:	Developing Countries, End users, Higher education, Information Science, User studies, Technology

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Abstract

Purpose

The research develops a theoretical model that highlights the determinants of the adoption of online teaching at the time of the outbreak of COVID-19. This study adopted a time series analysis (TSA) to understand the factors leading to the adoption of online teaching.

Methodology

Empirical data were gathered from 222 university faculty members by employing an online survey. In the first phase, data were collected from those faculty members who had no experience of conducting online classes but were supposed to adopt online teaching as a result of the COVID-19 pandemic and subsequent lockdown. After two weeks, a slightly modified questionnaire was forwarded to the same group of faculty members, who were conducting online classes to know their perception regarding the adoption and conduct of online teaching.

Findings

Both the proposed conceptual frameworks were investigated empirically through confirmatory factor analysis (CFA) and structural equation modeling (SEM). Significant differences were found in the perceptions of faculty members regarding before and after conducting classes through online teaching.

Originality

This study contributes to the literature by presenting and validating a theory-driven framework that accentuates the factors influencing online teaching during the outbreak of a pandemic. This research further extends UTAUT2 by introducing and validating three new constructs namely: facilitative leadership, regulatory support, and project team capability. Based on the findings, practical insights are provided to Universities to facilitate adoption, acceptance, and use of online teaching during a healthcare emergency leading to campus lockdowns or the imposition of restrictions on the physical movement of people.

Keywords– UTAUT2; online teaching; behavioral intention; actual use

1 Introduction

The COVID-19 pandemic has taken the shape of an epic crisis. The entire world has been severely impacted by the disease, with several thousand people already dead, and the world economy taking a tremendous beating. This has led to unemployment, social unrest, and fueled uncertainty. In the absence of a vaccine, the only choices left for preventing further infections are social distancing and quarantine, which have been enforced by governments around the world through a mandatory lockdown in their respective countries (Mackenzie, 2020; Hamzelou, 2020; Mitjà et al., 2020; Ghosh et al., 2020). Lockdowns come with their downsides as the population has to cope with this sudden loss of freedom and restriction of movement. In India, for instance, there was a total nationwide lockdown announced in March 2020, which also included all educational institutions. For higher education institutions, mid-March is the middle of an academic semester, and as a result, institutions feared the loss of academic contact hours. However, the only way to cope with the situation was to shift from physical to virtual classrooms and promote online teaching and learning. Furthermore, despite the widespread availability of online learning technologies, their use is inefficient and sparse especially in higher education as a result of which senior management in higher education institutions (HEIs) are unable to measure the effectiveness of the use of such technologies or the inefficiencies in the system due to the lack of use of such technologies (Liu et al., 2020).

The Ministry of Human Resources Development (MHRD), which through its various agencies (such as the University Grants Commission–UGC) regulates higher education in India, rolled out several initiatives to promote online education but many HEIs were first movers and voluntarily initiated the process much in advance. Online teaching as a response to pandemics and COVID-19, in particular, 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 et al., 2020). "School's out, the class's in", "suspending classes without stopping learning", specifically refers to China's education and teaching activities during the postponement period during the COVID-19 pandemic prevention and control period (Leung et al., 2020). Other countries across the world have also adopted online learning and virtual classrooms to promote learning. In Portugal, for instance, the government has created a website (https://apoioescolas.dge.mec.pt/) to provide various free online teaching tools to teachers. Similarly, in response to COVID-19, the world's largest MOOCs platforms Coursera and edX are offering a variety of free courses, with edX offering several free courses from Harvard and The Massachusetts Institute of Technology (MIT).

This study is an attempt to assess the adoption of online teaching in light of the COVID-19 pandemic induced lockdown. The study provides useful information for university authorities to implement hassle-free online teaching in an environment of lockdown. This study is unprecedented from many perspectives: (a) It studies the adoption of technology in higher education during an ongoing pandemic situation, which is still unfolding. This is a new context and several studies have proven earlier that the context in a study is critical while framing strategies for technological adoption especially the process of technology re-design, and adaptation by individuals and groups (Liu et al.,2020; Heilesen and Josephsen, 2008; West et al., 2006); (b) According to Liu et al., (2020), technology adoption by higher education teaching staff remains disparate and inconclusive. There was an immediate transition to shift all the existing courses in an online mode in response to the pandemic (Sangeeta and Tandon, 2020). As a complete online course requires adequate usage of multimedia tools like audio and video contents and extensive support from the technical support teams. The majority of faculty members faced the challenges like early preparation, lack of online teaching experience as well as unable to teach technical courses in-depth.

Further, the readiness of the students to attend technical online classes was also highlighted as the main concern of the university faculty members. Most of the students were unable to participate initially. The nature of participation and engaging students online was another challenge noticed by university faculty members. While teaching online, the role of online instructors transforms from knowledge transmission agents to professional guiding students (Juan et al., 2011). This role of a facilitator is more challenging when the instructor is new to online settings. This challenge of "disconnect between the way teachers were taught to teach" (p. 4) has also been highlighted in the previous study of Anderson et al., (2011).

Furthermore, adoption by academics is seen as binary when in reality, it should be seen as a qualitative process based on diffusion (Porter et al., 2016; Humbert, 2007). Keeping this in consideration, this study has followed a time series analysis (TSA)in which academics adoption intent was first measured in the early stages of the university lockdown, followed by the second round of survey after two weeks, when they had adopted online teaching. The study will contribute meticulously to the literature and provide numerous implications for the Universities. This research will help the Universities to frame guidelines for the adoption of online teaching by the academicians. This research evaluates the adoption and usage of online teaching from the teachers' perspective, a gap that this research tries to fill. This research further extends UTAUT2 by introducing and validating three new constructs namely:

facilitative leadership, regulatory support, and project team capability. Based on the findings, practical insights are provided to Universities to facilitate adoption, acceptance, and use of online teaching during a healthcare emergency leading to campus lockdowns or the imposition of restrictions on the physical movement of people.

The rest of this paper is organized as follows: Section 2 reports the theoretical background and hypotheses formulation. The 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, and Section 6 discussing the empirical findings in detail and excerpts implications, limitations, directions for future research, and conclusions.

2. Theoretical background and hypotheses development

2.1 Frameworks of Technology Adoption

Technology adoption encompasses how people adopt technology for use (Louho et al., 2006). In this context, 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 et al., 1991) and Unified theory of acceptance and use of technology (UTAUT and UTAUT2) (Venkatesh et al., 2003; Venkatesh et al., 2012).

