Understanding Students' Behavioral Intention to Adopt Blended Learning : Modified UTAUT Model

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Abstract

Purpose : The presented study explored the critical antecedents of blended learned adoption by students in India. It extended the unified theory of acceptance and use of technology (UTAUT) with attitude (ATT) and self-management of learned (SL) as additional constructs.

Methodology : The proposed model was tested empirically using confirmatory factor analysis (CFA) and structural equation modeling (SEM). The data were collected through a questionnaire from 383 New Delhi, Indian students for a period from January 2020 to December 2021.

Findings : The analysis of the data revealed that effort expectancy (EE), performance expectancy (PE), facilitating conditions (FC), and SL had significant positive effects on behavioral intention (BI) and ATT toward blended learning. The impact of socially influenced (SI) and PE on BI and ATT, respectively, was statistically not significant; FC exerted a positive influence on EE. Further, ATT was an important factor in creating BI as well as for actual usage (AU) of blended technology. The impact of BI on AU was also positive and significant.

Practical Implications : The present study made an important contribution to the extant literature by proposing a modified framework for identifying the students' BI and actual use of blended learning. The study was expected to provide useful insights into the formulation, promotion, and implementation of blended learning in educational institutions in India. In light of the ongoing advancements in technology, it was imperative to proactively foresee and effectively manage the issues that may arise concerning its integration within the field of education. This research would facilitate institutions in anticipation of forthcoming transformations within the educational domain.

Originality : The originality of this study resides in its focus on how two mediators—ease of use and usefulness—played a pivotal role in changing students' perceptions of blended learning. Notably, while social influence and performance expectations had no statistically significant effect on BI and ATT, respectively, enabling situations had a favorable effect on effort expectations.

Keywords : **blended learning, UTAUT, performance expectancy, effort expectancy, social influence, behavioral intention, attitude**

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The use of information and communication technology (ICT) in educational settings has resulted in substantial shifts in both the teaching and learning processes. This paradigm shift has had a significant influence on education on all fronts, from pre-kindergarten classrooms to academic institutions at the university level. A brief review of the significance of information and communications technology and how it has

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revolutionized is presented here. The combination of ICT with more conventional teaching strategies resulted in the development of blended learning models. This flexible method of education, which combines in-person and online training, may cater to a variety of students' preferred modes of education (Aggarwal, 2017; Arora & Srinivasan, 2020; Kundu, 2021). ICT has brought a paradigm shift in the teaching and learning processes in the 21st century. The concepts of penless and paperless classrooms are emerging; mind maps are being presented as innovative teaching methods; students are involved in virtual labs. The usage of emerging technologies in education aims at providing a flexible virtual learning environment (Castro, 2019; Geng et al., 2019). The amount of technology used in the ICT-based learning system sets it apart from traditional teaching pedagogy. It also gradually transfers control and accountability of the learning process to the students, providing them with flexibility in their learning. The use of ICT-enabled learning systems is becoming critical for higher education institutions (HEIs) (Popenici & Kerr, 2017).

Education institutions are constantly assessing and implementing newer teaching techniques. With the use of e-books, tablets, emails, teleconferences, and virtual classroom communities, technology has transformed the way that education is delivered and learned. HEIs can enhance their learning processes through a variety of technological advancements, but as with anything good, there are drawbacks and obstacles. These include the need for significant infrastructure investment, content creation by the institutions, and increased accountability and self-discipline on the part of the students (Ali, 2020; Ceesay, 2021). Therefore, there is a need to effectively integrate the content, approach, and ICT (Cubeles & Riu, 2018; Kundu, 2021).

One of the new teaching-learning methods that fulfils these criteria is the blended learning approach (Dhawan, 2020). Blended learning has been reckoned as one of the top teaching-learning techniques emerging in educational institutions (Ahmad, 2020; Dhawan, 2020; Ying & Yang, 2017). The potential of technology has been empirically examined in many studies that have reported a positive effect of technology on teaching and learning (Dhawan, 2020). It promotes the use of the virtual environment by using the new technology that acts to capture the interest and attention of the students in the classrooms (Dhawan, 2020). It is an approach that mixes the best practices of online and face-to-face modes (Boyle et al., 2003). Combining technology with the traditional mode of teaching results in improved pedagogy and makes it easy for the students to access information. In this approach, the students are not restricted to the classroom walls, to the pedagogy used by the teacher, and not by the pace of the lecture (Ying & Yang, 2017). According to Boyle et al. (2003), blended learning encourages students to share their expertise and information with others and contributes to the creation of an interactive environment. Blended learning supports teaching and learning (Kanwal & Rehman, 2017), and it can be a suitable approach for an emerging country like India, which has a large student population and lacks primary infrastructure teaching resources and funds to build them. The empirical studies provide clear evidence that the traditional mode of classroom teaching, if used with the online mode, creates a better learning environment (Bruff et al., 2013).

The present study attempts to identify the factors that develop a positive attitude (ATT) toward blended education, create a favorable behavioral intention (BI), and motivate them to use it. To achieve this objective, we have employed the modified unified theory of acceptance and use of technology (UTAUT) model to explore the determinants of students' intention and actual use of blended learning. The constructs included in our model are performance expectancy, effort expectancy, social influence, facilitating conditions, BI, ATT, and actual usage (AU). Through the perspective of the modified UTAUT model, the research attempts to investigate areas where there is little data or where there is a lack of research in the context of understanding students' BI to accept blended learning. Few researchers have looked at the influence of cultural influences on students' BIs to embrace blended learning. There are not many studies investigating the adoption of blended learning technology from the viewpoint of students. Therefore, it is expected that our study will be meaningful to fill this gap. The modified UTAUT model's implementation attempts to close the knowledge gap about cultural variations in ATTs and behaviors around technology adoption in education. It offers beneficial perspectives on the creation, development, and use of blended learning in Indian educational institutions. The conduction of research holds significant potential in assisting institutions in their preparedness for forthcoming transformations within the educational domain.

