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Sheshadri Chatterjee & Kalyan Kumar Bhattacharjee

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Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling

Sheshadri Chatterjee[1] · Kalyan Kumar Bhattacharjee[1]

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Abstract
Emergence of the use and application of Artificial Intelligence (AI) in higher education in India has opened new possibilities and challenges. Use of AI in will bring in effective change of governance in the entire internal architecture of Indian Institutes of higher education. The prospect of use of AI includes investigation of educational implications as to how teachers would enrich them, how students would learn, and how accurate and prompt decisions can be taken in the institutes of higher education. This is important since the workload has been multiplied due to massification of higher education. Such being the scenario, help of AI is highly essential. The question of adoption of AI in higher education is an important issue in this perspective. The purpose of this study is to explore how the stakeholders would be able to adopt it. For this, we have taken help of many adoption theories and models including 'Unified Theory of Acceptance and Use of Technology' (UTAUT) model. We have developed hypotheses and a conceptual model and got it validated through survey with the help of feedbacks from useable 329 respondents. It has been found that the model can help the authorities to facilitate adoption of AI in higher education.

Keywords AI · Attitude · Behavioural intention · Education · India

1 Introduction

In the past two decades, the higher education in India has experienced a sharp spurt of development (The Times of India 2018). Some experts opine that such development is

✉ Sheshadri Chatterjee
sheshadri.academic@gmail.com

Kalyan Kumar Bhattacharjee
kalyan_bhat@hotmail.com

1 Indian Institute of Technology Delhi, Hauz Khas, New Delhi 110016, India

due to measures initiated by private sectors. Some others opine that these initiatives are exploitative, half-cooked and substandard. It has lowered the entire structure of higher education in India (Agarwal 2005). Eroding autonomy of educational institutions, inflexible educational structures, unwise affiliating systems, slow disposal systems, and miserably low level of financing from public or even from private sectors are considered as the root causes of deteriorating standard of Indian higher education (Agarwal 2005). Hence, so far as teaching-learning scenario and administrative activities are concerned in the level of imparting higher education in India, it demands the immediate need of a paradigm shift (Menon et al. 2014). Various facets of higher education are needed to be refreshed (Silander and Stigmar 2019). For ensuring good quality of education, special attention is to be focussed on some basic parameters (Kremer et al. 2013). It is opined by the researchers that there is urgent need of implementation of latest technology in Indian higher education like Artificial Intelligence (AI) (Croxford and Raffe 2015).

With the help of AI, learning can be customized. It can cater to the specific needs for all categories of the students. Every student would enjoy receiving a completely new and unique educational approach that is tailored to individual needs of the students. AI-powered library can help in better learning experience in higher educational institutes (Cox et al. 2019). AI could help in such tailored individual approach of learning. Different applications of AI would help personalizing learning experience (Kumar 2019). However, the present AI technology may not be fully prepared for such experience and may need more time to develop. Chatbots can help to provide personalized help to solve any critical issue. It can provide solutions to individual students' needs. AI-enabled chatbot could help answering individual student's query with accuracy as the technology matures (Chrisinger 2019). This AI-powered chatbots can provide answer to the students outside of the regular classes. This kind of AI-powered system can also help in admission queries of the students, administrative decision making and so on. AI technology may also be useful for preparing 'smart content' (Kumar 2019). This could be digitized guides of textbooks, customizable digital learning interfaces at all level of education. In a way, AI could help in higher education in many ways (Ahmad 2019).

The work-load due to massification of students is increasing. In this juncture, there is need of application of modern technology like AI to address this ominous situation (Andrea et al. 2015). However, unless the students, teaching and non-teaching staffs including administrative staffs (stakeholders) adopt AI, its benefit cannot be perceived. However, it appears that there are a very few explicit studies regarding adoption of AI in higher education in Indian context (Agarwal 2005).

In this scenario, this study emphasises to identify the factors influencing the adoption of AI in higher education. The following research questions are to be addressed in this context.

- *How applications of AI would impact the higher educational system of India?*
- *What are the antecedents impacting the attitude of the stakeholders of higher educational institutes of India towards adoption of AI?*
- *Whether the behavioural intention of the stakeholders of the higher educational institutes of India can influence the adoption of AI?*

2 Literature review

AI has opened new possibilities and encouraging challenges in the affairs of higher education in India (Silander and Stigmar 2019). It has provided immense opportunities to fundamentally strengthen governance with higher effectiveness and efficiency (Nasrallah 2014). In the context of realization of applications of AI in higher education in India, we can interpret AI as computing systems capable of engaging in human-like processes such as adapting, learning, synthesizing, correcting and using of various data required for processing complex tasks (Stefan and Sharon 2017). AI is expected to help a lot to the students, teachers, administrative staffs and researchers and thus, there is a need to take help of AI in higher education (Menon et al. 2014; Stefan and Sharon 2017). Thus, the stakeholders are to be motivated to adopt this modern technology (AI) which is expected to fetch overall developments of higher educational system in India (Norris and Phillips 2013).

