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# Gravitating towards blockchain in sustainable higher education: a hybrid SEM-ANN technique

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## Abstract
The current study investigates the determinants affecting users' intention to adopt blockchain technology in higher educational institutions (HEIs) through structural equation modeling (SEM), Artificial Neural Network, and the extended UTAUT2 model. The results from the SEM analysis serve as the inputs for the ANN models, and the root mean square error (RMSE) is utilised to evaluate the predicted accuracy of the ANN models. Data were gathered from university students in Bangladesh with a structured questionnaire. The findings demonstrate that performance expectancy, hedonic motivation, facilitating conditions, perceived trust, self-efficacy, and perceived risk significantly influence behavioural intention. Furthermore, perceived trust, self-efficacy, and perceived risk significantly influence actual usage. This study enhances existing knowledge by proposing a novel path association, providing valuable insights for blockchain developers and higher educational institutions to devise effective policies for the successful implementation of blockchain technology in sustainable education of developing nations.

**Keywords** Blockchain, Sustainable education, Emerging technology, Artificial Neural Network (ANN)

## 1 Introduction
At present, individuals are inclined to a diverse set of knowledge with the robust expansion in technology. Over the last few decades, securing information transparency and accountability in all aspects of life has been one of the most challenging tasks, especially in the educational sector. Moreover, the education sector holds the highest priority as a nation can build up the knowledge of its young generation. So, technology integration in the education landscape has become a cornerstone of the digital transformation of the twenty-first century (Fernández-Batanero et al., 2024). The world has undergone a notable change in the paradigm of global education systems, reflecting a growing need for technology adaptability and e-learning content in this sector. Therefore, blockchain has become a more popular means of e-learning platform because of its efficiency, security, and openness in managing educational information.

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As a result, blockchain has a positive influence on students' learning performance along with its secured and transparent decentralization of information which will lead to a sustainable education system [50], (Bhaskar et al., 2021). While traditional e-learning systems might have complications without having secured and authorized access to information [8], blockchain technology will make it more reliable for both educational institutions and administrative personnel in handling student information with data security, data integrity, and data efficiency [9, 19]. Thus, blockchain is a prerequisite for creating a smart campus in higher educational institutions, which will create a lifelong learning facility [10, 24]. It yields substantial benefits for academia and industry by enabling the secure and accessible sharing of educational materials and students' credentials [6, 64, 80]. This makes blockchain an essential tool for information management in the educational sector particularly for the developing countries' higher educational institutions [71].

Since the development of blockchain, several recent applications of blockchain have been studied in the last decade covering different areas such as the pharmaceutical industry [1, 38], healthcare monitoring [16, 84], garments industry [17], privacy preservation [44, 95], intellectual rights protection and network knowledge transformation [57], vehicular communication [32], and real estate sector [40].

Hence, contemporary literature exhibits that blockchain technology has widespread applications across various sectors. However, its adoption in educational institutions remains relatively low, particularly in developing countries due to high implementation challenges. The challenges are related to the technological, regulatory, organizational, and environmental aspects of the blockchain [75]. However, blockchain enables sustainable management of information and verification of student credentials [99]. Hence, blockchain adoption in education is worth further research. However, there are very few empirical studies related to blockchain in the educational sector in developing countries, particularly in Bangladesh. Since, unlike developed countries, Bangladesh lacks technological expertise, limited capacity, and immature governance infrastructure, the country lags in blockchain technology adoption [85]. Therefore, this study aims to expand the knowledge of the behavioral dynamics underlying blockchain adoption in higher education in Bangladesh.

Besides, this study identifies the students' behavioral intentions of using blockchain. Also, this empirical research will contribute to the current knowledge by proposing a new paradigm in the educational sector. In addition, the purpose is to help industry stakeholders, lawmakers, and educational institutions better utilize blockchain technology to improve student learning.

In this study, "Unified Theory of Acceptance and Use of Technology" (UTAUT2) has been employed as a conceptual model through which existing literature on blockchain adoption has been enriched by incorporating three new variables- "Self-efficacy", "Perceived Trust" and "Perceived Risk". From the findings of existing literature, we found that self-efficacy has a significant role in new technology adoption [5, 28]. Additionally, lack of trust and risk are major barriers to technology adoption [46]. Hence, SE, PT, and PR are incorporated into the model. There was no study that tested those additional factors by adopting two methods in assessing students' intention to blockchain adoption. Finally, this study addresses the gaps in the literature by extending the basic UTAUT2 model with new factors and testing and validating the model using two methods, SEM and ANN. Furthermore, this study provides prominent insights regarding developing countries as Bangladesh is a representative of a developing nation and is in transition to graduating from the least developed countries group [94].

The following sections of this paper are as follows: Sect. 2 presents a conceptual model and literature review; Sects. 3 and 4 represent the hypothesis developments and methodology respectively, Sect. 5 and 6 represent data analysis and discussion. Finally, the conclusion of the study, limitations, and future research scopes are presented consecutively.

## 2 Conceptual framework and hypothesis formulation

Numerous studies on blockchain technology adoption have been conducted after gaining its very first attention in 2008 as of having significant influences on most industries [76, 88] that offers several advantages, such as increased security, provenance, efficiency, transparency, cost reduction, automation, and trust [48]. In today's interconnected world, adopting secured technology like blockchain is essential across all industries, especially in the higher educational sector, where knowledge sharing holds the highest importance worldwide [27, 33, 87].

A blockchain is a decentralized database containing records dispersed over multiple processing nodes, structured as a chronological chain of blocks. Every block has data that has been hashed cryptographically. Blockchain proponents see it as a key component of trustless transactions, providing a wealth of opportunities for safe and practical value transfers between parties [31]. Blockchain reduces the need for middlemen by enabling data sharing across companies within an ecosystem, doing away with the necessity for a central authority. This decentralized structure reduces knowledge asymmetries and guarantees cost-effective operations. Furthermore, blockchain is a strong and dependable solution since it is resilient to disruptions in centralized databases [27]

However, to make more user-friendly adoption, identification of the driving factors of using a disruptive technology has been seen as an essential need [25],C. [56]. Blockchain adoption in the educational sector has been examined through several lenses for instance: perceived usefulness, attitudes, perceived facilitating condition, perceived effort expectancy, social influences, performance expectancy, quality of system and information, users' satisfaction, technology trust, and service quality [13, 29, 65, 72]. A summary of current literature on the factors affecting blockchain adoption in the educational sector has been depicted in Table 1.