The study makes a valuable contribution to the present literature on the adoption of new technology by users. The novelty of our study lies in the fact that it considers students' perspectives toward blended learning, which has not been adequately addressed in the literature. The study also makes practical implications for academicians, educational institutions, policymakers, and regulators by suggesting the measures needed to increase the acceptability and usefulness of blended learning for all stakeholders.

The research is in demand as per the current trend. Due to technological advancements and the COVID-19 pandemic, education has undergone substantial change, and blended learning is now more common than ever. Future trends in education can be predicted by knowing how students plan to use blended learning. Many educational institutions swiftly adopted remote and blended learning after the COVID-19 outbreak. To determine if these changes are likely to last or whether there is a return to conventional models, researchers are looking into students' BIs in a post-pandemic setting. Adapting teaching strategies is necessary for blended learning. Studying behavioral intents can help teachers create lessons that are in line with students' expectations and motivations.

The subsequent sections of the study contain a literature review, methodology, data analysis, data discussions, implications, and limitations of our study in that order.

Empirical Literature

Blended learning has been studied by many researchers across the world (Geng et al., 2019; Gupta & Maurya, 2022; Nath et al., 2019; Panigrahi et al., 2018; Pardamean & Susanto, 2012; Pradeepkumar & Panchanatham, 2011; Tarhini et al., 2017; Teo et al., 2019; Uğur & Turan, 2018; Yeop et al., 2019). Many theoretical models have been suggested in the literature, which aims at comprehending the users' adoption intention of new technology in the blended learning framework (please refer to Table 2 for details). The technology acceptance model (TAM), developed by Davis (1989), is one of the popular models for understanding and predicting the users' intention to adopt a technology. Several studies have used TAM in the context of blended learning (Chan et al., 2018; Chatterjee et al., 2020; Kanwal & Rehman, 2017; Lazar et al., 2020; Martín-García et al., 2019). An equally popular model in the literature to study technology acceptance behavior is the UTAUT and its extended version, modified UTAUT. This model is relatively more comprehensive than other models in explaining the technology adoption behavior of users. Few prominent studies (Chatterjee & Bhattacharjee, 2020; Khechine et al., 2020; Pardamean & Susanto, 2012; Prasad et al., 2018; Sultana, 2020; Tarhini et al., 2017; Uğur & Turan, 2018; Yakubu et al., 2020; Zhang et al., 2022) in the area of blended and online learning have used this model.

An insight into the literature provides clear evidence that the diffusion of blended learning is more pervasive in developed nations than the developing and underdeveloped countries (Andersson & Grönlund, 2009; Kanwal & Rehman, 2017). The primary justifications offered in the literature for this claim are that emerging countries have more distinct challenges than developed ones. In addition, the societal aspects, infrastructure accessibility and availability, individual creativity, and blended learning implementation guidelines all work against blended learning's adoption and expansion in these countries (Dey & Bandyopadhyay, 2019; Parkes et al., 2015). The existing studies report that technical development, perceived ease of use, perceived usefulness, system quality, performance expectancy, effort expectancy, societal norms, facilitating conditions, safety aspects, price value, and content value are the critical drivers for developing the BI for new technology and its usage (Lin & Lin, 2019; Prasad et al., 2018; Šumak & Šorgo, 2016; Tan, 2013). Along with these orthodox antecedents of technology acceptance, several exogenous variables have also been suggested in the literature, such as anxiety, ATT, self-efficiency, external control, technical skills, primary motivators, demonstrability, image, system flexibility, and extrinsic motivation motivators.

According to research on blended learning, there are some significant drawbacks to online learning in addition to its many advantages (Dhawan, 2020; Parkes et al., 2015). A few important impediments to the growth of blended learning are delays in administrative approvals, lack of infrastructure, technical difficulties, and difficulty in access. Besides this, the non-availability of the committed faculty, lack of motivation for blended learning, inadequate education facilities, cost of using technology, response to change, and level of teachers' knowledge are also responsible for the poor adoption rate of blended learning, especially in the context of developing countries (Farid et al., 2018). Table 1 provides a summary of a few significant research studies that examined the factors influencing the integration of learning technology in developing countries.

Table 1. ***Snapshot of Previous Studies***

Study	Model	Context	Sample Size	Techniques	Findings
Sangeeta & Tandon (2021)	Modified UTAUT model with ATT as an additional construct.	India	643	SEM and CFA	The research validated that performance expectancy and facilitating conditions are essential for creating BI and positive ATTs toward blended learning. Social influence was also crucial for BI but not for ATT. However, no significant impact of effort expectancy was observed on BI and ATT.
Gupta & Maurya (2022) ; Liyanagunawardena et al. (2013)	Technological factors, user-related factors, environmental factors, intention to adopt, complete, and continue MOOCs, MOOC features, and quality.	India	197	Stepwise Regression	Technical features, user characteristics, and MOOC features were important drivers of MOOC acceptance by students. Environmental factors were significant for students' initial intentions to adopt MOOCs ; whereas, quality was essential for sustaining the interests of the students in completing and continuing the MOOCs.
Chatterjee & Bhattacharjee (2020)	Perceived risk, performance expectancy, effort expectancy, facilitating conditions, ATT, BI, and adoption of artificial intelligence.	India	329	SEM	Perceived risk, effort expectancy, facilitating conditions, and BI were important for assessing the ATT toward the use of technology in higher education, while no significant impact of performance expectancy was found over adoption intention for the use of artificial intelligence in higher education.
Virani et al. (2023)	Social influence, perceived	India	286	CFA and SEM	Social influence, perceived ease