In all developed and developing countries, the concerned governments want to enhance quality of education. This can be achieved by adopting modern technology like AI (Cremer and Bettignies 2013). The applications of AI would modernize the system of assessment and evolution of students' capabilities. From this, the students would be able to learn as to where they are (Bigg, and J., and Tang, C. 2007). Throughout the World, to expand sphere of higher education with application of modern technologies, all the governments are expanding their investments (Buckner 2011). This will help to adopt AI for improving qualities of higher education (Bonder et al. 2001). Through different studies, it has been ascertained that learning with the help of AI is always better (Scieluna et al. 2012) than those obtained by traditional teacher-centric settings (Nasrallah 2014). India is also gaining momentum for application of AI in higher education. This would motivate the stakeholders to adopt AI. Question lies as to how the potential users' acceptance-attitude can be aligned towards this? We know that users' acceptance of modern technology is often portrayed as a major research area in contemporary Information Technology Literature (Williams et al. 2009). There are many theories and models to explain the intention of potential users to use innovative technology like AI. These theories and models are based on the sense of Information System (IS), Sociology and Psychology. We are not mentioning all these as it would elongate the discussions unnecessarily. When synthesizing acceptance behaviour of users, researchers faced many identical determinants from the existing theories and models and usually choose one of the models or theories befitting with their concerned studies ignoring contributions of other theories and models. Venkatesh et al. (2003) found that the UTAUT model could explain almost 70% of variance concerning to behavioural intention while other models and theories could explain 17% to 53% of variance concerning to behavioural intention using identical data. So, the UTAUT model (Venkatesh et al. 2003) is considered helpful to interpret intention of users to accept a modern technology like AI. Many researchers used this model with some modifications by omitting some constructs and including other new constructs befitting with the context of their studies. They have achieved good results (Chong 2013).

3 Development of hypotheses and conceptual model

From the studies of literature review, we have seen that under identical data, the UTAUT (Venkatesh et al. 2003) possesses better explanative power compared to other theories or models. There are four exogenous factors of UTAUT model which are Performance Expectancy, Effort Expectancy, Facilitating Conditions and Social Influence. The stakeholders in the present context are literate persons either the staff of institutes of higher education or the teachers or the students or the researchers. They are not expected to be influenced by the societal impacts. Hence, in our consideration, we have dropped the construct, Social Influence. We have considered its three other constructs. Moreover, the other main reason for selecting UTAUT model is that this UTAUT model includes other eight existing models (Venkatesh et al. 2003). The integrated constructs of UTAUT have characterized those constructs utilised in earlier different models. It is, in this sense, considered as an all-inclusive model for synthesizing acceptance attitude and behaviour of the stakeholders for adopting AI (Carter and Belanger 2005). We have seen that attitude has been widely acknowledged in interpreting intention of users for technology acceptance. We have taken this (Attitude) as a mediating factor (Chong 2013). Attitude has been considered as mediating variable between Performance Expectancy and Behavioural Intention; between Effort Expectancy and Behavioural Intention; between Effort Expectancy and Behavioural Intention as has been done in several studies (Alshare and Lane 2011; Cox 2012). We have included a new construct, 'Perceived Risk' as an important exogenous variable as is also found in another study (Abu-Shanah and Pearson 2009). The Facilitating Condition is proposed to have direct linkage with Behavioural Intention as has been considered in another studies (Venkatesh et al. 2012a, 2012b). In this way, we theorized that Perceived Risk, Performance Expectancy, and Effort Expectancy have impact over Behavioural Intention mediating through Attitude. Facilitating Condition has been considered to have direct impact on Behavioural Intention. This would influence the adoption (Dwivedi et al. 2017). We have relied on UTAUT model, but, we did not consider the moderators (age, gender, experience and voluntariness) used in this model. This is because we are primarily interested in interpreting how the exogenous constructs are related with attitude and behavioural intention directly. We have not considered these moderators in the present context because it is expected that attitude of the stakeholders would not be influenced by these moderators as all the stakeholders here are literate. We believe that we have been able to substantiate why we have chosen these constructs like Perceived Risk (PR), Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Condition (FC), Attitude (ATT), and Behavioural Intention (BI) to interpret Adoption of AI in Higher Education (AAHE). Now, we will try to explain the constructs separately and would develop the hypotheses and the model.

3.1 Perceived risk (PR)

Perceived Risk (PR) is usually interpreted as a perception of conviction that the user would sustain loss when he/she seeks an outcome (Warkentin et al. 2002). AI is an internet-based technology. Perceived Risk (PR) is a blending of behavioural insecurity and environmental insecurity. Unfriendly nature of the internet-functions is instrumental for behavioural insecurity and capricious nature of internet is responsible for environmental insecurity (Zhang and Maruping 2008). Studies reveal that if PR is reduced, it impacts significantly on the attitude of the users (Susanto and Goodwin 2011). Theoretical model relating to e-commerce reveals that PR negatively but significantly influences Attitude of the users (Teo and Liu 2007). Thus, perceived risks are related with the negative feeling of the users of AI in higher education. In the context of the above discussions, it is hypothesized that:

H1: *Perceived Risk (PR) has a negative and significant influence on the users' Attitude (ATT) towards Adoption of AI in Higher Education.*

3.2 Performance expectancy (PE)

It is interpreted as the extent to which a user believes that use of new system would help him or her in attaining considerable gain in his/her job performance (Venkatesh et al. 2003). Performance Expectancy is construed to be similar and identical with perceived usefulness, outcome expectancy and relative advantage. These beliefs have been used in earlier adoption theories (Cox 2012). Perceived usefulness or relative advantage are the same as Performance Expectancy (PE). It has significant and positive impact on Attitude (ATT) (Lin et al. 2011). With these considerations, the following hypothesis is developed.