Among these, UTAUT2(Unified theory of acceptance and use of technology) by Venkatesh et al., (2012) has been applied widely in various domains to understand users' behavior concerning different technologies. But the model is yet to be validated within the online teaching platform for various reasons (Tseng et al., 2019). As UTAUT2 considers the perspective of voluntary users (i.e., consumers), it matches well with online teaching. UTAUT2 is compatible with online teaching practices as faculty members include interactive simulations and animations in their teaching session which is not only entertaining and exciting (LaaserandToloza, 2017), but also helps to enhance perceived value as teachers can disseminate their knowledge widely (Li et al., 2016) while confined to their homes during a pandemic or any healthcare emergency. Therefore, this research considers UTAUT2 as a theoretical underpinning to investigate factors leading to the adoption of online teaching at the time of the pandemic outbreak.UTAUT2 was validated for mobile internet adoption and Venkatesh et al. (2012) invited academicians and researchers to further validate the framework using miscellaneous technologies and in diverse cultures. UTAUT2 has been contemplated as a significant model in IS adoption and proved superior to competing models (Venkatesh et al., 2012; Hong *et al.,*2011; Tandon *et al*., 2018; Dwivedi et al., 2020). UTAUT2 has been widely tested by researchers on different technologies like online shopping (Tandon et al., 2020), healthcare (Ahlan and Ahmad, 2015; Alamet al., 2020), online booking of hotels(Chang et al., 2019), online gaming (Ramirez-Correa et al., 2019), and e-government services (Al-Shafi et al., 2009). There is sparse literature available on the validation of UTAUT 2 in educational settings, especially in developing countries. Only a few studies have validated UTAUT2 in educational settings such as the adoption of the MOOC by teachers (Tseng et al., 2019), the effectiveness of online videos vs in-person training (Aria and Archer, 2018) adoption of multi-media enhanced content (El-Masri and Tarhini, 2017), acceptance of technology and teachers' activities in virtual classrooms (Radovan and Kristl, 2017). However, due to inconsistency in the findings of these studies, further research is required to validate UTAUT2 as a theoretical framework in educational settings.

As the outbreak of COVID-19 was unexpected, the direct communication and human touch between the students and the instructors were lost. Both university teachers as well as the students faced technical glitches initially leading to slow-down of learning. The time and flexibility concerns lead to a non-serious attitude among the students. A few students were uncomfortable to comprehend the technical and numerical subjects. Lack of empowerment was also another issue faced by the university teachers. Faculty members conducting online classes need to design and prepare the course content within a fortnight thereby creating another challenge for themselves. There were an urgent need and support from the technical team. Academicians need to converse with students by integrating multimedia to improve upon the learning experience which again requires adequate support from the project team. The comfort level of faculty members' with technology plays a significant role in their willingness to teach online. Therefore, variables like regulators' support, project team capability, and facilitating leadership have been identified as vital factors influencing the adoption of online teaching in India. To understand the significance of these variables in the adoption of online teaching, researchers have adopted regulators' support, facilitating leadership, and project team capability as three add-on constructs that affect the adoption of online teaching during pandemic outbreaks.

2.2 Hypotheses development

This research study develops hypotheses based on UTAUT2 and validates performance expectancy, effort expectancy, facilitating conditions, social influence, price value, and hedonic motivation.

Performance expectancy (PE) is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance'' (Venkatesh et al. 2003, p. 447). Previous research studies on technology adoption (Davis, 1989; Venkatesh et al., 2012), meta-analyses (Dwivedi et al., 2019; Williams et al., 2015), and empirical studies on online learning (Chiu and Wang, 2008; El-Masri and Tarhini, 2017; Mosunmola et al., 2018; Pynoo et al., 2011), indicated the significant and vital impact of performance expectancy on behavioral intention. Previous research studies have emphasized the significant impact of PE on the intention to adopt web-based learning tools (Tseng et al.,2019; El-Masri and Tarhini, 2017; Tarhini et al., 2016; Pynoo et al., 2011).In this study, PE has been validated to comprehend the perception of academicians about online teaching during the COVID -19 outbreak. In this study, it is projected that if university teachers consider that online teaching is beneficial and may add to their teaching experience, then they are more likely to indulge themselves with the system. Therefore, the following hypotheses have been postulated:

H1(a): Performance expectancy will positively influence university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

HI(b): Performance expectancy positively influences university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

Effort Expectancy (EE) is analogous to ease of use (TAM) and is defined as "the degree of ease associated with the use of the system'' (Venkatesh et al. 2003, p. 450). The literature available indicates the mixed impact of EE on BI, for example, EE had a weak impact on BI in the study of Pynoo et al., (2011) but emerged as a strong predictor in a majority of the studies (Gruzd et al., 2012; Šumak et al., 2011; El-Masri and Tarhini, 2017; Mosunmola et al., 2018). In the context of this research, EE was included to investigate whether online teaching is easy to use. Academicians will adopt the online mode of delivery only when they will find the whole system easy to use and understand so that they can conduct classes smoothly. The following hypotheses have been proposed based on the above discussion:

H2(a): Effort expectancy will positively influence university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

H2(b): Effort expectancy positively influences university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

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). It refers to the perception of the extent to which the existing organizational and technical infrastructure supports the use of technology (Wiliams et al., 2011; Banerjee and Dey 2013). In the context of this research, FC will be validated by the perception of the academicians whether they can access the essential sources and support to deliver classes online. The FC is a vital construct to understand the intention of humans to adopt any technology (Tandon and Kiran, 2019; El-Masri and Tarhini, 2017; Mosunmola et al., 2018). FC has emerged as the strongest predictor within the e-learning context in most of the studies (Sawang et al. 2014; El-Masri and Tarhini, 2017; Wong, 2016) but in the study of Pynoo et al., (2011), FC had a weak impact on behavioral intention. Therefore, it is important to investigate whether FC has a direct relationship with the adoption of online teaching by academicians. Following hypotheses have been proposed based on the above discussion:

H3(a): Facilitating conditions will positively influence university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

H3(b): Facilitating conditions positively influence university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

*Social Influence (SI)*represents "the degree to which an individual perceives that important others believe he or she should use the new system'' (Venkatesh et al. 2003, p. 451). Social influence considers the opinions and impact of thoughts and activities on the technology adoption of a person (Tosuntas et al., 2015). Professional colleagues, siblings, friends, and peers have a positive or negative influence on intention towards any technology (Tandon and Kiran, 2019; Alalwan et al., 2016; Teo and Noyes, 2014). The adoption of online delivery of classes is generally influenced by superiors/lecturers' pressures (Tseng et al., 2019; El-Masri and Tarhini, 2017; Tosuntas et al., 2015; Pynoo et al., 2011). Therefore, the related hypotheses based on the above discussion are:

H4(a): Social influence will positively influence university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

H4(b): Social influence positively influences university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