	usefulness, perceived ease of use, content quality, ATT toward MOOCs, and intention to adopt MOOCs.				of use, and quality of content exerted a statistically important effect on the ATT toward using MOOCs ; whereas, perceived usefulness was not crucial for studying it. Furthermore, the ATT was found to be a significant antecedent of the adoption intention of MOOCs.
Chatterjee et al. (2020)	Perceived usefulness, ease of use, expected risk, effort expectancy, price value, BI, and adoption of the mobile application.	India	271	Partial least square-SEM	The study validated the statistically significant impact of perceived usefulness, ease of use, and effort expectancy on a BI for mobile education, while the impact of perceived risk was negative on BI. The BI was also observed to be an essential driver of the adoption of mobile applications for education.
Tseng et al. (2019)	Performance and effort expectancy, facilitating conditions, social impact, hedonistic motivation, price value, BI, and usage.	Taiwan	161	Partial least square-SEM	The BI of teachers to adopt MOOCs is a function of performance expectancy, facilitating conditions, social influence, and price value. However, no significant impact of effort expectancy and hedonic motivation was observed on the adoption of MOOCs by teachers.
Gan & Balakrishnan (2018)	Perceived usefulness, ease of use, self-efficacy, system and information quality, uncertainty avoidance, and adoption intention.	Malaysia	328	Partial least square-SEM	The study reported that information quality, system quality, enjoyment, and avoidance of uncertainty are essential determiners of technology adoption intention, whereas no significant effect of perceived usefulness, perceived ease of use, and self-efficacy was observed.
Ghazal et al. (2018)	Technical experience, system, service, and information quality.	Malaysia	174	Partial least square-SEM	All the factors forming part of the study are essential determinants of students' acceptance and satisfaction of learning management systems.
Pardamean & Susanto (2012)	Performance and effort expectancy, social pressure, intention to use, and AU.	Indonesia	49	SEM	Performance expectation and social pressure caused a significant positive impact,

					while effort expectancy had an adverse effect on BI. Demographic variables were not crucial in studying the BI toward blended learning.
Uğur & Turan (2018)	Basic UTAUT model constructs, system interactivity, and area of scientific expertise.	Turkey	242	SEM	Performance expectancy, scientific expertise, system interactivity, and effort expectancy were significant drivers of BI for e-learning technologies.
Sultana (2020)	Basic UTAUT model with mobility and self-management learning.	Bangladesh		SEM	Performance expectation, magnitude of efforts needed, and self-management learning were important for assessing the BI toward mobile cloud learning.
Thomas et al. (2020)	UTAUT constructs	Caribbean countries	1,726	SEM	The study validated that the UTAUT model was important in identifying the online learning intention.
Kanwal & Rehman (2017)	Perceived usefulness, perceived ease of use, subjective norms, self-efficacy, internet experience, anxiety, enjoyment, accessibility, system characteristics, and ATT toward e-learning.	Pakistan	354	CFA	The study reported that perceived ease of use can be determined by self-efficacy, prior experience, enjoyment, and system characteristics, while perceived usefulness was influenced by system characteristics alone.
Tarhini et al. (2017)	Subjective norms, work-life quality, perceived usefulness, and perceived ease of use.	Lebanon	569	SEM	All chosen constructs had a positive and significant impact on e-learning acceptance.

The literature reviewed shows that blended learning is dependent on technology and brings forth the following research problems. It is imperative to investigate the potential impact of various student demographics and socio-economic backgrounds on their BIs. The promotion of digital equity in education can be facilitated by addressing potential gaps in technology adoption. The incorporation of many technical tools and platforms is a common practice in blended learning. Examining the intents of students can provide valuable insights into the effectiveness of different technologies and highlight areas that may need additional development or support. The topic of education holds global significance, and the implementation of blended learning exhibits variations throughout different regions of the world. Research conducted on BIs in international settings can offer valuable cross-cultural perspectives on the acceptability of technology in educational contexts.

Policy development involves the establishment of guidelines and regulations by governmental bodies and educational institutions intending to facilitate the integration of technology in the field of education. The investigation of BIs can provide valuable insights for policymakers, enabling them to make informed decisions that are in line with the requirements and preferences of students. In light of the ongoing advancements in technology, it is imperative to proactively foresee and effectively manage the issues associated with the integration of technology in the field of education.

Theoretical Framework and Hypotheses

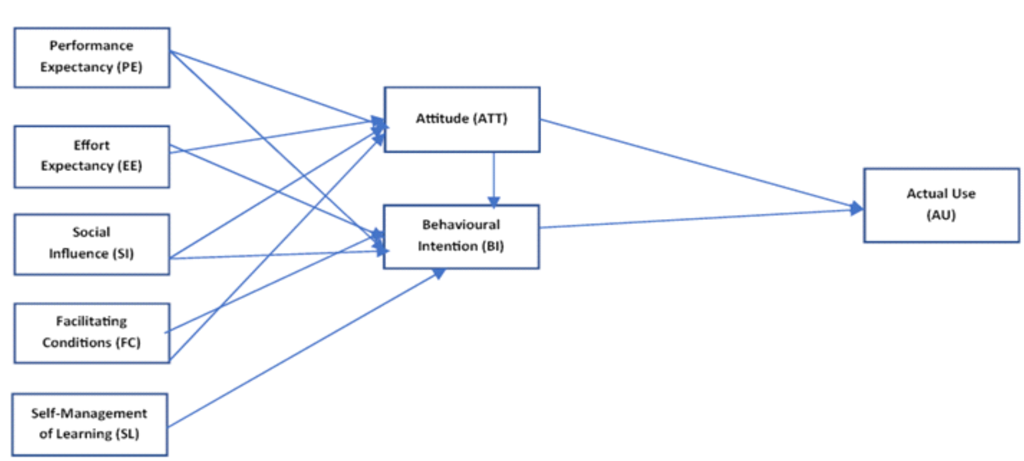
Many theoretical models have been suggested in the literature that explain the critical antecedents of technology adoption intention and its use. Table 2 lists a few well-known models that have been utilized in the relevant empirical research.