H2: *Performance Expectancy (PE) has a positive and significant impact on Attitude (ATT) of users in Adopting AI in Higher Education.*

3.3 Effort expectancy (EE)

It is defined as the extent of simplicity concerning to use of a new system (Davis 1989; Davis et al. 1989). Perceived ease of use and Complexity as contained in other models carry same concept of EE (Venkatesh et al. 2003). The theoretical underpinning of the other models reveals that perceived ease of use (which is similar in concept with EE) is considered to be a significant and effective predictor of Attitude (ATT) in the field of technology adoption research (Lu et al. 2005). This relationship has been sufficiently supported in another studies (Hung et al. 2013). With these discussions, the following hypothesis is formulated.

H3: *Effort Expectancy (EE) has significant and positive influence on Attitude (ATT) towards Adoption of AI in Higher Education.*

3.4 Facilitating conditions (FC)

It is defined as the extent concerning to which an individual believes that the conducive technical and allied infrastructure are effectively available to support the usage of the new system (Venkatesh et al. 2003). The sense FC includes sense of behavioural control and compatibility of the other models (Lee and Lin 2008). A direct connection has been developed between FC and Behavioural Intention (BI) (Venkatesh et al. 2012a). Empirical Studies transpire that in matters concerning to technology adoption by individuals, there is significant influence of FC on BI (Chiu et al. 2012). It is observed that in the use of e-filing by US taxpayers, FC was meaningfully significant in interpreting BI of the taxpayers (Schaupp and Carter 2010; Carter et al. 2012). With these discussions, the following hypothesis is provided.

H4a: *Facilitating Conditions (FC) have positive and significant impact on Behavioural Intention (BI) of the users in Adopting AI in Higher Education.*

Besides, it is proposed that FC has positive and significant impact on Effort Expectancy (EE). This has been supported in other studies (Alrawashdeh et al.

2012). In analysing the factors impacting customers in using the e-services of Indonesian Airlines, it was observed that FC influence positively Effort Expectancy (EE) (Urumsah et al. 2011). It is believed that providing good quality of technical infrastructure or providing initial training to the users in adopting a new technology which comes under FC may help the users to realise the system clearly. Judged from the standpoint, it is hypothesized as follows.

H4b: *Facilitating Conditions (FC) has positive and significant impact on Effort Expectancy (EE).*

3.5 Attitude (ATT)

To perform a target behaviour positive or negative, feelings are exhibited by individuals. This covers the sense of Attitude (Fishbein and Ajzen 1975). Davis et al. (1989) in this theory of Technology Acceptance Model (TAM) postulates that Behavioural Intention (BI) is assessed by the Attitude of an individual towards using a system. Studies help us to construe that Attitude (ATT) influences the Behavioural Intention (BI) of users (Ajzen 1991) as is found in Theory of Planned Behaviour (TPB). The Attitude (ATT) acts as a strong mediating variable to interpret Behavioural Intention (BI) as is found in many other studies (Aboelmaged 2010; Cox 2012). In support of this analysis, there are many research studies (Hung et al. 2009). In reference to all these inputs and realizing the effects of Attitude (ATT) on Behavioural Intention (BI) of the users in Adopting AI in Higher Education, the following hypothesis is derived.

H5: *Attitude (ATT) of individuals in Adopting AI in Higher Education positively and significantly impacts on the Behavioural Intention (BI) of users.*

3.6 Behavioural intention (BI) and adoption of AI in higher education (AAHE)

Behavioural Intention (BI) is associated with a sense of assessing the strength of intention of individual contextual to perform a specific behaviour (Fishbein and Ajzen 1975). This Behavioural Intention (BI) is an effective predictor of performing the actual activities in which that intention is expressed (Zhang and Guterrez 2007). BI acts here as a mediating variable effectively influencing to perform the behaviour in favour of that activity to which one's intention is expressed (Nasrallah 2014). Judged from this important standpoint, the following hypothesis is formulated.

H6: *Behavioural Intention (BI) of users to Adopt AI in Higher Education positively and significantly impacts on the Adoption of AI in Higher Education (AAHE).*

After thorough discussions regarding development of the model and after explaining the mechanisms of developing the hypothesis, the conceptual model is shown in Fig. 1.

The hypotheses so conceptually formulated are to be tested and the model so conceptually developed is to be validated through appropriate methodology.

4 Research methodology

To validate the conceptual model and the hypotheses, Partial Least Square (PLS) regression analysis has been adopted. This requires survey works. For this, we have prepared some questionnaires by the help of scale development step by step