To inspect the acceptance and use intention of technology, especially in education and information sharing, several conceptual models have been used. These conceptual models will reveal the prominence of users' perception as a theoretical ground explaining the real scenario [78]. The UTAUT2 model was employed to determine the constructs of the students' behavioural intentions to utilise blockchain technology, as it possesses predictive power. This model was also implemented in numerous studies to evaluate blockchain adoption [9, 18, 97]. Besides, recommended that the model be modified and expanded to be applied in particular in the adoption context, which makes it more suitable for this study. Therefore, UTAUT2 has been modified, which is a fresh theoretical approach. The proposed conceptual model incorporates components from previous studies on technology adoption, but it has been adapted to account for the unique conditions of the educational field. Besides, another author [91] stated that the initial UTAUT2 theory entails seven components: PE, EE, SI, FC, HM, Price Value (PV), and

**Table 1** Summary of the literature on blockchain integration in higher education. *Source*: Authors developed from prior literature

| Authors & year | Theoretical frameworks | Factors used |
|---|---|---|
| [13] | Extended TAM | Perceived ease of use (PEoU), effort expectancy (EE), perceived cost, attitudes, behavioral intention to use (BI), perceived convenience, perceived usefulness (PU), facilitating condition (FC), and social influences |
| [89] | Expanded TAM | Trialability, BI, relative advantage, compatibility |
| [12] | Extended TAM and UTAUT | PU, PEoU, performance expectancy (PE), EE, social influence (SI), FC, blockchain efficiency, BI, system quality, information quality (IQ), service quality (SQ), user satisfaction, and technology trust |
| [41] | Integrated TAM and TOE framework | Relative advantage, PU, PEoU, scalability concern, top management support, competitive pressure, and regulatory policy |
| [29] | TAM and Emerging Technologies Expectations Model (ETEM) | Technological evolution, technological revolution, social evolution, social revolution, ease of use and knowledge |
| [65] | TAM and IS | PU, PEoU, IQ and SQ |
| [92] | UTAUT | FC, EE, PE, SI, and trust |

Technology Acceptance Model (TAM), Emerging Technologies Expectations Model (ETEM), Information System (IS) Success Model

Habit (HT). The goal of adding Perceived Risk, Perceived Trust, and Self-efficacy unique elements to the model is to increase its applicability by better capturing the nuances of the educational field. SE is widely applicable to the education sector as the adoption of new technology is supplementary to the industry [73]. Besides, students' efficacy will determine their intentions to use blockchain in the educational sector. Similarly, the system will handle sensitive students' data. Trust and risk, thus, affect users' intention and actual use behavior (AUB).

Though blockchain technology is in the early phase of development, its application in the educational sector is quite significant. Some universities are actively investigating how it may help with digital transformation. To tackle the problem of fake credentials, most of these systems have been focused on the verification of student credentials, such as degree documents. Some blockchain-based platforms in education are Blockcerts [61], Disciplina [67], Educhain [59], EduCTX [71]. Despite the widespread applications of blockchain across the globe, its adoption in the higher educational sector, particularly in developing countries is very low. Blockchain adoption in education assists employers in selecting the right employees and verifying potential candidates' credentials easily [75]. Therefore, information management and credential verification blockchain plays a vital role but users' perception towards blockchain adoption remains relatively new and underexplored. This study explores the behavioural intentions of Bangladeshi students in higher educational institutions, aiming to fill a notable gap in the existing literature. Consequently, the subsequent hypotheses have been developed to explore the behavioural intention and actual usage of blockchain in higher educational institutions among students in Bangladesh.

### 2.1 Performance expectancy (PE)

PE implies a general perception that people adopting technology will upgrade their performance [68]. PE is a tool that encourages users to adopt this disruptive technology to be innovative and effective [60]. Besides, the study of Toader et al. [88],Abu Afifa et al. [3] and Wamba & Queiroz (2019) expressed that PE has a positive impact on users' blockchain use intention. Several scholars, such as Pieters et al. [68], Alam et al. [5], Merhi et al. [63], Queiroz & Fosso Wamba [4, 69]) expressed that, PE is one of the indicators to identify consumers' intentions to use blockchain technology because a new technology has a greater acceptance when it meets up the consumers' expectation. So, the hypothesis can be demonstrated as below:

*H1* PE positively impacts BI to adopt blockchain in higher educational institutions.

### 2.2 Effort expectancy (EE)

EE is the level of convenience and ease of use of a system [7, 90]. When people experience the ease of using a new system, the acceptance level will be higher among them. Several research investigations have consistently validated the impact of effort expectation on the intention to embrace blockchain [3, 68, 88]. Other authors such as Alam et al. [5], Merhi et al. [63] also state similar viewpoints on the influence of effort acceptancy on behavioral intention of using blockchain in higher educational institutions. On the contrary, BI is not influenced by EE which is confirmed by several studies [42, 82]. Therefore, the hypothesis is:

*H2* EE positively impacts BI to adopt blockchain in higher educational institutions.

### 2.3 Social influence (SI)

SI refers to the extent to which a person acknowledges the opinions of other significant individuals that they should use a novel application [90]. SI predicts the behavior of people and what they usually see in society [5]. It is the extent of identifying motivation by other people's actions and beliefs for using a new technology [91]. According to the study of Merhi et al. [63], C. Lee & Coughlin [56], SI is positively related to BI. Besides, most of the young people are influenced by the beliefs and actions of peer groups than the old people [11]. On the contrary, SI has no positive impact on students' BI, which also supports the findings of the study of [7] and contradicts [5] and Merhi et al. [63]. From these statements, we can put up the below hypothesis:

*H3* SI positively impacts BI to adopt blockchain in higher educational institutions.

### 2.4 Hedonic motivation (HM)

The level of delight experienced by employing technological innovation is explained as HM, and it is recognized as playing a crucial influence in shaping technology adoption (Venkatesh et al., 2012). Users feel motivated to embrace new technology due to have potential influence on their comfort and fulfillment of enjoyment [4, 14], HM positively influences the intention of using new technology [5, 63]. However, several studies do not support this positive association between HM and BI on blockchain adoption found in the public sector [18]. The hypothesis for this can be demonstrated below:

*H4* HM positively impacts BI to adopt blockchain in higher educational institutions.

### 2.5 Habit (HT)

HT has been conceptualized as a perceptual variable that reflects prior experiences. A prior experience becomes a habit when individuals plan to carry out their activities spontaneously and it is described as a state where people act and behave intrinsically according to their nature and learning experiences (Venkatesh et al., 2012). HT has a positive influence on BI by using blockchain [5]. Khalid et al. (2020) found that HT has no significant and positive relationship with BI. Consequently, we can put up the below hypothesis:

*H5* HT has a positive relationship with the BI to use blockchain in higher educational institutions.