Our study is based on modified UTAUT, which has been extensively used in the literature in identifying the antecedents of the technology adoption intention of the users. UTAUT is an empirically tested model for assessing the BI to accept a new technology (Chatterjee & Bhattacharjee, 2020; Tarhini et al., 2017; Uğur & Turan, 2018; Yakubu et al., 2020; Yeop et al., 2019; Zhang et al., 2022). Besides this, it has also been extended and synthesized with many other frameworks for developing new theories or models (Khechine et al., 2020; Pardamean & Susanto, 2012; Prasad et al., 2018; Sultana, 2020). In our study, we considered all the constructs of the UTAUT model and further customized this mode by adding two constructs of self-management of learning and user's ATT based on the findings of empirical studies (Dwivedi et al., 2019), which state that ATT is an essential mediator between beliefs and intention and self-management of learning. The use of ATT as a determinant for predicting the

Table 2. ***Theoretical Models for Studying Technology Adoption Intention***

S. No.	Theoretical Model	Developed by
1	Diffusion of Innovation Theory	Rogers (2003)
2	Theory of Reasoned Action	Ajzen & Fishbein (1975)
3	Social Cognitive Theory	Bandura (1986)
4	Technology Adoption Model and Extended Technology Adoption Model	Davis (1989) ; Venkatesh & Davis (2000)
5	Theory of Planned Behavior	Ajzen (1991)
6	UTAUT and UTAUT 2	Venkatesh et al. (2003) ; Venkatesh et al. (2012)
7	Modified UTAUT	Dwivedi et al. (2019)

Figure 1. ***Proposed Model of the Study***



usage of technology has also been validated empirically in many studies (Dwivedi et al., 2019; Gamal Aboelmaged, 2010; Kanojia et al., 2022; Sangeeta & Tandon, 2021; Tandon et al., 2016) that ATT is a crucial driver of technology acceptance by a user. It is also in harmony with TAM, which says that if technology is easy to understand, a positive ATT develops.

Furthermore, we did not consider the four mediators of the original UTAUT model based on the suggestions in the studies of Sangeeta and Tandon (2021) and Tseng et al. (2019). This study aimed to validate the modified UTAUT for anticipating BI and usage of blended learning in the Indian context. Figure 1 explains the paradigm that we have suggested. We have included explanations for each of the constructs in our conceptual model.

Performance Expectancy (PE)

It refers to the expectation of achieving the objectives by using technology (Venkatesh et al., 2003). In the context of blended learning, it means how efficiently and effectively information can be shared and retrieved by using the online mode of teaching (Wang et al., 2009). Many studies have postulated a positive relationship between PE and BI and PE and ATT toward technology in the literature. The relationship has been expressed as a set of hypotheses, as follows:

- **H1 :** PE has a favorable impact on BI's adoption of blended learning.
- **H2 :** PE has a favorable impact on ATT toward blended learning.

Effort Expectancy (EE)

"EE is the degree of ease associated with the use of the system" (Venkatesh et al., 2003). It has been validated as an essential antecedent of ATT and BI for a technology (Venkatesh et al., 2003; Wang et al., 2009). The effect of EE on the adoption intention of technology has been reported in many studies (Wang et al., 2009; Zhang et al., 2022). Consequently, the following hypotheses have been formed based on assumptions :

- **H3 :** EE has a favorable impact on BI's adoption of blended learning.
- **H4 :** EE has a favorable impact on ATT toward blended learning.

Social Influence (SI)

SI means the opinion and beliefs of the peer group, reference group, or other influential persons about a technology. In the context of blended learning, the opinions of faculty members, students, and other stakeholders can be considered as social influences. Studies have validated that SI exerts a significant positive impact on the BI to use technology and ATT toward it (Briz-Ponce et al., 2017; Lin & Lin, 2019; Zhang et al., 2022). Thus, the following propositions have been made :

- **H5 :** SI has a favorable impact on BI's adoption of blended learning.
- **H6 :** SI has a favorable impact on ATT towards blended learning.

Facilitating Conditions (FC)

FC means the "support provided by the organization to use the technology and the systems" (Venkatesh et al., 2003). For blended learning, the support made by the university or educational institution can be in the form of infrastructural development, providing access to the resources by students and teachers remotely, providing training for using the new technology, and removing bottlenecks regarding the use of the system. The empirical evidence of the significant direct effect of FC on the BI, ATT, and EE has been reported in many previous studies (Chatterjee & Bhattacharjee, 2020; Tan, 2013; Venkatesh et al., 2003; Yakubu et al., 2020; Zhang et al., 2022). Therefore, the following hypotheses have been postulated :

- **H7 :** FC has a favorable impact on BI's adoption of blended learning.
- **H8 :** FC has a favorable impact on ATT toward blended learning.
- **H9 :** FC has a favorable impact on EE.