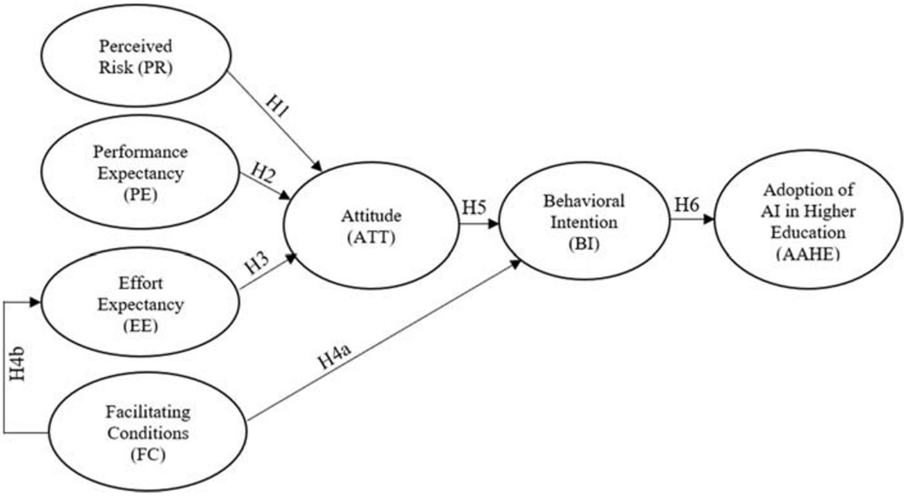

Fig. 1 Conceptual Model

architecture with assistance of opinion of some experts (Carpenter 2018). In this way, we could prepare 33 questions in the form of statements. The questions were mostly related to different aspects of AI technology for higher education sector. They were mostly related to customization of educational content, AI powered chatbot technology to answer individual student's query outside of the classroom. Few of the questions were also related to ease of using AI technology by the users, perceived risks of using AI technology in higher education such as answering queries of students, AI technology for handling admission procedure and so on. The questionnaire has also covered the area of performance of the AI technology and effort needed of different stakeholders of higher education to learn to use AI technology to cater their needs. A summary of all these questions in the form of statements have been given in Appendix B. Table 6. and Fig 2

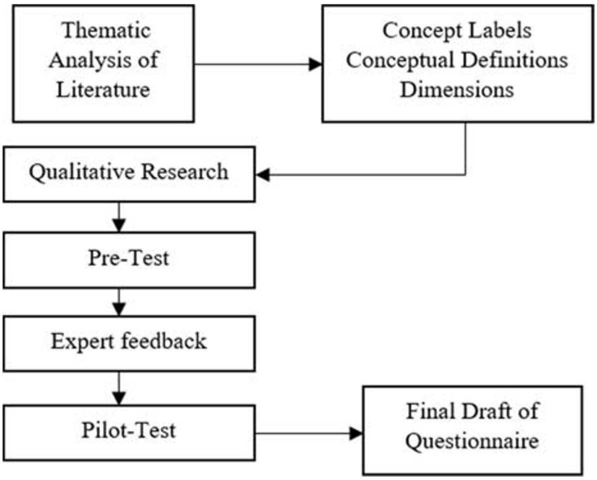

Fig. 2 Steps to prepare questionnaire, Source: Carpenter 2018 (p. 25)

Table 1 Demographic Profile of Respondents

Participants	Number	Percentage (%)
Students	205	62.31
Teachers	80	24.32
Administrative Staff	44	13.37

The step by step architecture can be visualized in the following figure.

For selection of respondents, we selected some Indian Higher educational institutes at random. We selected some renowned Universities across India situated in Delhi, Kolkata, Mumbai and Bengaluru (4 metropolitan cities of India). We contacted students, faculties (teachers) and administrative staffs of those higher institutes. They were 476 in number. We collected their emails and procured their consents for providing feedbacks against those 33 questionnaires. We sent the questionnaires with a request to send feedbacks within 60 days (August and September 2018). We received 359 responses within the stipulated period. We took opinion of some experts regarding effectiveness of those 359 responses. They opined that out of 359 responses, 30 responses are vague and biased. We did not consider those. The feedbacks of 329 responses were quantified in the usual manner in 5-point Likert scale against those 33 questionnaires. This is within the acceptable range because no. of questionnaires: no. of responses lies between 1:4 to 1:10 (Deb and David 2014). The entire survey works took November and December 2018 excluding the time of collection of feedbacks. The demographic profile of these 329 useable respondents is shown in Table 1.

4.1 Computation of LF, AVE, CR and MSV

To test if the questionnaires so prepared are reliable with reference to their own construct, we have estimated Loading Factors (LF) of all the questionnaires (items). To examine if the constructs so identified are valid, we have estimated Average Variance Entreated (AVE), Composite Reliability (CR) and Maximum Shared Variance (MSV) of each construct (Forenell and Larker 1981; Anderson and Gerbing 1988). The lowest permissible value of LF is 0.707 (Borroso et al. 2010), of Composite Reliability (CR) of each construct is 0.5 (Hair et al. 2011) and of AVE is 0.7 (Urbach and Ahlemann 2011). The value of each MSV of each construct should be less than its corresponding value of AVE. All the estimated vales are within acceptable range. It confirms that the items are reliable, and the constructs are valid and reliable. The entire results are shown in Appendix A.Table 5.

4.2 Construct reliability, multicollinearity and discriminant validity test

For confirming that the constructs so identified are reliable and consistent, we estimated Cronbach's alpha of each construct. It provides a clear indication regarding internal consistency of items which measure the same construct (Zikmund 1994). Be it mentioned here; lowest acceptable value of each construct should be 0.6 (Hair Jr. et al.

Table 2 Estimation of Cronbach's α, VIF and AV (Discriminant Validity Test)

	PR	PE	EE	FC	ATT	BI	AAHE	AVE	α	VIF	Item No.
PR	**0.893**							0.797	0.892	3.7	4
PE	0.534	**0.908**						0.825	0.901	3.9	5
EE	0.501	0.544	**0.911**					0.830	0.876	4.1	5
FC	0.533	0.561	0.556	**0.912**				0.832	0.912	4.0	5
ATT	0.511	0.517	0.533	0.493	**0.917**			0.841	0.896	4.4	5
BI	0.504	0.511	0.499	0.506	0.537	**0.924**		0.854	0.910	4.4	5
AAHE	0.590	0.562	0.501	0.561	0.546	0.504	**0.909**	0.826	0.887	4.9	4

2010). The results show that the values of α are all less than 0.6. Hence, the constructs are consistent.