Hedonic Motivation (HM) has been defined as "an internal form of incentive, which may include fun, enjoyment, or pleasure derived from using any technology" (Venkatesh et al., 2012, p.161). Hedonic motivation is an intrinsic motivation that signifies the degree to which enjoyment is resultant of using IT (Park et al., 2012; Mittal et al., 2020). A strong positive association was found between hedonic motivation and intention to adopt e-learning (Lewis et al., 2013; Raman and Don, 2013). It is projected in this study that academicians are intrinsically interested and feel excited while delivering online classes. Those faculty members who perceive online teaching as entertaining are more likely to adopt and deliver classes online. Subsequently, based on the above discussion, the following hypotheses are proposed:

H5(a): Hedonic motivation will positively influence university faculty members'behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

H5(b): Hedonic motivation positively influences university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak

Price Value (PV) has been defined as, "consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh et al., 2012, p.161). Price value indicates the perceived benefits of technology concerning monetary value and cost (Sweeney and Soutar, 2001). The direct associations between price value and behavioral intention have been justified by prior investigations on UTAUT (Tandon and Kiran, 2019; Tarhini et al., 2016) and online learning (Raman and Don, 2013; El-Masri and Tarhini, 2017; Tseng et al., 2019). It is expected that if teachers believe that the benefits of online teaching are greater than the monetary cost, then probably, they may adopt online teaching. Accordingly, the following hypotheses have been posited:

H6(a): Price value will positively influence university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

H6(b): Price value positively influences university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

UTAUT has been investigated in the context of the adoption of learning practices, but the literature is highly inconsistent. For example, Tesng et al., (2019) validated UTAUT2 to understand the adoption of MOOC courses by teachers and found significant relationships between all the constructs of UTAUT2, except for effort expectancy. Nikou and Eonomides (2019) validated the extended TAM and found perceived ease of use, facilitating conditions as determinants of behavioral intention to use mobile-based assessments. Pynoo et al., (2011) examined UTAUT to study the digital learning environment among teachers. The findings of the study confirmed the minimal role of effort expectancy and facilitating conditions, while performance expectancy and social influence had a strong impact on the acceptance of the digital learning environment. Further, effort expectancy had a weak impact on behavioral intention in the study of Pynoo et al., (2011), but emerged as a strong predictor in the study of Gruzd et al., (2012). Similarly, the studies of Pynoo et al., (2011) and Teo and Noyes (2014) confirmed a strong influence of social influence but the studies of Gruzd et al., (2012) countered this. Furthermore, facilitating conditions emerged the strongest predictor in the studies of Tesng et al., (2019) and Nikou and Eonomides (2019), but was found weak construct in the studies of Pynoo et al., (2011), and Gruzd et al., (2012). Due to inconsistent findings, there is a need to validate UTAUT2 in educational learning.

Regulatory Support (RS) plays an important role in the adoption of practicing any technology within a country. Dutton et al., (2004) advocated that adopting any new technology by academicians is driven by various political agendas. Regulatory bodies in India (UGC, AICTE) realized the economic impact of the pandemic and facilitated e-learning (Jain and Kathpalia, 2020). The processes and protocols established by regulatory bodies assist in the adoption of any technology. During the outbreak of COVID 19, the Ministry of Human Resources Development (MHRD), came out with several initiatives to promote online education, but several HEIs voluntarily initiated the process much in advance. To understand the role of regulatory bodies following hypotheses have been posited:

H7(a): Regulators' support will positively influence university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

H7(b): Regulators' support influences university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

Project team capability (PT) has been defined as, "the technical and interpersonal skills of the members of the project team" (Liu, 2011). In Universities, various protocols and procedures are established, which facilitate the adoption of any technology. In the University setup, adequate support and training from the team members assist in conducting classes without any hassles. The presence of a competent team permits them to practice their expertise and understanding to facilitate internal processes (Wolff, 2008).

H8(a): Project team capability will positively influence university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

H8(b): Project team capability influences university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

Facilitative Leadership (FL) includes the leadership of senior management and HODs (Heads of the Department). Support from top management plays an indispensable role in strengthening and resource allocation thereby redefining priorities (Liu, 2011; Blevins and Brill, 2017). Swan (2009) highlighted that facilitative leadership leads to wide participation in such initiatives at the departmental level. Nichols (2008) emphasized that encouragement from senior management facilitates the adoption of technologies leading to ease of use, which boosts the implementation of any technology. The awareness and readiness of personnel to adopt any technology depend upon the messages and signals derived from top management (Zailani*et al.*, 2014). Therefore, sustenance from top management and innovativeness of personnel in an organization stimulates perceived usefulness thereby simplifying technology adoption.

Based on the above discussion following hypotheses have been framed:

H9(a): Facilitating leadership will positively influence university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

H9(b): Facilitating leadership influences university faculty members' behavioral intention to adopt online teaching during the COVID-19 pandemic outbreak.

Ajzen (1991) reported behavioral intentions of individuals' readiness to engage in a given behavior are an immediate antecedent of actual behavior. According to Davis (1989), intentions signal a choice that an individual has made on whether to perform a particular action or not. Besides, intentions are the outcome of a mental deliberation procedure and commitment that possibly requires a significant amount of time. Prior studies have argued that the actual behavior is determined by their intentions to perform the behavior (Park et al., 2015; Zhao et al., 2016). Further, Rauniar et al., (2014) also confirmed a positive relationship between intentions and actual use. Thus, the following hypothesis is proposed:

H10: Behavioral intention leads to the actual use of online teaching.

2.3 Time-series analysis (TSA) Approach

TSA can be effectively utilized to measure the effectiveness of interventions (Kratochwill, 1978). As suggested by Marston (1988, p.15), "TSA eliminates the need for random assignment of subjects and it is possible to analyze the functional relationship between the interventions and outcomes." The study by Linden and Yarnold (2018) confirmed that TSA is considered a fairly strong quasi-experimental design, primarily through its control over regression to the mean. The study by Velicer and Fava (2003) also insisted upon the preference of TSA as it helps to comprehend the underlying naturalistic process and the pattern of change over time. There are limited research studies that have used TSA covering the Information Technology domain. Jolie and Matthew(2006) conducted a study to understand the role of Internet self-efficacy and outcome expectations in Internet usage through three-part TSA and confirmed the role of support and encouragement in the formation of self-efficacy and outcome expectations. Therefore, a TSA approach is obligatory in extracting the causes and effects of intricated relationships. Further, studying the perceptions regarding the adoption of online teaching overtime allows improved understanding as to whether their impact is temporary or whether the impact is permanent.

3. Methodology

3.1 Instrument Development

After an extensive literature revision, a survey instrument was elaborated based on established measurement scales. Most of the items were adapted from the UTAUT2 (Venkatesh et al., 2012). Two scales were developed, one to be sent to faculty members before the start of online classes and the other after during classes. The scale items were modified in the context of the online delivery of classes at the time of the pandemic. The scale of project team capability is based on the work of Zailaniet al., (2014). The scale items of "Regulators' support" and "Facilitative leadership" are new scale items, developed by researchers to comprehend the Indian scenario of online delivery of classes during the pandemic. All these scales were customized to fit in the online delivery of class context.