### 2.6 Facilitating condition (FC)

When a person finds the capabilities in existence of organizational and technological infrastructure that make it easier to use the new system, it is denoted as FC (Venkatesh et al., 2003). When it comes to the operational development of a system, FC has a significant influence on PEoU, which leads to a BI shift toward digital learning platforms. FC has a positive relationship with the BI use of blockchain in higher educational institutions [5] Besides, FC is positively related to BI but not to AUB found in the study conducted on e-learning adoption by (M. [96, 98]). Drawing on these results, we put up the following:

*H6a* FC positively impacts BI to adopt blockchain in higher educational institutions.

*H6b* FC positively impacts the AUB of blockchain in higher educational institutions.

### 2.7 Perceived trust (PT)

Perceived trust is related to confidence in embracing disruptive technology in the frame of blockchain adoption [47]. As the actions of academic staff and students are tracked and recorded on the blockchain, the trust dynamics change with blockchain from depending on third-party institutions to trusting the technology itself [22]. Results from earlier studies indicate individual's intentions to use blockchain are highly influenced by the trust level. People's readiness and excitement to interact with blockchain are significantly influenced by how much they trust the technology and the parties involved [88]. This is especially important for consumers who are less tech-savvy or new, as their choice to adopt cutting-edge technologies like blockchain is greatly influenced by their initial level of trust [43]. Consequently, we put up the following theories:

*H7a* PT positively impacts BI to adopt blockchain in higher educational institutions.

*H7b* PT positively impacts the AUB of blockchain in higher educational institutions.

### 2.8 Self-efficacy (SE)

SE refers to the competency to perform a designated task with the help of new technology or system which will drive the person to long-term use of that technology [39]. The intention to use digital learning platforms is more strongly connected with technical self-efficacy [26]. Moreover, it is uncovered that self-efficacy has a potentially positive effect on usability in online learning [2, 5, 21]. Therefore, we can develop the hypothesis as given below.

*H8a* SE positively impacts BI to adopt blockchain in higher educational institutions.

*H8b* SE positively impacts the AUB of blockchain in higher educational institutions.

### 2.9 Perceived risk (PR)

PR defines the extent of perception of threat among people that may appear in the near future [55]. Besides, people might be influenced by the risk factors of new technology adoption [62]. PR plays a significant role since blockchains contain students' sensitive data. Maintaining the privacy of students' sensitive information is crucial in education, particularly when sharing private and sensitive information with others [23]. Alkhammash et al. [9] revealed that PR has a direct influence on the BI to use blockchain in the educational sector. On the other contrary, the study of Q. Zhang et al. [97] did not express any association between PR and BI and AUB. Hence, we can have the below hypothesis.

*H9a* PR positively impacts BI to adopt blockchain in higher educational institutions.

*H9b* PR positively impacts the AUB of blockchain in higher educational institutions.

#### *2.9.1 Behavioral intention (BI)*

Social scientists have studied users' propensities to embrace new technologies through behavioral intention, which is related to a person's subjective likelihood of utilizing a certain technology in the future and personal belief [47]. BI is a reliable meter of AUB, according to several empirical research. Research by [90] shows a correlation between BI and AUB. Considering the administrative limitations that educational institutions must contend with, this is particularly pertinent. As a result, the hypothesis can be obtained:

*H10* BI positively impacts the AUB of blockchain in higher educational institutions.

## 3 Research methodology

The positivity philosophy has been used for this research while testing hypotheses that are developed in the previous section of this paper. Here, the hypothesis has been developed based on previous knowledge and literature. Figure 1 shows the conceptual model highlighting the hypotheses.

### 3.1 Data collection

Using a survey, necessary data has been collected. The period for the survey was from August 2023 to April 2024 comprising 39 assessment items, which were used to assess the constructs incorporated in the modified UTAUT2 model. The questionnaire was developed based on the Likert scale representing "strongly disagree" to "strongly agree" as 1 to 5 scale points. The questionnaire has two sections: Sect. 1 encompasses demographic variables, such as age, and gender, and Sect. 2 contains statements about the items related to each latent variable. In addition, a pilot study with 40 individuals has been conducted to guarantee a high degree of validity and reliability. Literature shows that for a pilot study, a sample size of 10 [77] or 12 [45] is sufficient.

Convenience sampling has been applied for sample selection because it allows information from possible participants depending on their availability with the assurance of respondents' awareness of adopting blockchain technology in the educational sector.

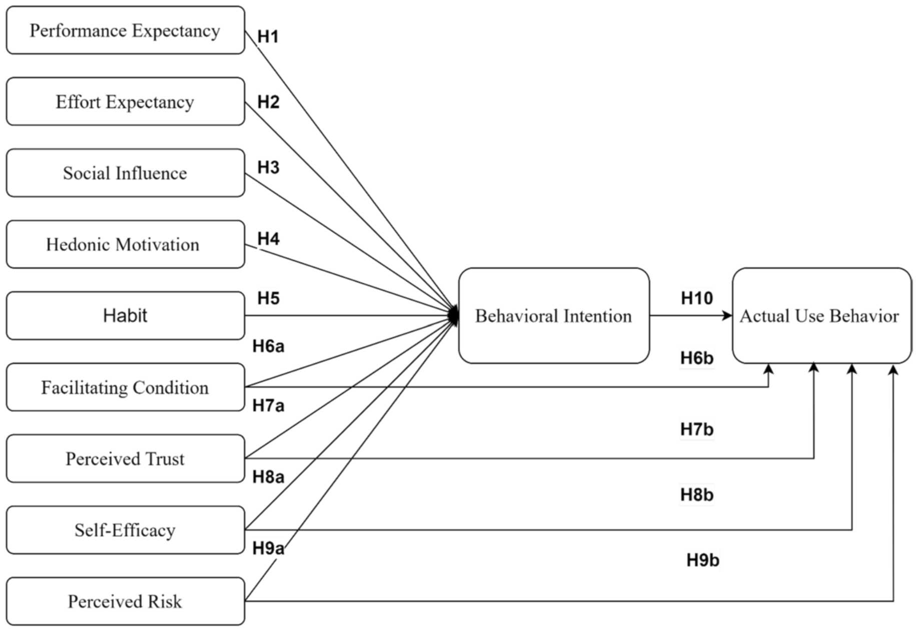


**Fig. 1** Research model

The questionnaire was provided to 450 students at different public and private universities in Bangladesh via online platforms and received 441 completed responses from participants. So, the effective rate is 98%. Participants were well informed about their answers, which would only be used for academic study. So, they were urged to base their replies on their own knowledge and experience.

### 3.2 Ethical endorsement for data collection

In Bangladesh, under institutional guidelines and national regulation, research in the social science area is not obliged to be approved. Nevertheless, ethical approval was obtained from the Departmental Ethics Committee for Research Involving Human Subjects at the University of Dhaka (Reference Number: IBDUREC-2023–14) prior to the initiation of data collection. Informed consent was also obtained from all respondents, who were assured that their involvement in the current research was entirely voluntary.