If the inner meanings of the constructs so identified become very close to each other, we say that the identification of constructs suffer from the multicollinearity defect. In that case problem crops up to proceed with PLS regression analysis to validate the conceptual model. For this, Variance Inflation Factor (VIF) of each construct is to be found out (James et al. 2017). The values of VIF should be within 3.3 to 5 (Kock and Lynn 2012) which is said to be the acceptable range. The entire results are shown in Table 2.

When each item is found to be strongly related with its own construct and weakly related with other constructs, we say that the discriminant validity test has been established. To test this, Average Variance (AV) of each construct is to be computed. AV is square root of corresponding AVE. If it is found that AV of each construct is more than the correlation coefficients of that construct with other constructs, we say discriminant validity test has been established (Gefen and Straub 2005). It appears from the value of AV of a construct shown in diagonal place is in the concerned table is greater than the corresponding correlation coefficients shown in off-diagonal places. It confirms the discriminant validity test. (Fornell and Larcker 1981). The entire results are shown in Table 2.

The values of VIF lie between 3.5 to 5 which indicates that the data is free from multicollinearity defect.

4.3 Structural equation Modelling (SEM)

Relation among the latent variables is assessed with the help of SEM. The estimation is done with the help of AMOS 22. SEM verifies if the structure of the model is in order and correct. It also helps to verify if the structure has been capable of representing the data. The results are highlighted in Table 3.

This Table 3 shows that the parameters are all within standard acceptable limits which confirms that we have been able to establish adequacy of the model fit.

With all these discussions and after computation of different parameters, we represent the structural model with path weights and level of significance. This is shown in Fig. 3.

Table 3 Model Fit Summery Relating to the Research Model

Fit Index	Recommended value	Value in the model
Chi-Square (χ2)/Degree of Freedom (*df*)	≤ 3.000 (Kline 2005)	2.016
Goodness of Fit Index (GFI)	≥ 0.900 (Hoyle 1995)	0.907
Adjusted Goodness of Fit Index (AGFI)	≥ 0.800 (Segars and Grover 1993)	0.842
Comparative Fit Index (CFI)	≥ 0.930 (Hair et al. 2006)	0.957
Tucker Lewis index (TLI)	≥ 0.950 (Sharma et al. 2005)	0.962
Root Mean Square Error (RMSE)	≤ 0.070 (Steiger 2007)	0.024

We have also estimated the R^2 values. R^2 is known as Coefficient of Determinant. It means the proportion of variance in the dependent variable which can be predictable from independent variable or variables. To what extent the dependent variable can be explained by independent variable or variables is known from this coefficient (R^2). Power of explanation is provided from the knowledge of value of R^2. The detailed results are shown in Table 4.

4.4 Result of the study

The results show that there are seven hypotheses H1, H2, H3, H4a, H4b, H5 and H6. From the analysis, it appears that there is insignificant effect of PE on ATT of the users to use AI in higher education. This is because the concerned path coefficient is as low as 0.021 with significance level p > 0.05 (ns). That is why this hypothesis H2 has not been supported. It appears that EE can be explained by FC to the extent of 74%. PR has negative impact on ATT as the concerned path coefficient is −0.206 with significance level $p < 0.001$. The three exogenous

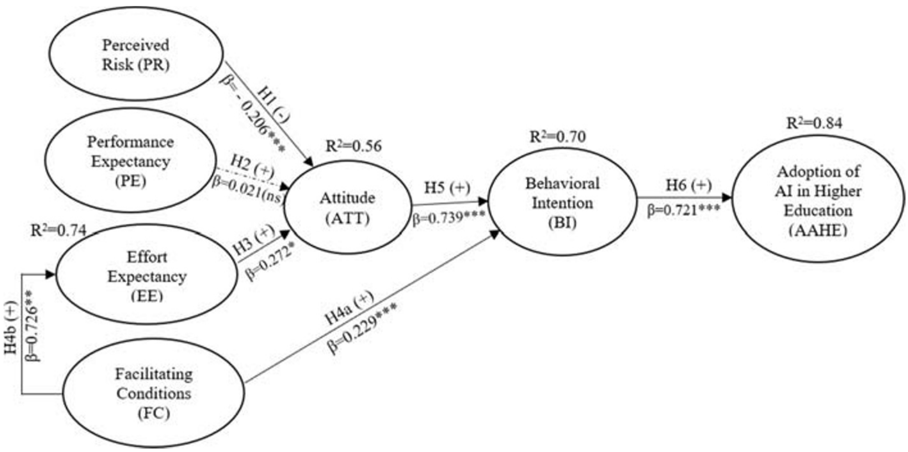

Fig. 3 Structural Model with Path Weights and Significance Level ns $p > 0.05$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Table 4 Path Weights with Estimation of R^2

Effect	Hypothesis	Path	Sign	β-value	Significance Level	R^2	Remarks
Effect on ATT						0.56	
By PR	H1	PR → ATT	–	0.206	***(p < 0.001)		Supported
By PE	H2	PE → ATT	+	0.021	ns		Not Supported
By EE	H3	EE → ATT	+	0.272	*(p < 0.05)		Supported
Effect on EE						0.74	
By FC	H4b	FC → EE	+	0.726	**(p < 0.01)		Supported
Effect on BI						0.70	
By FC	H4a	FC → BI	+	0.229	***(p < 0.001)		Supported
By ATT	H5	ATT → BI	+	0.739	***(p < 0.001)		Supported
Effect on AAHE						0.84	
By BI	H6	BI→AAHE	+	0.721	***(p < 0.001)		Supported

variables like PR. PE and EE can explain ATT to the tune of 56%. On the other hand, ATT and FC can explain BI to the tune of 70%. The medicating variable BI can explain the target AAHE to the tune of 84%. The explanative power of the model is 84%. ATT has greater influence on BI compared to influence of FC on BI since the concerned path coefficients are 0.739 and 0.229 respectively. It appears that influence of ATT on BI is the highest as the corresponding path coefficient is highest 0.739. The model so provided is effective as its explanative power is comparatively appreciable, that is, 84%.