Self-Management of Learning (SL)

SL is defined as the extent to which an individual feels he or she is self-disciplined and can engage in autonomous learning (Smith et al., 2003). In blended, online, and technology-based learning, the need for this form of self-discipline is more justified (Smith et al., 2003). People that are self-managed in their learning are predicted to develop a favorable BI for it, according to empirical data in the literature (Wang et al., 2009). As a result, the following hypothesis is put forth:

- **H10 :** SL will have a positive influence on BI to use blended learning.

Attitude (ATT)

It is referred to as a person's mental disposition toward a phenomenon. Our study has shown ATT as the mediating variable for performance expectancy and BI and between effort expectancy and behavioral intention. This lies in the fact that if a technology is as per perceived expectations and does not require special efforts, it can create a positive or negative ATT toward it, influencing BI to adopt it (Dwivedi et al., 2019). The positioning of ATT in our model is consistent with many previous studies (Dwivedi et al., 2019; Gamal Aboelmaged, 2010). Based on empirical findings, it is expected that ATT will positively influence BI and the AU of blended learning technology. Accordingly, the hypotheses proposed are as follows:

- **H11 :** ATT has a favorable impact on BI's adoption of blended learning.
- **H12 :** ATT has a favorable impact on the AU of blended learning.

Behavioral Intention (BI)

BI means the willingness of a person to use technology. The results of empirical findings establish that BI exerts a statistically significant influence on the actual use of technology (Chatterjee & Bhattacharjee, 2020; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Accordingly, based on the modified UTAUT model, the following hypothesis is constructed as presented below:

- **H13 :** BI has a favorable impact on the AU of blended learning.

Methodology

The study adopted a questionnaire as a data collection tool, typically referred to as "survey research" or "quantitative research." Mixed sampling techniques involving judgmental sampling, convenience, and snowball

Table 3. *Demographic Details of the Respondents*

Category	Number	%age	Category	Number	%age
Gender			**Education**		
Boys	123	34.75%	Pursuing Graduation	132	37.29%
Girls	231	65.25%	Pursuing Post-Graduation	151	42.66%
Residence			Pursuing Ph.D.	71	20.05%
Urban area	332	93.785%	**Experience with Blended Learning**		
Rural Area	22	6.215%	No experience	0	0.00%
			3 months	129	36.44%
Sample Size	**354**	**100%**	6 months	174	49.15%
			More than 6 months	51	14.41%

sampling are used for sample selection. The respondents for our study were students studying in different universities and colleges located in New Delhi, India. The respondents were approached online with the help of email and Google surveys because of COVID-19 restrictions. Online surveys are convenient and reduce bias (Evans & Mathur, 2018). The questionnaire used for the survey is divided into two parts; in the first part, we seek the demographic details shown in Table 3, while in the second part, the degree of agreement on different statements for different constructs is solicited on a Likert scale from 1 to 5. The assessment scale developed by Venkatesh et al. (2013) is utilized in the study to assess the students' utilization of BI and AU of blended learning strategies.

The suggested model will aid in comprehending the factors that led up to students' intentions and usage of blended learning methods. We conferred with a group of specialists, comprising researchers, academics, and other subject-matter experts, to evaluate the face validity of our scale. The panel's recommendations are put into practice to enhance the measurement scale. Therefore, it is imperative to control this menace with some possible measures (Podsakoff et al., 2003). One of the procedural remedies for controlling it is maintaining the anonymity of the respondents. For our study, the anonymity of the respondents is ensured, and efforts were made to collect unbiased, sincere, and complete responses from the respondents. Another way to control the common method bias is to improve the scale items as per the context (Podsakoff et al., 2003), which is also duly followed. Factor analysis is also employed to control it further. The total variation shown by our factor analysis is 62%, exceeding the 50% threshold set by Podsakoff et al. (2003) for data devoid of common procedure bias. By using this practice, which involves approaching 457 individuals, 383 of whom provide a response, the sample size is justified. A total of 29 of the 383 replies are deemed incomplete and are subsequently removed. A total of 354 respondents' responses serve as the basis for the final analysis. Additionally, according to Wolf et al. (2013), this sample size is sufficient for doing confirmatory factor analysis (CFA) and structural equation modeling (SEM).

Data Analysis and Results

The data mobilized from the sample is analyzed by applying CFA (for assessing the reliability and validity of the model) and SEM to verify and validate the hypotheses formulated in the study, which is considered an effective tool for validating hypotheses (Byrne, 2016; Hair et al., 1998).

Item Loadings

For individual items, loading should be greater than 0.7 (Chin, 1998); however, loadings greater than 0.5 are also considered acceptable. Out of 25 items, loadings of 21 items are greater than 0.7, and only three items, PE1, FC2, and BI2, have a loading between 0.7 and 0.5, thus acceptable. Furthermore, there is no evidence of cross-loadings of the items, which also confirms the reliability of distinct items for the different constructs. The loadings of the different items for the constructs are given in Table 4.

Reliability and Validity of the Model

The internal consistency of our model has been assessed with the help of a reliability measure of Cronbach's alpha and composite reliability (CR). The value of both measures is greater than 0.7 for all the constructs of our model (Hair et al., 1998; Taber, 2018), indicating that our model's internal consistency is very well established. To confirm the convergent validity of a model, the value of average variance extracted (AVE) should exceed 0.5 (Bagozzi & Yi, 1988). In our model, AVE is greater than this threshold value for all the constructs. Hence, for our model, convergent validity is also established.

Additionally, the variance inflation factor (VIF) is applied to identify multicollinearity. The study's findings must be verified since, in the event of multicollinearity, they could give misleading cues. All of our notions have VIF values less than 5 (see Table 4), which is acceptable according to empirical research. The discriminant validity of the model is confirmed through the correlation of the items with their respective constructs. For this purpose, we compare the square root of the AVE value of a construct with its correlation coefficient with all other constructs. Subsequently, it is observed that this value for a construct is higher than its coefficient of correlation with the rest of the constructs, which confirms the discriminant validity of the model (Henseler et al., 2009). These results are presented in Table 5.