The questionnaire was organized into two sections. Section-1included questions on demographic details of the respondents, whereas Section-2 covered scale items on major constructs in the included proposed model.

3.2 Data collection procedures

As the study was conducted during the lockdown, therefore mixed-method sampling technique was employed to collect data from the respondents. 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, have been used to contact respondents. The link of the preliminary questionnaire was referred to as research scholars and academicians of the university to check for the face validity of the questionnaire. This pilot group suggested amendments in drafting, language, and applicability of scale items. The scale was modified according to the suggestions provided by this group. The language of a few items was also modified to improve clarity.

The web-based survey was conducted due to ease in collecting the data and maintaining anonymity with respondents. This procedure helps in reducing bias (Llieva*et al.,*2002; Andrews *et al.,*2003). Another advantage of an online survey is that the researcher gets complete responses as respondents answer all the required questions, thereby reducing missing data (Andrews *et al.,*2003). Further, an online survey saves responses from respondents into a data file directly, thereby, reducing the burden of inputting the data and emitting transcription errors (Evans and Mathur, 2005). The economical and affordable nature of online surveys has been recognized in previous studies also (Llieva*et al.,*2002; Evans and Mathur, 2005). Further, since the study conducted involved TSA approach with academicians as respondents, an online survey was preferred so that they could respond as per their convenience.

A mixed method sampling technique was employed to collect data from the respondents. According to Onwuegbuzie and Collins (2007), mixed method sampling is highly imperative where the respondents are unknown and difficult to reach. Yet, this is the case in the region of Northern India. Therefore, non-probability sampling techniques such as convenience, purposive (also known as judgmental), and snowball sampling methods, have been used to contact respondents.Two leading State Universities of North India were selected to conduct this survey. An online link covering scale items was mailed to the faculty members of these Universities. In the first round, the link was forwarded to those faculty members who had no experience of conducting online classes but were supposed to adopt online teaching as a result of the COVID-19 pandemic and subsequent lockdown. After 15 days, another link with slightly modified scale items was forwarded to the same group of faculty members, who were conducting online classes to know their perception regarding the adoption and conduct of online teaching.

To control for social desirability bias, respondents were assured of their response anonymity and motivated to respond sincerely as much as possible (Podsakoff et al., 2003; De Leeuw et al., 2008). Using the aforementioned methodology, a total of 235 filled up responses were received in return. However, a few responses in both the surveys were found incomplete or unengaged and after scrutiny, only 222 valid responses were analyzed. Kline (2010) suggested that a sample of 200 responses or larger is suitable for a complicated path model.

Since an online survey was carried out to collect data, common method bias could emerge due to a high correlation among constructs. To minimize common method bias, all constructs were subjected to a principal component factor analysis with varimax rotation. The results of the unrotated factor analysis revealed 8 factors with each construct accounting for 67% of the variation. Thus, no specific factor was noticeable (Podsakoff *et al.,* 2003) indicating the absence of common method bias in the dataset.

In the sample, there is a fair inclusion of respondents across gender 45.7% males and 53.8% females, and a good representation of each age group, education level, and employment status. Table 1 reports the characteristics of the respondents in more detail.

Table1: ***Respondents' characteristics***

Category N=222	**N**	**%**
Male	102	45.7
Female	120	53.8
Age	**N**	**%**
25-35	112	50.2
36-45	87	39.0
Above 45	23	10.3
Education	**N**	**%**
Others	10	4.5
Postgraduate	114	51.1
Doctorate	98	43.9
Designation	**N**	**%**
Assistant Professor	111	50.1
Associate Professor	72	32.4
Professor	38	17.0
Others	1	0.5
Experience of taking online classes	N	%
2 Weeks	79	35.6
3-6 weeks	119	53.60
More than 6 weeks	24	10.81

4. Data analysis and findings

The data analysis process was conducted employing a two-step analytical approach. In the first phase, a confirmatory factor analysis (CFA) assessed the measurement model including reliability, validity, and fit on items before conducting and after conducting online classes. Second, a structural equation model (SEM) in both cases estimated the structural model to test the hypotheses.

4.1 Study 1

4.1.1 Validating the Measurement Model

Confirmatory factor analysis (CFA) was carried out to evaluate the measurement model on the data received from faculty members before the start of online classes (Table 2). Further, standardized loadings were used to assess the indicators' reliability and 0.50 was taken as a minimum threshold for the retention of measurement items (Fornell and Larcker, 1981).

Convergent validity was assessed through item loadings, composite reliability (CR), and AVE (Average variance extracted of each construct). Table 2 shows that AVE and CR of all the constructs are more than the threshold value i.e., AVE>-0.50 and CR> 0.70 on all occasions thereby signifying evidence of convergent validity (Bagozzi and Li, 1988). Further, the instrument also indicated satisfactory discriminant validity as an estimate of each construct is larger than the squared correlations of this construct to any other construct (Fornell and Larcker, 1981).

Table 2: Measurement Model of items before the start of online classes

Variables		Std. Estimate	Std. Error	Critical Ratio	Average Variance Extracted	Composite Reliability
Performance Expectancy	PEB1	0.755				
Mean=4.2173	PEB2	0.799	0.106	12.122	0.595	0.855
Std. Dev=0.71688	PEB3	0.801	0.101	12.162		
	PEB4	0.729	0.093	10.946		
Effort Expectancy	EEB1	0.82				
Mean=3.7523	EEB2	0.825	0.076	14.276	0.606	0.86
Std. Dev=0.84453	EEB3	0.731	0.078	12.064		
	EEB4	0.732	0.07	12.096		
Facilitating Conditions	FCB1	0.834				
Mean=4.1475	FCB2	0.788	0.061	13.774	0.616	0.865
Std. Dev=0.69250	FCB3	0.693	0.07	11.507		
	FCB4	0.818	0.059	14.573		
Social Influence	SIB1	0.843				
Mean=4.0270	SIB2	0.765	0.08	12.805	0.673	0.86
Std. Dev.=0.84926	SIB3	0.85	0.063	14.759		
Hedonic Motivation	HMB1	0.822				
Mean=4.2297	HMB2	0.919	0.062	17.233	0.774	0.991
Std. Dev=0.74554	HMB3	0.895	0.058	16.571		
Price Value	PVB1	0.806				
Mean=4.2387	PVB2	0.868	0.064	14.534	0.711	0.88
Std. Dev=0.72849	PVB3	0.854	0.069	14.248		
Regulators' support	GPB1	0.916				
Mean=4.3679	GPB2	0.716	0.069	11.94	0.608	0.821
Std. Dev=0.63603	GPB3	0.688	0.061	11.326		
Project team capability	PTB1	0.897				
Mean=4.2417	PTB2	0.873	0.057	17.88	0.755	0.902
Std. Dev=0.67500	PTB3	0.835	0.059	16.532		
Facilitating leadership	FLB1	0.869				
Mean=4.5090	FLB2	0.84	0.062	14.963	0.688	0.869
Std. Dev=0.58785	FLB3	0.777	0.056	13.434		