### 3.3 Data analysis

The PLS-SEM is used as the suggested conceptual model for validation. The model was evaluated, and the hypotheses were tested via SmartPLS while survey data were examined using SPSS 21 software. SEM offers a confirmatory method that is more reliable than linear regression in terms of correcting measurement errors and provides insights into the patterns of many indicator variables. PLS-SEM also could estimate causality models with theoretical underpinnings and covariance-based SEM methods in estimating the connection between variables [35]. There were two phases to the analysis. First, the validity and reliability of the measurement model have been assessed, and second, a bootstrapping technique is applied for hypothesis testing.

To confirm the determinants shaping users' behavior intentions for blockchain adoption in HEIs, artificial neural networks (ANNs) have been employed. Additionally, the relative significance of the predictors generated from SEM has been ranked using ANN since it could identify non-linear and non-compensatory correlations without breaching multivariate assumptions that PLS-SEM does not [5, 15, 58, 83]. Besides, the unique technique has also improved the model's predictive capacity and given it resilience against noise. Among the several ANN model categories, the current study used a multilayer perceptron neural network model and hyperbolic tangent activation function for model training with a learning rate of 0.1. Although problem complexities ascertain the number of hidden neurons to be used, one hidden node is widely utilized in technology acceptance models [86]. Moreover, Wang and Elhag [93] recommended limiting the hidden layer between the number of input and output. Therefore, this study uses one hidden layer.

In this study, the training and testing data have been designed as 90% and 10%, respectively [60, 66]. In ANN models, there is a risk of having an overfitting problem, which has been addressed using a tenfold cross-validation method (Ahmed, 2023, [96, 98]). Moreover, the models have been validated with widely used Root Mean Square Error (RMSE). Since ANN cannot determine statistically significant variables and hypothesis testing, significant input variables have been found using SEM models prior to the adoption of neural network models [20, 86].

## 4 Analysis and result

### 4.1 Demographic features

There are 39.1% female and 60.9% male replies out of 441 total presented in Table 2. Among the responders, the majority (85%) are between the ages of 21 and 40, with 11.8% being under 20.

In this case, 80.3% of responders are either bachelor's degree holders or graduates. 19.7% of responders are postgraduate students. Usually, the 400-sample size is sufficient for PLS analysis because it is more than 10 times larger than the arrows pointing to an endogenous variable [34].

### 4.2 Multivariate diagnostic tests

As per the study by Hair et al. [35], verification is required to confirm the validity of multivariate assumptions if there is no multicollinearity and the distribution is normal with a satisfactory sample size. To evaluate the multicollinearity issue among latent variables, the study examined Variance Inflation Factor (VIF) values. Kline [49] suggests that VIF values should not exceed 10. VIF values have been presented in Table 6 to confirm that all VIF values are within the accepted level. Thus, there are no multicollinearity

**Table 2** Respondents' information (N = 441)

| Demographic data | Frequency | Measurement (%) |
|---|---|---|
| Gender | | |
| Male | 269 | 60.9 |
| Female | 172 | 39.1 |
| Age (Years) | | |
| Under 20 years | 52 | 11.8 |
| 21–40 years | 375 | 85.0 |
| Above 40 years | 14 | 3.2 |
| Educational qualification | | |
| Graduate/ Bachelor | 354 | 80.3 |
| Postgraduate and above | 87 | 19.7 |

problems among the latent constructs. As this study employed only one data collection mode, there is a high probability of having a "common method bias" (CMB). The statistical findings are devoid of CMB, as the VIF values are less than 3.3, as shown by Kock (2017). Kline (2023) determined that data is deemed normally distributed if skewness values are below 3.00 and kurtosis values are within 8.00. Here, the normality of the data set is assured due to having skewness and kurtosis values are well below the standard value.

### 4.3 Measurement model

To assess the measurement model, four elementary measures have been used such as item reliability, internal consistency, convergent, and discriminant validity. Item reliability is measured by individual indicator's loading. Item loadings shown in Table 3 are more than the cut-off value of 0.7 confirming item reliability as recommended by [35]. As presented in Table 3 the Cronbach's alpha and composite reliability values for all constructs of the study are more than the standard threshold value, which is 0.7 for both measures. Therefore, this study has the presence of consistency and reliability of all proposed latent variables [30]. In Table 3, the "Average Variance Extracted" (AVE) values range from 0.703 to 0.837, meeting the suggested cut-off level, which is 0.50 as proposed by [35]. Hence, the requirements for fulfilling the convergent validity are deemed reasonable. Table 4 exhibits that the square root of the AVE surpasses the correlation among the constructs, affirming discriminant validity. The Heterotrait-Monotrait (HTMT) ratio of correlations as recommended by [36] has been depicted in Table 5 for affirming discriminant validity among constructs as all values are below 0.90.

### 4.4 Structural model

SmartPLS 4 has been used to calculate the path coefficients and the R-square values of endogenous constructs. Hypotheses have been tested using bootstrapping with 5000 samples and the outcomes are displayed in Table 6. The statistical outcomes represent that the relationship between PE and BI, HM and BI, FC and BI, PT and BI, PT and AUB, SE and BI, SE and AUB, PR and BI, PR and AUB, BI and AUB were statistically satisfied at 5% level of significance as the $p$ values for those hypotheses were below 0.05. Therefore, hypotheses H1, H4, H6a, H7a, H7b, H8a, H8b, H9a, H9b, and H10 were accepted. However, surprisingly, EE and BI, HT and BI, SI and BI, FC and AUB were found insignificant at a level of 0.05 ($p < 0.05$). Thus, H2, H3, H5, and H6b were rejected.

### 4.5 Goodness of fit (GoF)

GoF validates the predictive capability of the selected model [37]. It calculates the mean R square of the endogenous variables and the geometric mean of the average communality. The GoF indices vary from 0 to 1 and are classified into three distinct groups: small (0.10), medium (0.25), and large (0.36). He also suggested that, as there is no direct method to measure the global GoF index in PLS software, the GoF is calculated using the formula below.

$$
\begin{aligned}
&GoF = \left(\text{average communality} * \text{average } R^2\right) \\
&= 0.762364 * 0.589 \\
&= 0.670
\end{aligned}
$$