Table 4. ***Individual Items' Loadings***

PE		*EE*		*FC*		*SI*		*SL*		*ATT*		*BI*		*AU*	
Item	**Val.**	**Item**	**Val.**	**Item**	**Val.**	**Item**	**Val.**	**Item**	**Val.**	**Item**	**Val.**	**Item**	**Val.**	**Item**	**Val.**
PE1	0.783	*EE1*	0.746	*FC1*	0.835	*SI1*	0.758	*SL1*	0.874	*ATT1*	0.821	*BI1*	0.782	*AU1*	0.763
PE2	0.791	*EE2*	0.837	*FC2*	0.762	*SI2*	0.834	*SL2*	0.802	*ATT2*	0.711	*BI2*	0.776	*AU2*	0.806
PE3	0.783	*EE3*	0.762	*Fc3*	0.817	*SI3*	0.765	*SL3*	0.798	*ATT3*	0.759	*BI3*	0.810	*AU3*	0.735
PE4	0.741	*EE4*	0.826	*FC4*	0.733			*SL4*	0.864						

Table 5. ***Reliability and Validity of the Model***

Construct	***PE***	***EE***	***FC***	***SI***	***ATT***	***BI***	***AU***	α	**CR**	**AVE**	**VIF**
PE	**0.879**							0.852	0.828	0.773	2.8
EE	0.627***	**0.887**						0.901	0.817	0.787	2.1
FC	0.538***	0.363***	**0.904**					0.847	0.854	0.818	3.2
SI	0.443***	0.432***	0.537***	**0.912**				0.796	0.805	0.831	2.6
ATT	0.426***	0.493***	0.415***	0.483***	**0.907**			0.815	0.779	0.823	2.5
BI	0.418***	0.469***	0.406***	0.421***	0.536***	**0.890**		0.887	0.843	0.792	2.8
AU	0.325***	0.428***	0.474***	0.435***	0.358***	0.547***	**0.898**	0.754	0.791	0.806	2.4

Note. *** correlation is significant at a 1% level of significance ; Values in the diagonal cell are average values extracted (AVE).

Results of Structural Equation Model (SEM)

To explore the association between different latent variables included in the study as proposed, we applied SEM with the help of AMOS software. SEM helps assess whether the model framed is appropriate and represents a true association between the latent variables included in the study. Table 6 displays the findings of the model fit indices for the measurement model and the structured model. The values of all the parameters are within the threshold, which means that our model is a good fit. Figure 2 presents the structured model that illustrates the link between the constructs with path weight.

Our model has 13 hypotheses, out of which 11 hypotheses have been supported, but the impact of SI on BI (H5) and the impact of PE on ATT (H2) is insignificant at a 5% level of significance. Five exogenous variables, PE, EE, SI, FC, and SL, together explain the endogenous variable with 69% variations in ATT, and these four factors and ATT explain 63% variations in BI. Similarly, FC explains 68% of changes in EE and ATT, and BI and FC together explain 71% of changes in AU. The value of the explained variance is greater than the suggested value of 10% for

Table 6. ***Model Fit Indices of the Measurement and Structured Model***

Fit Index	Suggested Value	Actual Computed Values of a Measurement Model	Actual Computed Values of a Structured Model
$\chi^2/d.f.$	<3 (Bollen, 1989)	2.892	2.874
GFI	>0.9 (Hair et al., 1998), >0.8 (Bollen, 1989 ; Greenspoon & Saklofske, 1998)	0.904	0.906
AGFI	>0.8 (Hair et al., 1998)	0.875	0.877
CFI	>0.9 (Hair et al., 1998)	0.923	0.928
TLI	>0.9 (Forza & Filippini, 1998)	0.917	0.921
NFI	>0.8 (Forza & Filippini, 1998)	0.938	0.939
RMSEA	<0.08 (Browne & Cudeck, 1993)	0.0539	0.0521