5 Key findings

The results highlight that

- Perceived Risk (PR) and Effort Expectancy (EE) have significant impact (for PR, it is negative and for EE, it is positive) on the attitude (ATT) of the stakeholders of higher education institutes for adoption of AI.
- Performance Expectancy (PE) has not significant impact on the attitude (ATT) of the stakeholders of higher education institutes for adoption of AI.
- Facilitating Conditions (FC) has significant and positive impact on Effort Expectancy (EE) and on Attitude (ATT) of the stakeholders of higher education institutes for adoption of AI.
- Behavioural Intention (BI) has significant and positive impact on the adoption of AI in higher education.

The model is a simple model helpful for the concerned authorities to implement adoption of AI that would improve the overall performances of higher educational institutes of India.

6 Limitations and directions for future research

With this study, we have provided a model with high explanative power. However, still it can hardly be stated that this research study is not without some specific limitations. In India, use of AI in higher education is in crawling stage. No adopters of AI in higher education are found till date in India. Hence, all the syntheses are predictive. In the survey works, we obtained 329 usable responses. All these inputs obtained were from non-adopters of AI in higher education. Thus, this result cannot be generalised. It should be used to adopters with appropriate caution. When data could be gathered from actual adopters of AI in higher education, we need to extend the model by inclusion of at least another construct "actual use" and this model so proposed is needed to be validated with inputs from adopters. This uncovered issue is left for future researchers to deal with. Besides, there was still some scope to include other boundary conditions for adoption of AI in higher education. They are like 'image', 'output expectancy' and so on. These were not considered since without such consideration; the explanative power of the model became 84% which is high. The proposed model needs to be revalidated after inclusion of these factors to assess if the explanative power can be enhanced. It is left for the future researchers to cover these points. We have considered usable 329 inputs. This consideration can hardly represent the general picture of Indian Higher Education system. Future researchers are to conduct investigation with longitudinal time and longitudinal data which might represent the model in a more generic form. We have taken help of UTAUT model (Venkatesh et al. 2003) but did not consider the four moderators used in UTAUT presuming, they will not affect the literate stakeholders in this context. It is not a fact that non-consideration of the effects of these moderators would fully undermine the outcome of our theoretical model. But it may be construed as a limitation since we have not used UTAUT model (Venkatesh et al. 2003) in its eternity. Future researchers might use these moderators and examine to what extent the result, if at all, can be improved. The explanative power of our model is 84%. Critiques might criticise that by inclusion of other boundary conditions, the explanative power of this theoretical model could have been enriched. Future researchers might nurture this point to provide the model with cent percent explanative power.

7 Theoretical implication

In this study, we have taken help of UTAUT model (Venkatesh et al. 2003). This model has proposed to include a collection of four constructs PE, EE, FC and Social Influence (SI). Out of these four constructs, PE and EE represent technological context. The remaining two constructs FC and SI represent implementational context (Schaper and Pervan 2007). The UTAUT model has not explicitly included determinants of adoption covering individual context. In this study where students, teachers and administrative staff of institutes of higher education are the principal stakeholders in adopting AI in higher education, the factors affecting individual context are required for consideration. That is why in our theoretical model, we have included Attitude (ATT) as one of the mediating variables. This has been done in prior research (Alshare and Lane 2011). Our proposed theoretical model has performed better since its explanative power is as high as 84%. This is presumably for the fact that we have considered in this study some better-suited constructs to explicitly explain the adoption behaviour of the stakeholders. We have not straight forward copied out UTAUT model. No research on adoption of AI in higher education in Indian context has been developed so far explicitly. In that sense, this proposed theoretical model is considered to contribute theoretical knowledge to stakeholders on the adoption of AI in higher education in India. We have considered a construct Perceived Risk (PR) as an exogenous variable. It is claimed to have strengthened the overall performance of this proposed theoretical model. Trust of the stakeholders in the adoption of AI is considered as an important factor. But we have here considered Perceived Risk (PR) since some researchers have equated trust with behaviours of stakeholders which convey risk-taking (Lewis and Weighert 1985). Therefore, inclusion of PR as an exogenous variable is a special contribution in our proposed theoretical model. Again, the effect of impact on EE by FC has not been considered in UTAUT model or even in its extension. This indicates that knowledge, available infrastructure and system opportunities collectively construed as FC render the users easy to use AI in higher education. There are enough possibilities that the users would more adopt it. Besides, it appears that FC alone can explain EE to the extent of 74% and hence it may be considered that such consideration (effect of FC on EE, H4b) has enriched in explaining the Adoption of AI in higher education by the stakeholders. This is an important contribution of this theoretical model. Whether the stakeholders would align to adopt AI in their higher studies or in their administrative works cannot be influenced by the society. That is why one exogenous variable of UTAUT, that is, SI has not been considered in our theoretical model. Inclusion of ATT and BI as endogenous variables is claimed to have increased the performance of our theoretical model as its explanative power is as high as 84%. Consideration of moderators has not been made in our theoretical model though they were considered in UTAUT model (Venkatesh et al. 2003). It is argued that this model is beneficial to the concerned field where these moderators would produce no effective sense. This is inferred because without consideration of these moderators, we have been able to achieve 84% explanative power. This is considered considerably high. Non-consideration of these moderators is considered a special contribution to this theoretical model.