**Table 3** Convergent validity and reliability

| Constructs | Items | Item loadings | Mean | SD | Cronbach's alpha | Composite reliability | $R^2$ | AVE |
|---|---|---|---|---|---|---|---|---|
| AUB | AUB1 | 0.881 | 2.645 | 0.937 | 0.904 | 0.933 | 0.629 | 0.777 |
| | AUB2 | 0.887 | | | | | | |
| | AUB3 | 0.903 | | | | | | |
| | AUB4 | 0.855 | | | | | | |
| BI | UI1 | 0.901 | 2.927 | 0.938 | 0.902 | 0.939 | 0.549 | 0.837 |
| | UI2 | 0.932 | | | | | | |
| | UI3 | 0.91 | | | | | | |
| EE | EE1 | 0.84 | 2.806 | 0.957 | 0.87 | 0.906 | | 0.757 |
| | EE2 | 0.802 | | | | | | |
| | EE3 | 0.813 | | | | | | |
| | EE4 | 0.781 | | | | | | |
| | EE5 | 0.816 | | | | | | |
| FC | FC1 | 0.803 | 2.841 | 0.991 | 0.784 | 0.859 | | 0.703 |
| | FC2 | 0.719 | | | | | | |
| | FC3 | 0.798 | | | | | | |
| | FC4 | 0.783 | | | | | | |
| HT | HT1 | 0.885 | 2.702 | 1.001 | 0.814 | 0.885 | | 0.719 |
| | HT2 | 0.857 | | | | | | |
| | HT3 | 0.8 | | | | | | |
| HM | HM1 | 0.72 | 1.943 | 0.895 | 0.752 | 0.856 | | 0.766 |
| | HM2 | 0.863 | | | | | | |
| | HM3 | 0.857 | | | | | | |
| PT | PT1 | 0.751 | | 0.917 | 0.872 | 0.913 | | 0.724 |
| | PT2 | 0.899 | | | | | | |
| | PT3 | 0.895 | | | | | | |
| | PT4 | 0.851 | | | | | | |
| PR | PR1 | 0.904 | 2.78 | 0.823 | 0.818 | 0.891 | | 0.733 |
| | PR2 | 0.875 | | | | | | |
| | PR3 | 0.785 | | | | | | |
| PE | PE1 | 0.851 | 2.737 | 0.919 | 0.905 | 0.934 | | 0.779 |
| | PE2 | 0.892 | | | | | | |
| | PE3 | 0.905 | | | | | | |
| | PE4 | 0.881 | | | | | | |
| SE | SE1 | 0.882 | 2.965 | 1.023 | 0.888 | 0.929 | | 0.813 |
| | SE2 | 0.9 | | | | | | |
| | SE3 | 0.922 | | | | | | |
| SI | SI1 | 0.855 | 2.851 | 1.029 | 0.858 | 0.913 | | 0.778 |
| | SI2 | 0.888 | | | | | | |
| | SI3 | 0.902 | | | | | | |

The global (GoF) value for the proposed model in this study is 0.670, significantly exceeding the standard value of 0.36 as recommended by [53] exhibiting the predictive accuracy of the model.

### 4.6 Neural network analysis

ANN models are significant machine learning tools used for data analysis. ANN models emulate the human brain as ANN models learn hidden patterns and relationships in the data in the form of training and reflect the output of the learning in the form of testing [86]. Multiple neurons store collected knowledge, which is reflected as synaptic weights. Synaptic weights are adjusted during the training phase utilising a tenfold iterative process through the backpropagation process. In comparison to SEM and regression

**Table 4** Correlation matrix and square root of the AVE

| | AUB | BI | EE | FC | HT | HM | PT | PR | PE | SE | SI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| AUB | **0.882** | | | | | | | | | | |
| BI | 0.727 | **.915** | | | | | | | | | |
| EE | 0.536 | 0.461 | **0.811** | | | | | | | | |
| FC | 0.491 | 0.52 | 0.441 | **0.777** | | | | | | | |
| HT | 0.551 | 0.455 | 0.402 | 0.474 | **0.848** | | | | | | |
| HM | 0.578 | 0.579 | 0.534 | 0.455 | 0.572 | **0.816** | | | | | |
| PT | 0.62 | 0.601 | 0.428 | 0.521 | 0.492 | 0.643 | **0.85** | | | | |
| PR | 0.653 | 0.607 | 0.542 | 0.542 | 0.514 | 0.562 | 0.6 | **0.86** | | | |
| PE | 0.584 | 0.578 | 0.581 | 0.436 | 0.446 | 0.542 | 0.51 | 0.43 | **0.88** | | |
| SE | 0.44 | 0.353 | 0.477 | 0.392 | 0.498 | 0.556 | 0.46 | 0.42 | 0.33 | **0.9** | |
| SI | 0.571 | 0.466 | 0.488 | 0.432 | 0.472 | 0.55 | 0.59 | 0.5 | 0.5 | 0.43 | **0.882** |

**Table 5** HTMT values

| | AUB | BI | EE | FC | HT | HM | PT | PR | PE | SE |
|---|---|---|---|---|---|---|---|---|---|---|
| BI | 0.802 | | | | | | | | | |
| EE | 0.603 | 0.518 | | | | | | | | |
| FC | 0.567 | 0.598 | 0.534 | | | | | | | |
| HT | 0.626 | 0.497 | 0.466 | 0.594 | | | | | | |
| HM | 0.685 | 0.683 | 0.648 | 0.564 | 0.689 | | | | | |
| PT | 0.692 | 0.676 | 0.492 | 0.624 | 0.569 | 0.787 | | | | |
| PR | 0.75 | 0.697 | 0.648 | 0.671 | 0.597 | 0.687 | 0.702 | | | |
| PE | 0.645 | 0.639 | 0.652 | 0.498 | 0.517 | 0.632 | 0.566 | 0.502 | | |
| SE | 0.476 | 0.375 | 0.541 | 0.472 | 0.578 | 0.671 | 0.505 | 0.483 | 0.35 | |
| SI | 0.645 | 0.523 | 0.562 | 0.52 | 0.546 | 0.669 | 0.676 | 0.592 | 0.566 | 0.483 |

**Table 6** Hypotheses testing

| Hypotheses | Paths | β (Co-efficient) | P-values | VIF | Standard deviation (STDEV) | T statistics | P-values | Comment |
|---|---|---|---|---|---|---|---|---|
| H1 | PE→BI | 0.272 | 0.000 | 1.904 | 0.057 | 4.793 | 0.000 | Yes |
| H2 | EE→BI | −0.03 | 0.547 | 2.032 | 0.05 | 0.603 | 0.547 | No |
| H3 | SI→BI | −0.021 | 0.717 | 1.851 | 0.058 | 0.363 | 0.717 | No |
| H4 | HM→BI | 0.159 | 0.009 | 2.441 | 0.061 | 2.595 | 0.009 | Yes |
| H5 | HT→BI | −0.002 | 0.973 | 1.822 | 0.052 | 0.034 | 0.973 | No |
| H6a | FC→BI | 0.13 | 0.006 | 1.68 | 0.047 | 2.744 | 0.006 | Yes |
| H6b | FC→AUB | 0.004 | 0.929 | 1.645 | 0.045 | 0.09 | 0.929 | No |
| H7a | PT→BI | 0.18 | 0.005 | 2.318 | 0.064 | 2.797 | 0.005 | Yes |
| H7b | PT→AUB | 0.156 | 0.003 | 1.984 | 0.053 | 2.924 | 0.003 | Yes |
| H8a | SE→BI | −0.047 | 0.393 | 1.701 | 0.055 | 0.854 | 0.043 | Yes |
| H8b | SE→AUB | 0.109 | 0.009 | 1.346 | 0.042 | 2.619 | 0.009 | Yes |
| H9a | PR→BI | 0.271 | 0.000 | 2.089 | 0.058 | 4.647 | 0.000 | Yes |
| H9b | PR→AUB | 0.241 | 0.000 | 1.984 | 0.055 | 4.379 | 0.000 | Yes |
| H10 | BI→AUB | 0.447 | 0.000 | 1.921 | 0.052 | 8.669 | 0.000 | Yes |