Figure 2. ***Structured Model with Path Values***

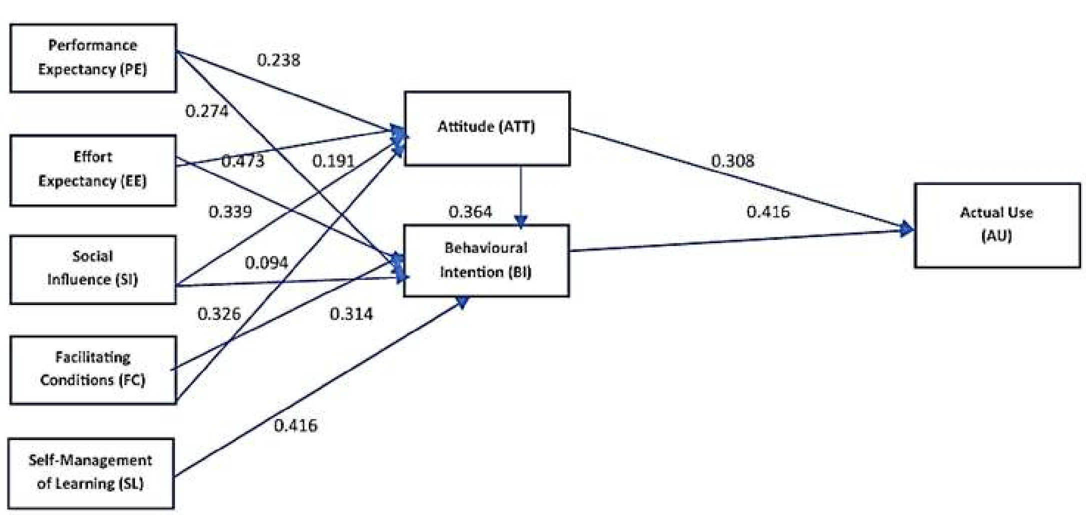


Table 7. ***Results of the Structural Equation Model***

Hypotheses	Path	β - Value	*p*-value	R^2	Result
H1	*PE – BI*	0.274	*** (< than 0.01)	**0.63**	Supported
H3	*EE – BI*	0.339	*** (< than 0.01)		Supported
H5	*SI – BI*	0.094	(> than 0.10)		Not Supported
H7	*FC – BI*	0.314	*** (< than 0.01)		Supported
H10	*SL – BI*	0.416	***(< than 0.01)		Supported
H11	*ATT – BI*	0.364	*** (< than 0.01)		Supported
H2	*PE – ATT*	0.238	(> than 0.10)	**0.69**	Not Supported
H4	*EE – ATT*	0.473	*** (< than 0.01)		Supported
H6	*SI – ATT*	0.191	** (< than 0.05)		Supported
H8	*FC – ATT*	0.326	*** (< than 0.01)		Supported
H9	*FC – EE*	0.639	*** (< than 0.01)	**0.68**	Supported
H12	*BI – AU*	0.416	*** (< than 0.01)	**0.71**	Supported
H13	*ATT – AU*	0.308	*** (< than 0.01)		Supported

Note. ***, **, * means significant at 1%, 5%, and 10% levels of significance, respectively.

all the dependent variables, which confirms that our model is stable and robust. However, the unaccounted portion of variance can be because of other variables that could not be included in our study. Table 7 reports the findings of SEM. For almost all of the links that our study looked at, the results indicate a significant direct effect. Therefore, it can be concluded that the expanded UTAUT model offers a plausible interpretation of the connection between the model's different theoretical constructions and the practical application of blended learning.

Discussion

Blended learning is beneficial in expanding education to different parts of the country where it is impossible to establish the requisite infrastructure. During the lockdown period, when fear of COVID-19 was at its peak, it was necessary to boost online education classes to stop the spread of the coronavirus. The testing period for COVID-19 has taught the entire world that virtual classes can be helpful when it is not possible to hold the classes in physical form. Besides this, these online classes are in no way less effective than physical classes and are very convenient. Many empirical studies have been conducted in the past to assess students' perceptions of blended learning. Most of these studies are based on TAM, but there is still a dearth of good studies that validated the modified UTAUT model with the additional construct of ATT. The results of our study indicate that performance expectancy has a statistically significant positive impact on the BI for blended learning, but its impact on ATT is not statistically significant. These findings are in harmony with the previous studies (Chatterjee & Bhattacharjee, 2020; Dwivedi et al., 2019; Sultana, 2020; Uğur & Turan, 2018). The impact of effort expectancy on ATT and BI is positive and statistically significant. These results are also consistent with similar studies in the area (Chatterjee & Bhattacharjee, 2020; Chatterjee et al., 2020; Sultana, 2020; Tseng et al., 2019). One possible reason for this can be exposure to blended learning, and it has been observed that exposure to technology is a vital factor in forming the ATT toward technology, and blended learning is a relatively new concept in the Indian scenario. It has also been observed that facilitating conditions positively and significantly impact ATT and BI (Tan, 2013; Yakubu et al., 2020; Zhang et al., 2022). Therefore, new facilities which promote blended learning must be provided to the students.

Along with this, workshops providing training about using online technology should also be carried out to popularise the concept of blended learning amongst the stakeholders. Social influence also positively impacts ATT and BI, but the impact of social influence is not statistically significant for our study. The impact of self-management of learning on the BI to adopt blended learning is also significant. It means that a person with greater self-management ability is more likely to accept blended learning. These findings in our study validate the empirical results of many previous studies (Smith et al., 2003). Therefore, it is vital to create a sense of self-management among the students to popularize hybrid learning. ATT toward blended learning also has a positive and significant impact on the BI and adoption of blended learning by the students (Chatterjee & Bhattacharjee, 2020; Thomas et al., 2020). The positive and significant impact of facilitating conditions on effort expectancy is also confirmed by the findings of Chatterjee and Bhattacharjee (2020).

Managerial and Theoretical Implications

The current study has many meaningful implications for governments, regulators, and educational institutions. The study helps explore the important antecedents of BI and the usage of blended learning by the students. The study establishes a positive impact of performance expectancy over behavioral intentions toward blended learning. Therefore, efforts should be made to make the students aware of the perceived benefits and the utility of blended learning and instill a positive feeling toward it. Training and workshops should also be organized to make better use of this new technology. Facilitating conditions also have a favorable impact on the adoption of blended learning; thus, efforts should be made to provide adequate infrastructural support to facilitate online teaching in educational institutions, and efforts should be made to eliminate the doubts, misconceptions, and myths about technology. The impact of self-management is also positive on blended learning, which means that a sense of discipline and self-management should be developed among the students, enhancing their chances of accepting blended learning. Finally, the impact of BI on the usage of blended learning is also statistically significant and positive. Adopting technology for blended online learning is not very involving. Therefore, with little impetus, the students can be motivated to use blended learning.

Governments and educational institutions develop policies to facilitate the incorporation of technology in the field of education. The investigation of BIs can provide valuable insights for policymakers, enabling them to make informed decisions that align with students' requirements and preferences. In light of the ongoing advancements in technology, it is imperative to proactively foresee and effectively manage the issues that may arise concerning its integration within the field of education. This research will facilitate institutions in anticipation of forthcoming transformations within the educational domain.