8 Practical and policy implication

Our findings highlight that Attitude plays a decisive role in achieving goal of this study. This factor acts as an important mediator. This variance ‘Attitude’ has significant impact on Behavioural Intention of the individuals to adopt AI in higher education in India. It acts as a strong determinant of Behavioural Intention (H5). This leads to construe that authorities of institutes of higher education would find it helpful and beneficial to shape attitude of the stakeholders to mould their intention and behaviour. It is observed in our model that Performance Expectancy and Effort Expectancy act as antecedents of Attitude (H2 and H3). These two hypotheses lead to imply that individuals concerned put much importance to the technological issues. It assesses to what extent the adoption is useful (Performance Expectancy) and hazardless to use (Effort Expectancy). This is because these two exogenous variables (PE and EE) are concerned with technological issues of the AI. Hence, designers, developers and system managers of institutes of higher education are to concentrate on the usefulness of the system. They should be sincere in minimizing complexities concerning to exploration. This would help to manage the issue of acceptance and use of this innovative technology. To accomplish these, the authorities should be serious to accurately provide the essential requirements of the users to the developers. The selection of the technologies should be more consistent with the needs of the users. The design should not be complex. The users in using the system may not feel difficulties. The users are to be made aware regarding the capabilities of the system. This awareness of the users may be developed with the help of publication of product brochures, success stories and live demonstration (Alshare and Lane 2011; Dwivedi et al. 2015). The negative impact of Perceived Risk on Attitude (H1) implies that the authorities of institutes of higher education as well as of Human Resource Development Department of Government of India are to promote the privacy and security measures. The measures to be taken to address security and privacy challenges should be made known to the stakeholders. This would save the users from being victims of cyber frauds and security infringements. The stakeholders are to be trained regarding issues of cyber securities. Appropriate policy is to be framed to castigate the perpetrators appropriately. This would enhance the confidence level of the users of AI in higher education.

9 Conclusion

AI solutions have opened a new horizon of opportunities for teaching, learning as well as for administrative works in institutes of higher education, in India. The conception of use of AI is still in incubation stage. We have explored the possibilities of adoption of AI in higher education. We have provided a model identifying the determinants that would help and accelerate adoption of AI in higher education. We have mentioned that the institutes of higher education would enjoy effective advantages if they use AI. Again, it is essential to be kept in mind that education is basically human-based endeavour. It is not basically dependent on technology solution. Education is considered as human-centric issues. Sole reliance on technology in education would not fetch expected results. Whatever would be the cutting-edge advancements of technologies, humans are scheduled to identify problems. Critiques would be there to identify risks. Humans would raise many questions surrounding issues of higher education to nurture creativity. All these are supposed to be augmented by humans and yes, solutions might be obtained with the help of technology accurately. In this respect, AI would play or might play a momentous role. Human-based endeavour and machine-based solutions should stand side by side to effectively nurture higher education in India to achieve success. Thus, the rapid hype of AI would be expected to ensure unquestioned panacea to those who are advancing through the path of higher learning, riding on the wheels of reality. Identifications of problems and issues in higher education are related with human efforts. Rapid and accurate solutions might come from inputs of AI. Judged from this point, apart from nurturing human skill and talent, applications of AI are essential. Hence, there is need to analyse how to effectively adopt it in the field of higher education. This study has given focus on the later part, that is, issues of adoption of AI in higher education. In this study, we initially hypothesized that Performance Expectancy would significantly impact positively on the Attitude (H2). But, after validation through statistical analysis, it is observed that PE has insignificant impact on ATT (H2). This is presumably why the stakeholders have yet not fully adopted AI technology in higher education in India. They have not been able to get scope to test if by using this technology (AI), their performance would be improved. We gathered from survey the inputs delivered through prediction. The analysis is predictive in this context. It is expected, when there will be complete adoption of AI in higher education in India, Performance Expectancy would positively and significantly impact on the attitude of the stakeholders to intend to adopt AI in higher education. Further, it is expected that the authorities and policy makers would depend on this proposed model to ensure adoption of AI in higher education in India. In brief, it is concluded as:

- The applications of AI in higher education system would easily enrich the stakeholders of higher educational institutes as they would get scope to accurately and quickly exchange of knowledge through AI which would improve the intellectual health of higher education system if such acquired knowledge is applied in practice strategically.
- Perceived Risk (PR) and Effort Expectancy (EE) have impact on the attitude of the stakeholders of higher educational institutes of India to adopt AI. This attitude would motivate the users' intention to use and adopt AI.
- The facilitating conditions would also help the users to exhibit acceptable and favourable intention to use AI in higher education system and the facilitating conditions would positively affect the users' effort expectancy.