Behavioral Intention	BIB1	0.747				
Mean=4.3904	BIB2	0.649	0.101	9.439	0.562	0.792
Std. Dev=0.52401	BIB3	0.841	0.079	12.397		

Table 3: Correlations

	PEB	EEB	FCB	HMB	PVB	SIB	GPB	PTB	FLB	BIB
PEB	***0.771***									
EEB	.580**	***0.778***								
FCB	.605**	.633**	***0.784***							
HMB	.658**	.746**	.752**	***0.879***						
PVB	.646**	.639**	.566**	.652**	***0.843***					
SIB	.554**	.569**	.565**	.577**	.653**	***0.820***				
GPB	.379**	.423**	.501**	.492**	.531**	.593**	***0.779***			
PTB	.515**	.508**	.575**	.480**	.466**	.495**	.430**	***0.868***		
FLB	.586**	.537**	.559**	.543**	.569**	.519**	.366**	.602**	***0.829***	
BIB	.657**	.653**	.703**	.627**	.647**	.666**	.645**	.654**	.608**	***0.740***

**. Correlation is significant at the 0.01 level (2-tailed).

PEB: Performance Expectancy, EEB: Effort Expectancy, FCB: Facilitating Conditions, HMB:Hedonic Motivation, PVB:Price Value, SIB: Social Influence, GPB: Government Regulators, PTB:Project Team Capability, FLB: Facilitating Leadership, BIB:Behavioral Intention

4.1.2 Structural Model before the start of online classes

This section examines the structural model. Table 4 also indicates the structural model reporting the theoretical associations between constructs before conducting online classes. The results claimed the following significant positive direct effects; (*i*) from performance expectancy to behavioral intention (Std. estimate=0.13, p=0.012) (*ii*) price value to behavioral intention (Std. estimate=0.203, p=0.000) (*iii*) from regulators' support to behavioral intention (Std. estimate=0.344, p=0.000); (*iv*) from project team support to behavioral intention (Std. estimate=0.352, p=0.000); (*v*) facilitating leadership to behavioral intention (Std. estimate=0.312, p=0.010). Few variables had an insignificant impact on behavioral intention *(vi)*from effort expectancy to behavioral intention (Std. estimate=0.131, p=0.007);*(vii)*facilitating conditions to behavioral intention (Std. estimate=-0.012, p=0.815); social influence to behavioral intention (Std. estimate=-0.059, p=0.19) and *(ix)*hedonic motivation to behavioral intention (Std. estimate=0.033, p=0.46) (Table 4). The model fit indices reflect a good fit to the data (χ^2/df = 4.562, GFI = 0.899, CFI = 0.905, TLI = 0.921, IFI = 0.902, RMSEA = 0.079) as per the recommended thresholds of Byrne (1994).

Table 4: Structural Model

No.	Hypotheses	Std. Estimate	S.E.	C.R.	P	Results
H1(a)	Performance expectancy→BI	0.13	0.032	2.525	0.012**	Supported
H2(a)	Effort expectancy→BI	0.061	0.028	1.153	0.249	Not Supported
H3(a)	Facilitating conditions→BI	-0.012	0.034	-0.234	0.815	Not Supported
H4(a)	Social influence→BI	-0.059	0.024	-1.311	0.19	Not Supported
H5(a)	Hedonic motivation→BI	0.033	0.027	0.739	0.46	Not Supported
H6(a)	Price value→BI	0.203	0.029	4.367	0.000***	Supported
H7(a)	Regulators' support→BI	0.344	0.028	8.683	0.000***	Supported
H8(a)	Project team support→BI	0.352	0.029	8.798	0.000***	Supported
H9(a)	Facilitating leadership→BI	0.312	0.024	9.729	0.000***	Supported

Note: 0.000*** Significant at $p< 0.001$

Insert Figure 1 here

4.2 Study 2

4.2.1 Validating the measurement model

Confirmatory factor analysis (CFA) was carried out to evaluate the measurement model on the data received from faculty members after they started conducting online classes (Table 5). Further, in this model also, standardized loadings were used to assess the indicators' reliability, and 0.50 was taken as the minimum threshold for the retention of measurement items (Fornell and Larcker, 1981). Convergent validity was assessed through item loadings, composite reliability (CR) and AVE (average variance extracted of each construct). Table 5 shows that the AVE and CR of all the constructs are more than the threshold value i.e., AVE>-0.50 and CR> 0.70 on all occasions thereby signifying evidence of convergent validity (Bagozzi and Li, 1988). Further, the instrument also indicated satisfactory discriminant validity as an estimate of each construct is larger than the squared correlations of this construct with any other construct (Fornell and Larcker, 1981).

Table 5: Measurement model after conducting online classes

Variables		Std. Estimate	Std. Error	Critical Ratio	Average Variance Extracted	Composite Reliability
Performance Expectancy	PEB1	0.77				
Mean=4.4358	PEB2	0.81	0.095	12.106	0.568	0.855

Std. Dev=0.68689	PEB3	0.774	0.121	11.539		
	PEB4	0.652	0.089	9.562		
Effort Expectancy	EEB1	0.806				
Mean=3.9527	EEB2	0.664	0.067	10.103	0.576	0.844
Std. Dev=0.77065	EEB3	0.819	0.07	12.912		
	EEB4	0.738	0.069	11.454		
Facilitating Conditions	FCB1	0.847				
Mean=4.4133	FCB2	0.741	0.061	12.593	0.655	0.883
Std. Dev=0.63377	FCB3	0.765	0.062	13.182		
	FCB4	0.876	0.057	16.106		
Social Influence	SIB1	0.698				
Mean=4.4489	SIB2	0.649	0.122	7.913	0.552	0.784
Std. Dev=0.60428	SIB3	0.864	0.151	9.37		
Hedonic Motivation	HMB1	0.775				
Mean=4.33634	HMB2	0.917	0.095	14.159	0.667	0.856
Std. Dev=0.72317	HMB3	0.748	0.111	11.552		
Price Value	PVB1	0.531				
Mean=4.2523	PVB2	0.899	0.283	8.037	0.606	0.815
Std. Dev=0.70866	PVB3	0.853	0.276	8.01		
Regulators' support	GPB1	0.916				
Mean=4.4294	GPB2	0.716	0.069	11.94	0.608	0.821
Std. Dev=0.55268	GPB3	0.688	0.061	11.326		
Project Team Capability	PTB1	0.787				
Mean=4.3919	PTB2	0.918	0.075	15.566	0.767	0.908
Std. Dev=0.70911	PTB3	0.916	0.078	15.53		
Facilitating leadership	FLB1	0.701				
Mean=4.5975	FLB2	0.89	0.155	11.957	0.647	0.845
Std. Dev=0.58575	FLB3	0.811	0.153	11.116		
Behavioral Intention	BIB1	0.804				
Mean=4.4797	BIB2	0.693	0.119	11.066	0.612	0.825
Std. Dev=0.63793	BIB3	0.843	0.083	14.313		
Actual Use	AU1	0.898				
Mean=4.5511	AU2	0.548	0.067	8.563	0.502	0.743
Std. Dev=0.71340	AU3	0.631	0.078	10.222		