Limitations of the Study and Scope for Further Research

Like many empirical studies, our study is not devoid of limitations. The study has been carried out in New Delhi only; therefore, drawing generalizations based on our study alone may not be correct as availability and exposure to blended learning technology may vary in different parts of the country. Also, education is a policy matter for government and regulators and is vital for the country's overall growth; therefore, it becomes imperative to consider the role of regulators and government in the intention to use blended learning and its usage, which is another limitation.

To enhance the validity of the scale, future research endeavors may consider incorporating students from different states and nations as participants, allowing for a comparative analysis of findings with those obtained in the present study. Further research endeavors could contemplate integrating an increased quantity of distant learning establishments to augment the scope of participation and, therefore, bolster the validity of the scale. It is strongly advised that additional researchers employ this scale in other situations, including K-12 education, traditional university systems, and different countries, to authenticate the UTAUT Model. Future study initiatives may enhance the phrasing of the items to obtain more accurate replies, hence facilitating the validation process of the UTAUT instrument. Therefore, a similar study can be replicated in other parts of the country as well. Besides this, we have not considered the moderating effect of various demographic variables studied in UTAUT and UTAUT2 theories (Venkatesh et al., 2003, 2012). Studies by future researchers may consider the moderating effect of these variables. The sample size can also be increased for future studies, which will help in making appropriate generalizations.

Authors' Contribution

Dr. Anjali Shokeen and Dr. Ashish Kumar conceived the concept and developed the qualitative and quantitative research designs for the empirical investigation. Dr. Swati Khanna and Dr. Ashish Kumar extracted reputable research papers, filtered them based on keywords, and generated study-relevant concepts and codes. Dr. Anjali Shokeen validated the analytical procedures and oversaw the research. Dr. Anjali Shokeen and Dr. Ashish Kumar conducted interviews, some in vernacular language and some in English. All the others subsequently transcribed and translated the same into English. Using SPSS 20.0, Dr. Anjali Shokeen performed the numerical calculations. The manuscript was jointly written by Dr. Anjali Shokeen, Dr. Swati Khanna, and Dr. Ashish Kumar.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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Appendix

Appendix. ***Measurement Scale***

PE	**Performance Expectancy (Sangeeta & Tandon, 2021 ; Venkatesh et al., 2003 ; Wang et al., 2009)**					
PE1	Blended learning provides me with immediate and convenient access to teachers and teaching resources (Sangeeta & Tandon, 2021).	1	2	3	4	5
PE2	Blended learning will help me improve my learning performance.	1	2	3	4	5
PE3	Blended learning will help me accomplish learning objectives quickly.	1	2	3	4	5
PE4	Blended learning will help me to use my time effectively.	1	2	3	4	5
EE	**Effort Expectancy (Sangeeta & Tandon, 2021 ; Venkatesh et al., 2003)**					
EE1	It is effortless for me to attend classes in a blended or online mode.	1	2	3	4	5
EE2	The interaction with online or blended learning is clear and understandable.	1	2	3	4	5
EE3	The blended learning model helps get immediate feedback for assignments and tests.	1	2	3	4	5
EE4	It is easy for me to take part in conversations during a class in blended or online mode.	1	2	3	4	5
FC	**Facilitating Conditions (Sangeeta & Tandon, 2021 ; Venkatesh et al., 2003)**					
FC1	I have access to the technology and resources necessary for blended learning.	1	2	3	4	5
FC2	I have the necessary knowledge to use the blended learning technique.	1	2	3	4	5
FC3	Attending lectures with a blended learning mode is compatible with other technologies I use.	1	2	3	4	5
FC4	I get help from my university/teachers when I face difficulty in the blended learning mode.	1	2	3	4	5
SI	**Social Influence (Sangeeta & Tandon, 2021 ; Venkatesh et al., 2003)**					
SI1	People whose views I value prefer that I should adopt blended learning.	1	2	3	4	5
SI2	My friends and relatives think that this is the right time for me to adopt blended learning.	1	2	3	4	5
SI3	People whom I trust think that I should use blended learning in the present scenario.	1	2	3	4	5
SL	**Self-Management of Learning (Smith et al., 2003)**					
SL1	I am a self-directed person from a learning perspective.	1	2	3	4	5
SL2	I am self-disciplined in my studies and can easily balance between study and leisure time.	1	2	3	4	5
SL3	I can control my study time efficiently and can complete my assignments on time.	1	2	3	4	5
SL4	In my studies, I set goals and have a high degree of initiative.	1	2	3	4	5
ATT	**Attitude (Chatterjee & Bhattacharjee, 2020 ; Mosunmola et al., 2018)**					
ATT1	I can learn the technology needed for blended learning quickly.	1	2	3	4	5
ATT2	Blending learning is useful for teaching-learning activities.	1	2	3	4	5
ATT3	Using blended learning for teaching is a good idea.	1	2	3	4	5
BI	**Behavioral Intention (Sangeeta & Tandon, 2021 ; Venkatesh et al., 2003)**					
BI1	I intend to use blended learning in the future.	1	2	3	4	5
BI2	I expect I will use blended learning in the time to come.	1	2	3	4	5
BI3	I plan to use blended learning in the future.	1	2	3	4	5
AU	**Actual Use (Sangeeta & Tandon, 2021 ; Venkatesh et al., 2003)**					
AU1	I attended classes in the online mode as well during the lockdown period.	1	2	3	4	5
AU2	I used blended learning platforms to share my notes, tests, and assignments with teachers and other students.	1	2	3	4	5
AU3	I am accustomed to blended learning now.	1	2	3	4	5

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