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Appendix

Table 5 Estimation of LF, AVE, CR and MSV

Constructs/Items	LF	AVE	CR	MSV
Perceived Risk (PR)		0.797	0.806	0.348
PR1	0.911			
PR2	0.917			
PR3	0.890			
PR4	0.850			
Performance Expectancy (PE)		0.825	0.859	0.316
PE1	0.927			
PE2	0.923			
PE3	0.902			
PE4	0.900			
PE5	0.890			
Effort Expectancy (EE)		0.830	0.890	0.309

Table 5 (continued)

Constructs/Items	LF	AVE	CR	MSV
EE1	0.907			
EE2	0.909			
EE3	0.919			
EE4	0.921			
EE5	0.899			
Facilitating Conditions (FC)		0.832	0.893	0.315
FC1	0.907			
FC2	0.904			
FC3	0.911			
FC4	0.919			
FC5	0.920			
Attitude (ATT)		0.841	0.876	0.298
ATT1	0.911			
ATT2	0.923			
ATT3	0.924			
ATT4	0.809			
ATT5	0.901			
Behavioural Intention (BI)		0.854	0.901	0.254
BI1	0.911			
BI2	0.927			
BI3	0.929			
BI4	0.924			
BI5	0.930			
Adoption of AI in Higher Education (AAHE)		0.826	0.861	0.348
AAHE1	0.903			
AAHE2	0.907			
AAHE3	0.911			
AAHE4	0.913			

Table 6 Summary of questionnaire

Items	Statements	Response [SD][D][N][A][SA]
PR1	I believe AI-powered educational content is not always correct	[1][2][3][4][5]
PR2	Application of AI for admission purpose is confusing	[1][2][3][4][5]
PR3	I shall not prefer to use AI application for administrative purpose	[1][2][3][4][5]
PR4	Use of AI technology for answering student's query is risky	[1][2][3][4][5]
PE1	It will be hard to develop a perfect AI application catering the needs of administration in higher education	[1][2][3][4][5]
PE2	AI powered learning activity will enhance the efficiency of higher education system	[1][2][3][4][5]
PE3	Educational content prepared by AI technology is useful	[1][2][3][4][5]
PE4	Using AI powered chatbot technology I can get accurate answer	[1][2][3][4][5]
PE5	Smart educational content can be prepared using AI technology	[1][2][3][4][5]
EE1	AI technology is not easy to learn	[1][2][3][4][5]
EE2	I need to put a lot of effort to learn AI technology	[1][2][3][4][5]
EE3	If I know the basic AI technology, I can easily learn AI based applications	[1][2][3][4][5]
EE4	I can have my query answered quickly using AI-chatbot technology	[1][2][3][4][5]
EE5	Individualized content can be prepared using AI-technology	[1][2][3][4][5]
FC1	My institute has all the necessary resources to use AI technology for smart content creation	[1][2][3][4][5]
FC2	I can have all the required resources to develop AI based smart content	[1][2][3][4][5]
FC3	My institute sponsor any AI related learning opportunity	[1][2][3][4][5]
FC4	All the classrooms of my institute are equipped with necessary devises for using AI technology for teaching purpose	[1][2][3][4][5]
FC5	My institute encourages its staff to use modern technology	[1][2][3][4][5]
ATT1	I can learn AI technology quickly	[1][2][3][4][5]
ATT2	AI technology is useful for teaching-learning activities	[1][2][3][4][5]
ATT3	Using AI technology for query answering is a good idea	[1][2][3][4][5]
ATT4	People should learn AI technology for the future need of the higher education sector	[1][2][3][4][5]
ATT5	AI technology can cater the individual needs more accurately	[1][2][3][4][5]
BI1	I believe AI technology is very easy to learn by beginner	[1][2][3][4][5]
BI2	I am willing to use AI technology for developing smart content	[1][2][3][4][5]
BI3	I believe AI technology could be used for answering student's query	[1][2][3][4][5]
BI4	I shall recommend all the stakeholders in higher education to explore AI technology for their learning purpose	[1][2][3][4][5]
BI5	I intend to use AI technology for teaching-learning purpose by next couple of years.	[1][2][3][4][5]
AAHE1	Application of AI in higher education is good for society	[1][2][3][4][5]
AAHE2	Application of AI in higher education will make education more interactive	[1][2][3][4][5]
AAHE3	Application of AI in higher education will make it cost effective	[1][2][3][4][5]
AAHE4	Application of AI in higher education will make the teaching-learning activity more interesting	[1][2][3][4][5]

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Dr. Sheshadri Chatterjee is a post-doctoral research scholar at Indian Institute of Technology Kharagpur, India. He has completed PhD from Indian Institute of Technology Delhi, India. He is having work experience in different multinational organizations such as Microsoft Corporation, Hewlett Packard Company, IBM and so on. Sheshadri has published research articles in several reputed journals such as Government Information Quarterly, Information Technology & People, Journal of Digital Policy, Regulation and Governance and so on. Sheshadri is also a certified project management professional, PMP from Project Management Institute (PMI), USA and completed PRINCE2, OGC, UK and ITIL v3 UK. He can be contacted at: sheshadri.academic@gmail.com.

Dr. Kalyan Kumar Bhattacharjee has completed his PhD in management from Department of Management Studies (DMS), IIT Delhi in the year 2015. Currently, he is serving Indian Institute of Technology Delhi as Joint Registrar. Prior to joining IIT Delhi he was serving Lal Bahadur Shastri Institute of Management (LBSIM) as Assistant Professor (in Systems). He has total 28 years of experience in academic administration and teaching.