Table 6: Correlations

	SI	GP	PE	EE	FC	HM	PV	SM	BI	AU	FL
SI	***0.742***										
GP	.552**	***0.779***									

PE	.419**	.387**	***0.753***								
EE	.355**	.308**	.522**	***0.758***							
FC	.328**	.397**	.406**	.313**	***0.809***						
HM	.306**	.373**	.545**	.478**	.419**	***0.816***					
PV	.366**	.342**	.439**	.389**	.425**	.394**	***0.778***				
PT	.399**	.552**	.410**	.246**	.433**	.266**	.280**	***0.875***			
BI	.494**	.394**	.528**	.469**	.456**	.592**	.432**	.440**	***0.782***		
AU	.399**	.301**	.503**	.432**	.321**	.456**	.293**	.268**	.427**	***0.708***	
FL	.391**	.671**	.458**	.341**	.584**	.446**	.388**	.500**	.491**	.381**	***0.804***

**. Correlation is significant at the 0.01 level (2-tailed).

PE: Performance Expectancy, EE: Effort Expectancy, FC:Facilitating Conditions, HM:Hedonic Motivation, PV:Price Value, SI: Social Influence, GP: Government Regulators, PT:Project Team Capability, FL: Facilitating Leadership, BI:Behavioral Intention, AU: Actual use

4.1.2 Structural Model while conducting online classes

The results claimed the following significant positive direct effects; (*i*) from performance expectancy to behavioral intention (Std. estimate=0.122, p=0.020) (*ii*) from effort expectancy to behavioral intention (Std. estimate=0.131, p=0.007); (*iii*) from hedonic motivation to behavioral intention (Std. estimate=0.294, p=0.00); (*iv*) from social influence to behavioral intention (Std. estimate=0.224, p=0.000); (*v*) facilitating leadership to behavioral intention (Std. estimate=0.13, p=0.010); (*vi*) Project team support to behavioral intention (Std. estimate=0.179, p=0.007); and *viii*) behavioral intention to actual use of online teaching (Std. estimate 0.786, p=0.000) (Table 7). Few variables had an insignificant impact on behavioral intention such as Facilitating conditions (Std. estimate=0.039, p=0.44, Regulators' support (Std. estimate=-0.161, p=0.058) and Price value (Std. estimate=0.039, p=0.38). The model fit indices reflect a good fit to the data (χ^2/df = 4.814, GFI = 0.902, CFI = 0.915, TLI = 0.907, IFI = 0.899, RMSEA = 0.079) 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. The study findings build an understanding of the factors leading to the adoption of virtual teaching by University professors at the time of the pandemic.

Table 7: Structural model after conducting classes

No.	Hypotheses	Std. Estimate	S.E.	C.R.	P	Results
H1(b)	Performance expectancy→BI	0.122	0.049	2.31	0.020**	Supported
H2(b)	Effort expectancy→BI	0.131	0.039	2.72	0.000***	Supported
H3(b)	Facilitating conditions→BI	0.039	0.051	0.772	0.44	Not Supported
H4(b)	Social influence→BI	0.224	0.062	3.782	0.000***	Supported
H5(b)	Hedonic motivation→BI	0.294	0.045	5.673	0.000***	Supported
H6(b)	Price value→BI	0.039	0.039	0.878	0.38	Not Supported
H7(b)	Regulators' support→BI	-0.161	0.07	-2.659	0.058	Not Supported
H8(b)	Project team support→BI	0.179	0.053	2.707	0.006**	Supported
H9(b)	Facilitating leadership→BI	0.130	0.053	2.524	0.010**	Supported
H10	BI→Actual use of online teaching	0.786	0.109	8.179	0.000***	Supported

Note: 0.000*** Significant at $p < 0.001$

Insert Figure 2 here

5. Discussion, implications, and limitations of the study

5.1. Discussion of the results

This research builds a two-stage theoretical model on the adoption of online teaching by faculty members of two leading state universities at the time of the pandemic outbreak. Through an in-depth analysis of data collected through two rounds of surveys, the study provides significant insights into factors influencing the adoption of online teaching at the time of pandemic outbreak COVID 19. Significant differences were observed in the behavioral intention of faculty members in both studies.

Performance expectancy emerged significant factor in both the studies which is consistent with other previous studies that confirmed that an increase in performance expectancy leads to an increase in intention to adopt any new technology(Venkatesh et al., 2012; Pynoo et al., 2011). Whereas, effort expectancy, which emerged insignificant in study1 became a significant predictor of behavioral intention in study 2. This supports the previous studies by Gupta et al., (2008) and Venkatesh et al., (2012). Therefore, it is understandable that effort expectancy was regarded as a baseline to adopt online teaching, whereas performance expectancy emerged as an important driver. As most of the teachers are digitally literate, therefore, effort expectancy had a weaker effect as compare to performance expectancy.

Surprisingly, facilitating conditions in both studies had an insignificant impact on behavioral intention to adopt online teaching. This finding is inconsistent with previously reported research studies of Venkatesh et al., (2012) and Raman and Don, (2013). Similarly, hedonic motivation also depicted varied results in both the studies. In the first study, hedonic motivation had an insignificant impact on behavioral intention. This could be clarified by the task nature i.e., using online teaching appeared more of a utilitarian task, and less like a hedonic task initially as the faculty members had no experience of online teaching. But in the second study, the faculty members found online teaching entertaining and full of excitement as they were able to connect with diverse audiences and work on their presentations to create interest among students provided fun and excitement to them (Hew and Cheung, 2014; Laaser and Toloza, 2017).

This research failed to explore the impact of habit on both behavioral intention and usage behavior (Venkatesh et al., 2012). This was predictable since the sample included most of the new users and a few experienced users. Therefore, it is unlikely that new users to develop habits allied with the adoption of a system. Additionally, UTAUT2 posits that habit has a minor role when the users are less experienced, but the reverse is true on more experienced users (Venkatesh et al., 2012; Tseng et al., 2019). Further, as non-users and users with less experience were considered in both the models, the habit was removed from UTAUT2.