analysis, ANN models are best suited to conceptualize both linear and complex non-linear associations between determinants and adoption behaviour as adopted by [15, 83]. This study adopted a multi-layer perceptron neural network model among multiple types of ANN models. Before adopting neural network models, significant input variables have been identified using SEM models as ANN is inappropriate in hypothesis testing and in determining the statistically significant variables [20, 86].

### 4.7 Results of neural network modelling

As there are two dependent variables namely: BI and AUB, two ANN models with three layers have been designed. For model A, BI is the output and FC, HM, PT, PE, PR, and SE have been used as input, since these variables have a statistically significant impact on BI, as reflected in Fig. 2. For model B, AUB is the output, and PT, SE, PR, and BI have been used as input, as reflected in Fig. 3.

The RMSE values of training and testing for both models have been depicted in Table 7. The mean value of RMSE in model A for training is 0.363 and for testing is 0.339 and for model B, the mean value of RMSE for training is 0.379 and for testing is 0.358. The mean RMSE for both models is also relatively low with a small standard deviation affirming the statistical reliability of the analysis.

Since neural network models are suitable for determining the significant determinants of outcome variables, the sensibility analysis has been presented to assess the average significance of the independent variables to measure the significant dependent variables. Then, the normalized relative importance of the predictors is measured by dividing the relative importance of the predicting variable by the maximum importance of the predicting variable. The importance of each independent variable has been demonstrated in Table 8.