Similarly, price value, which is an essential factor influencing faculty members' behavioral intention to adopt, and use online teaching emerged significant in study 1 but had an insignificant impact on behavioral intention in study 2. In the first study, the teachers believed that the perceived benefits of online teaching exceeded perceived costs while conducting online classes. Teachers can share subject knowledge to a larger audience (Tseng et al., 2019; Voss, 2013), which gives them a sense of accomplishment and compensates for the required time and determination. But while conducting online classes for the first time, many teachers felt tired while preparing assignments and courses. This can be overcome by providing support to teachers by giving them ample time to prepare course material and use it.

Furthermore, social influence, considered as a vital determinant of behavioral intention in the adoption of any technology emerged insignificant in study 1, which contradicts the results of previous studies (Venkatesh et al., 2012; Chopdar et al., 2018; Tseng et al., 2019). But in study 2, social influence emerged significantly with higher loadings, thereby making us deduce that how social groups apply their influence to motivate group members to implement a particular behavior through compliance mechanisms (Hsu and Lu, 2004; Raman and Don, 2013).

All three new constructs namely, Regulators' support, Project team capability, and Facilitative leadership emerged significant in study1, while in study two, regulators emerged insignificant. Policies framed by senior management help in the adoption of any novel technology and wide participation leading to legitimacy (Enderle et al., 2013). Unified frameworks by the senior management help to adopt these technologies (Porter et al., 2014). Project team capability emerged significant in both the studies and the finding is consistent with the work of Liu (2011). Therefore, the presence of a competent team, the interoperability of the system as well as chosen work style of a competent team leads to the adoption of any technology (Zailani et al., 2014; Liu, 2011).

5.2 Implications of the study

This research has significant practical implications for university administrators to promote teachers' adoption and use of online teaching during the pandemic. Among all the constructs, performance expectancy, hedonic motivation, and social influence emerged significant variables to influence behavioral intention. For performance expectancy, the main motive to adopt online teaching during the pandemic was unquestionably their usefulness. Likely, other universities in developing countries may not have adopted online teaching during the pandemic. Therefore, the university project teams and top management need to improve the perception of the teaching staff by communicating the benefits of online teaching. Similarly, the role of social influence cannot be ruled out in facilitating the teachers in universities to adopt online teaching. Those faculty members who have adopted online teaching may demonstrate a positive attitude towards online teaching, which may be linked to their performance assessment. Top management and administrators may also invite experienced faculty members to motivate and share their experiences with other faculty members. Faculty members may be provided a preliminary video to educate them about how to teach in virtual classrooms. Those faculty members who had a positive experience may be invited to train and respond to the probable questions of non-users. Since hedonic motivation also emerged significant in this study, therefore, training faculty members to make interesting presentations and enable open communication with students. These interactions among University faculty members and students make virtual classrooms a good learning experience.

6 Limitations and future research

Although the results are strengthened by the TSA nature of the data, this study has a few limitations. Future research studies may include a longitudinal research design by considering the extended period as it will help in extricating the causes and effects of complicated constructs. Further, analyzing the perceptions overtime improves understanding of phenomena as to whether their impact is for a shorter period or whether the impact is enduring. Since the study is conducted in North India, the results cannot be generalized to other parts of the country.

The model may be validated and tested in other parts of the country also and a comparative study could be considered in the future. This extended UTAUT2 may be replicated in other developing countries of the world also to see the applicability of the model. Further, this research investigated the adoption of online teaching from the perspective of UTAUT2, but only the main effects proposed by Venkatesh et al., (2012) were validated, while moderators were not validated. Future research studies may also validate the moderating effects on proposed relationships. The same model could be validated to study other platforms apart from online teaching, such as online learning by students, adoption of MOOC, etc.

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Appendix1: Scale items

	Scale items and their source					
	Performance Expectancy (Venkatesh et al., 2012)	**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., 2012)					
EE1	It is easy for me to deliver online lectures.	1	2	3	4	5
EE2	The language used by students during the 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., 2012)					
FC1	I have been provided with the resources necessary to deliver online classes by my University.	1	2	3	4	5
FC2	I have the necessary knowledge to deliver an 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
	Hedonic Motivation (Venkatesh et al., 2012)					
HM1	Online teaching is an exciting experience for me.	1	2	3	4	5
HM2	Teaching students through online mode is a pleasant experience for me.	1	2	3	4	5
HM3	Delivering lectures online is a fun experience for me.	1	2	3	4	5
	Price Value (Venkatesh et al., 2012)					
PV1	I think that online teaching is cost-effective for the university especially during a pandemic.	1	2	3	4	5
PV2	I feel that online teaching is cost-effective for me.	1	2	3	4	5
PV3	I feel that online teaching is cost-effective for the students	1	2	3	4	5
	Social Influence (Venkatesh et al., 2012)					
SI1	People whose opinions I value, prefer that I should teach online during a pandemic	1	2	3	4	5
SI2	My colleagues and peers think that I should adopt an online mode of teaching during a pandemic	1	2	3	4	5
SI3	People who are important to me think that I should adopt online teaching during a pandemic	1	2	3	4	5
	Regulators' Support (New Scale items)					
GP1	I think UGC/AICTE etc should support online teaching during the outbreak of a pandemic.	1	2	3	4	5
GP2	I think UGC/AICTE etc should provide the necessary infrastructure to pursue online teaching.	1	2	3	4	5
GP3	I think UGC/AICTE should liberalize the ICT policy specifically to promote the use of online delivery of lectures during a pandemic.	1	2	3	4	5
	Project team capability (Zailani and Iranmanesh, 2014)					
PC1	In my university, there is a formal and qualified team to facilitate online teaching during an epidemic.	1	2	3	4	5
PC2	The project team can understand the requirements of students of different departments.	1	2	3	4	5

PC3	The project team has a capable information system for the development of online delivery of classes.	1	2	3	4	5
	Facilitative Leadership (New Scale items)					
FL1	The senior management of the University supports online teaching during the pandemic	1	2	3	4	5
FL2	Senior management has allocated resources for conducting online classes during an epidemic	1	2	3	4	5
FL3	Senior management provides a unified framework operating at the departmental level for facilitating online teaching during a pandemic.	1	2	3	4	5
	Behavioral Intention (Venkatesh et al., 2012)					
BI1	I intend to teach online teaching during the 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 the spread of contagious disease.	1	2	3	4	5
	Actual Use (Venkatesh et al., 2012)					
AU1	I used online teaching frequently during the 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