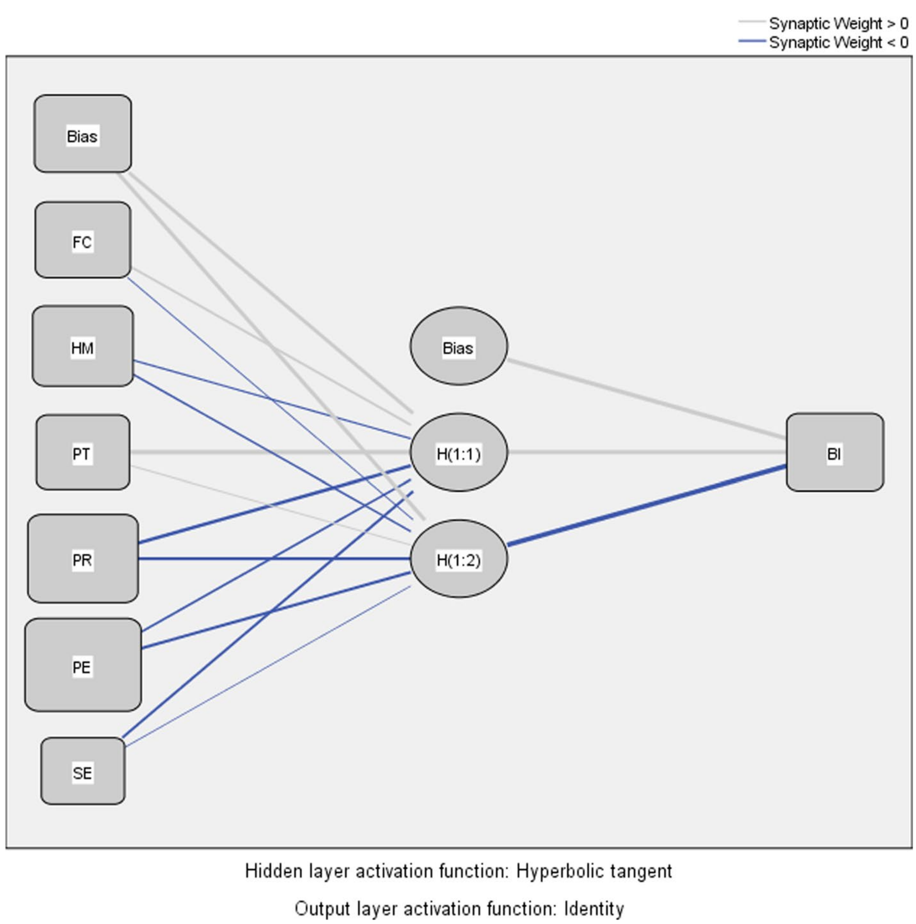


**Fig. 2** Model A

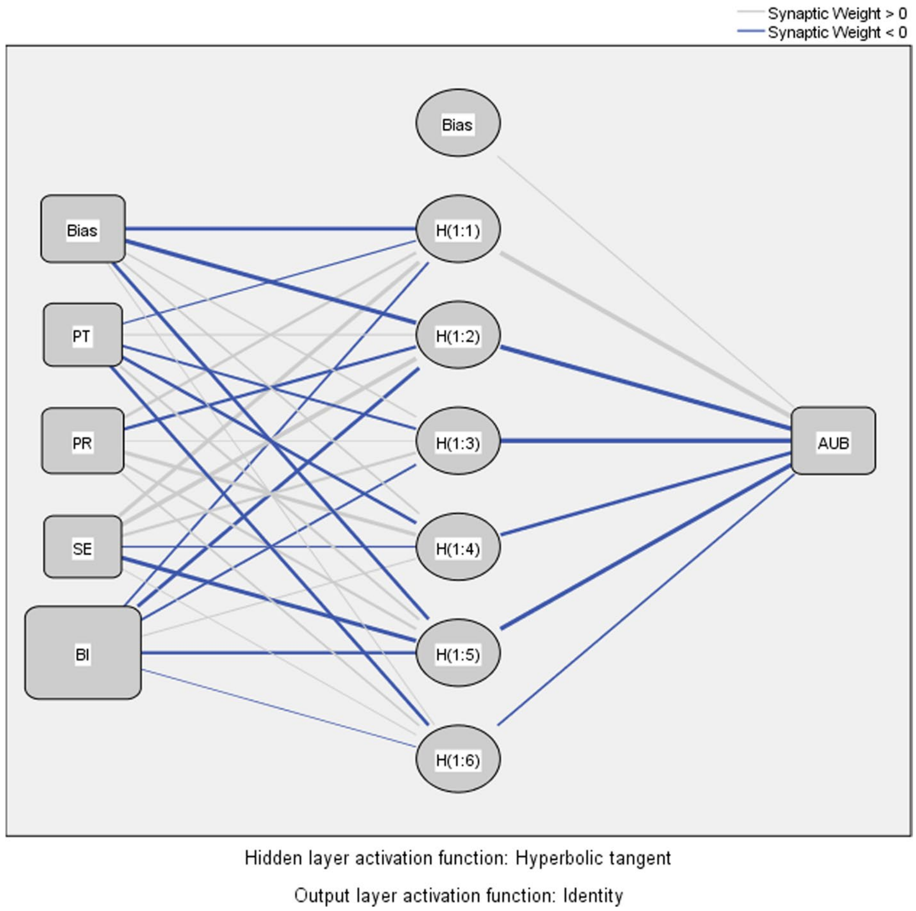


**Fig. 3** Model B

**Table 7** RMSE value

| ANN Network (N) | Model A | | Model B | |
|---|---|---|---|---|
| | Training | Testing | Training | Testing |
| N1 | 0.316611396 | 0.304625895 | 0.350749574 | 0.317861149 |
| N2 | 0.474901742 | 0.456513713 | 0.427952174 | 0.393696202 |
| N3 | 0.478366465 | 0.416091068 | 0.441651898 | 0.479271182 |
| N4 | 0.398108028 | 0.380142775 | 0.416936413 | 0.458502893 |
| N5 | 0.211405136 | 0.203863419 | 0.41232965 | 0.330189865 |
| N6 | 0.351716318 | 0.278092429 | 0.357746658 | 0.295583065 |
| N7 | 0.241159146 | 0.237652180 | 0.412365722 | 0.356370594 |
| N8 | 0.316539491 | 0.305062597 | 0.310337950 | 0.321828540 |
| N9 | 0.425788013 | 0.395445357 | 0.312504075 | 0.341505846 |
| N10 | 0.414423869 | 0.417220511 | 0.352504075 | 0.284937224 |
| Mean | 0.362901960 | 0.339470995 | 0.378507819 | 0.357974656 |
| SD | 0.091842042 | 0.085195120 | 0.048385392 | 0.066066805 |

**Table 8** Average and normalized importance of independent variables of Models

| Variables | Model A | | Variables | Model B | |
|---|---|---|---|---|---|
| | Importance | | | Importance | |
| | Average | Normalized | | Average | Normalized |
| FC | 0.43 | 0.44 | PT | 0.50 | 0.50 |
| HM | 0.54 | 0.56 | PR | 0.69 | 0.69 |
| PT | 0.52 | 0.54 | SE | 0.42 | 0.43 |
| PR | 0.81 | 0.84 | BI | 0.99 | 1.00 |
| PE | 0.96 | 1.00 | | | |
| SE | 0.41 | 0.43 | | | |

However, the ANN models exhibit that PE is the most important driver of blockchain adoption followed by PR, HM, PT, FC, and SE. Similarly, BI is relatively the most significant predictor of AUB followed by PR, PT, and SE.

## 5 Discussions

To understand the students' behavior of blockchain in higher educational institutions, an empirical study adopting extended UTAUT2 has been used. This study extended the UTAUT2 model with three variables namely perceived trust, self-efficacy, and perceived risk. The PLS-SEM-ANN method has been used for hypotheses testing and assessing the significance of the predictors of BI and AUB. The conceptual framework and the results presented in the analysis section insist that the BI and AUB in higher education could be reached to a maximum level. The result found in this study is somewhat in line with the existing literature though these are merely few. The necessary findings of the study have been discussed in the results section. It can be decided that BI and AUB depend on various factors having different levels of variation.

PE, HM, FC, PT, SE, and PR have a statistically momentous impact on BI and PT, SE, PR, and BI have a statistically significant impact on AUB. PE and BI are positively associated, and this result is supported by the studies conducted on blockchain in the supply chain [79, 81], non-expert context [68], digital currency context [42, 52]. However, performance in tertiary educational institutions strongly depends on the enhanced efficiency and traceability of transactions, which can be addressed by blockchain use. Therefore, PE strongly predicts blockchain adoption, which is in line with the outcomes of Lavaei Adaryani et al. [54].

Besides, FC has a significant consequence on BI but not on AUB, which is confirmed by studies on the adoption of e-learning (Z. [96, 98]). A supportive environment may change students' intention to adopt blockchain while users' innovativeness and perceived utility may hinder the transition from intention to actual use. The result goes against the traditional and theoretical findings in such a way that AUB is influenced by other internal factors of the users e.g., innovativeness. The findings for perceived risk and self-efficacy are supported by blockchain literature in other contexts [43, 51] and are not in line with the findings of [81]. As expected, intentional behavior is strongly influenced by perceived risk and self-efficacy. For instance, the findings [43] present that self-efficacy can strongly predict both intentions to use and actual use. Thus, our finding is opposite to the findings of [81].

Besides, HM and PT have a significant influence on students' intentions to use blockchain. The outcomes are in line with studies on blockchain in the European context [88] but contradict the studies on blockchain adoption in the government sector [18],Q. [97], Perceived risk has a vital association with BI and AUB which is also supported by [88] but contradicts (Q. [97]). As the target respondents are young students, they have an inherent motivation to explore new technology. HM is thus strongly associated with BI. PR significantly impacts not only BI but also AUB. If users trust the system, they are more likely to use it, as trust is a vital precondition for the adoption of any new information system. Toader et al. [88] also found similar results in European culture, but Zhang et al. [97] did not find any association between PR and BI and AUB.

Our findings show that BI is not influenced by EE which is supported by several studies [42, 82]. This finding emphasized that students in this country are already familiar with various digital tools, particularly learning management systems. Besides, the perceived benefit of using blockchain may undermine the effect of ease of use [42]. Hence, digital literacy reduces their effort for new technology such as blockchain. Therefore, respondents' intentional behavior is not affected by the effort of using blockchain. HT also does not impact BI, supporting (Khalid et al., 2020) and contradicting [5]. In Bangladesh, blockchain adoption is still in its initial stage. Hence, students have less engagement with this technology, making use of enjoyment a secondary consideration. Besides, for educational settings, extrinsic drivers, such as credibility, and confidence are more prominent than intrinsic motivation, making HM less significant.

Moreover, people are usually influenced by peer thoughts and words, but it does not assure peer influence in all cases. Thus, SI has no positive impact on students' behavioral intentions, which was also confirmed by Alazab et al. [7] and contradicted by Alam et al. [5] and Merhi et al. [63]. The findings of our study also contradict the original findings of the UTAUT2 model in the case of the developing country, Bangladesh. The reason can be attributed to only a few tertiary institutions and students who have used blockchain.