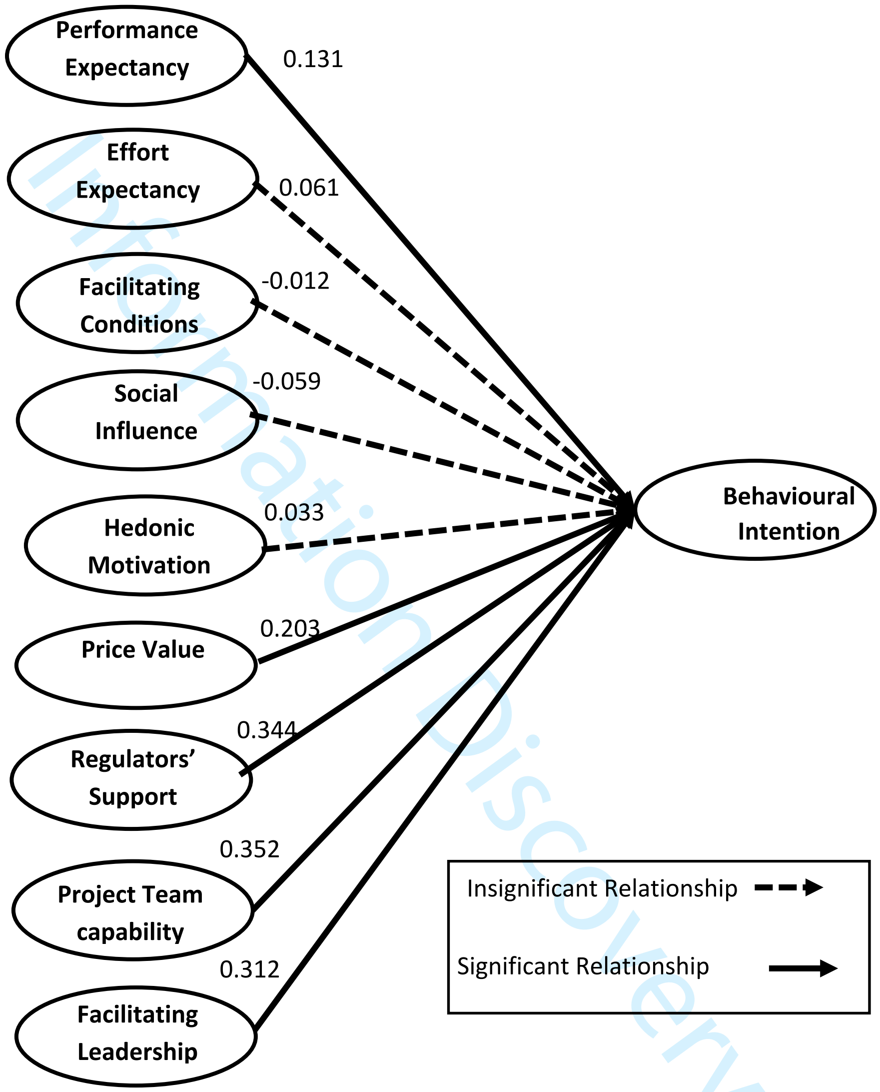

Figure1: Model before conducting online classes

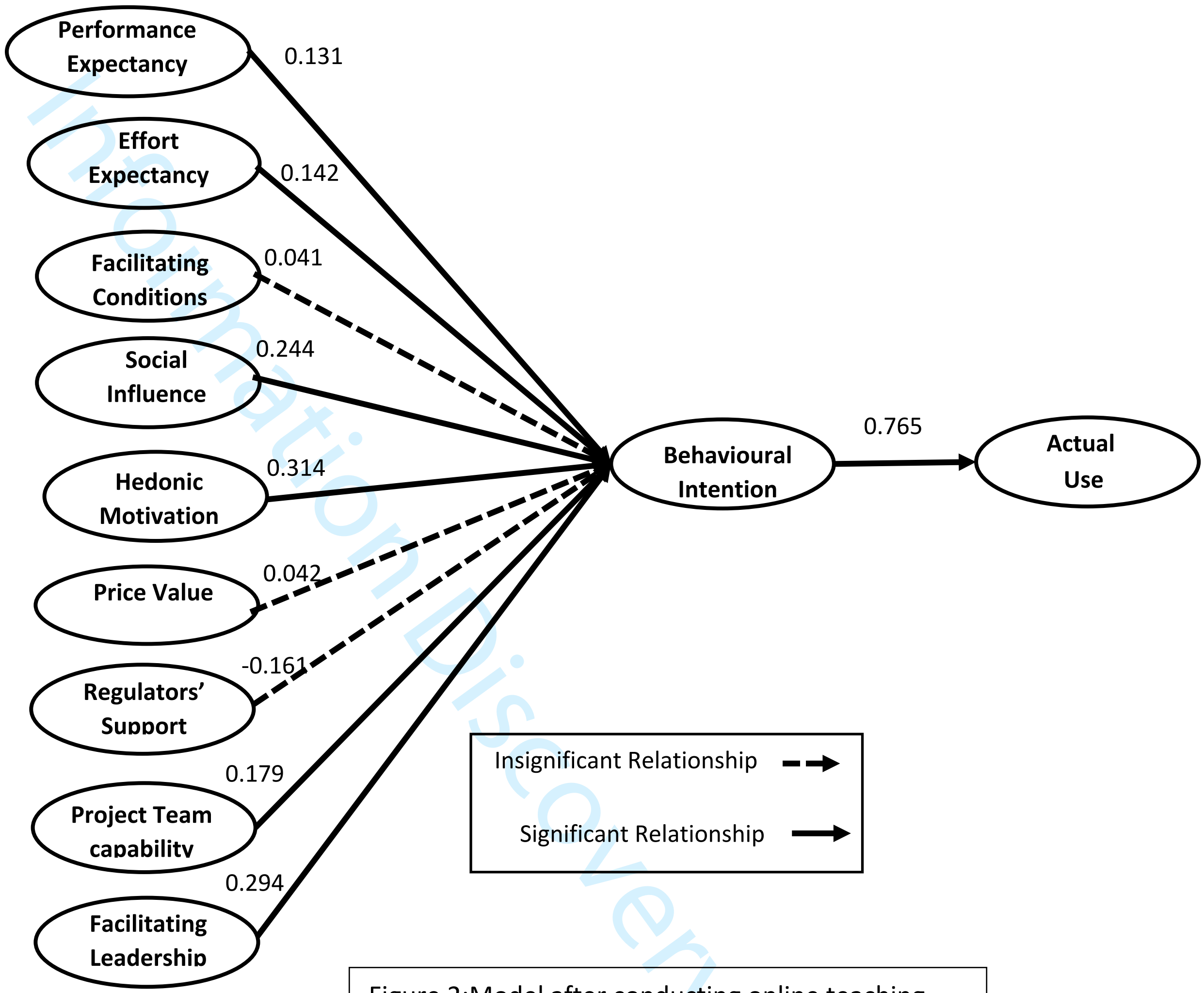

Figure 2:Model after conducting online teaching