Finally, the findings demonstrate that PE, HM, FC, PT, SE, and PR are important factors in blockchain adoption and use in tertiary educational institutions. Additionally, ANN analysis reveals that PE is the strongest predictor of blockchain adoption, followed by PR, HM, PT, FC, and SE. Besides, BI is the most significant predictor of the actual use of blockchain followed by PR, PT, and SE. Adoption of blockchain in education will enhance the traceability of students' credentials, ease of document verification process, and secure financial transactions e.g. tuition fee payment. Moreover, blockchain will significantly facilitate lifelong learning and decentralization of learning. Therefore, educational institutions should implement blockchain and consider significant determinants in increasing the success of adoption.

### 5.1 Conclusion

At present, blockchain adoption in higher educational institutions represents a significant shift towards enhancing transparency, security, and efficiency in managing educational information. It creates a more integrated and transparent information-sharing system in educational sectors all over the world. In our study, the extended UTAUT2 model has been used due to its higher predictive and explanatory power of using new technology. With the extended UTAUT2 model, the study aims to comprehensively understand the behavioral intentions and actual usage behaviors of the students in Bangladesh towards blockchain technology.

The findings of this empirical research state that PE, HM, FC, PR, SE, and PR have a statistically significant impact on behavioral intention. Besides, PT, PR, SE, and BI have a significant impact on AUB. Thus, tertiary education will benefit from the ease of document verification processes, financial transactions, and lifelong learning opportunities are getting more improved. Furthermore, HM has a significant impact on students' intentions of using blockchain in the educational sector, but SI has no positive impact on students' behavioral intentions. PT not only has a significant impact on BI but also AUB. Conversely, while FCs exert a notable influence on BI, they do not have an impact on AUB. Moreover, PR acts as a major driving factor for both the blockchain adoption intention and the subsequent AUB. These factors have a significant role in enhancing the efficiency, traceability, and security of knowledge and information sharing in educational institutions. Thus, blockchain technology emerges as a solution offering secured decentralization of information, leading the way for a sustainable educational system globally.

### 5.2 Theoretical implications

Theoretically, the results of the study add some contributions to the existing literature on blockchain adoption in tertiary education. This study integrated three new variables, i.e. PR, PT, and SE along with the essential factors of UTAUT2 and proposed several new path associations. Therefore, this study goes beyond the path association of the original UTAUT2 model as suggested by Venkatesh et al. (2012) and these new path associations have not been considered in the prior literature. Conversely, EE → BI, SI → BI, and FC → AUB were insignificant in blockchain adoption intention.

Although blockchain adoption has been tested in different contexts; i.e., banking [70], and supply chain, there is scanty literature having focuses on blockchain adoption by educational institutions. Besides, there is no such study that showed the factors affecting students' intention to adopt the system. This study, hence, adds significant findings to existing literature on blockchain. Moreover, this empirical study quantitatively measured the factors that are critical in adopting blockchain, practically in a developing country context. Besides, no studies tested those additional factors by adopting a two-approach methodology. The existing literature on blockchain adoption has been enriched by incorporating three new variables in a country like Bangladesh where resources are limited. Finally, this study addresses the gaps in the literature by extending the basic UTAUT2 model with new factors and testing a validating the model using two approaches, such as SEM and ANN.

### 5.3 Practical implications

In addition to contributing to the theory, the current research also contributes to the development of blockchain policies, frameworks, and guidelines needed for adoption in emerging economies. Designers, administrators, and blockchain experts utilise these findings to make effective decisions in capacity-building for designing, developing, and maintaining blockchain systems. Also, to remove any obstacles and to utilise opportunities on blockchain technology, the current study focuses on how user acceptance affects and also helps stakeholders retarded up employed. Furthermore, the introduction and integration of systems such as blockchain are a catalyst in the digitalisation of many industries. In developing countries in particular, such a change can yield stronger and more efficient, transparent, safe, and trustworthy systems and services. Therefore, different stakeholders and government agencies need to consider the significance of PE, HM, FC, PT, SE, and PR in promoting blockchain adoption in educational institutions.

## 6 Limitations and future research

This study considered respondents only from Bangladesh and confined to the education sector where the BI and AUB were at a single point in time instead of conducting a longitudinal study to measure the stated variables at different time points. So, the relationships identified are associative not casual and future studies may consider adopting a longitudinal approach to extend the scope of the current study. Besides, the study is based on the Bangladeshi context. Therefore, the findings cannot be transferred beyond the countries due to cultural and infrastructural differences. Forthcoming studies thus can gather data from other developing countries to generalize the results for developing countries. More specifically, the current study extended the basic UTAUT2 model with three variables only. Future studies may test other variables, i.e., the personal innovativeness of the users. In addition, the use of convenience sampling may limit the generalizability of the findings. Hence, further studies could incorporate probability sampling to enhance the representativeness of the current findings. Moreover, future research can incorporate demographic factors as moderators to provide more insightful results. Finally, data was collected from only a single group of respondents (i.e., students). However, for the efficacious implementation of such a new technology, it is crucial to measure the intentions and actual usage behavior of employees and authorities as well. Hence, a future study is expected to apply a mixed approach where qualitative results will be tested using quantitative interviews with experts, employees, and other stakeholders for a more effective outcome. Such a study may incorporate multiple stakeholders who may influence the success of blockchain adoption and encourage actual users to adopt.

## Supplementary Information

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Supplementary file 1.

#### Author contributions

R.A.R. and A.S. contributed to the conceptualization and methodology, data collection, data analysis, and the overall writing of the original manuscript. F.N. contributed to the questionnaire preparation, pilot survey, interpretation of the results, and the overall review and editing of the manuscript. A.N.M.S. contributed to the introduction, discussion, conclusion, review, and editing of the entire manuscript. M.N.H. contributed to the interpretation of the results, discussion, conclusion, review, and editing. H.A. contributed to the interpretation of the results and the overall editing of the manuscript.

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#### Data availability

Data can be made available upon reasonable request to the corresponding author.

### Declarations

#### Ethics approval and consent to participate

Ethical approval was obtained from the Departmental Ethics Committee for Research Involving Human Subjects at the University of Dhaka (Reference Number: IBDUREC-2023–14) prior to the commencement of data collection. Informed consent was also obtained from all respondents, who were assured that their participation in the research was entirely voluntary. The authors confirm that all methods were carried out in accordance with relevant guidelines and regulations.

#### Consent to publish declaration

Not applicable.

**Clinical trial number**
Not applicable.

**Competing interests**
The authors declare no competing interests.

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