Perceived Security Risk Based on Moderating Factors for Blockchain Technology Applications in Cloud Storage to Achieve Secure Healthcare Systems

Malik Mustafa,1 Marwan Alshare,1 Deepshikha Bhargava,2 Rahul Neware,3 Balbir Singh,4 and Peter Ngulube5

1Faculty of Computing Sciences, Gulf College, Muscat, Oman
2DIT University, Dehradun, India
3Department of Computing, Mathematics and Physics, Høgskulen på Vestlandet, Bergen, Norway
4Administrative Staff College of India, Hyderabad, India
5Malawi University of Science and Technology, Malawi

Correspondence should be addressed to Malik Mustafa; malik@gulfcollege.edu.om and Peter Ngulube; inv-019-18@must.ac.mw

Received 14 November 2021; Revised 4 December 2021; Accepted 8 December 2021; Published 19 January 2022

Due to the high amount of electronic health records, hospitals have prioritized data protection. Because it uses parallel computing and is distributed, the security of the cloud cannot be guaranteed. Because of the large number of e-health records, hospitals have made data security a major concern. The cloud’s security cannot be guaranteed because it uses parallel processing and is distributed. The blockchain (BC) has been deployed in the cloud to preserve and secure medical data because it is particularly prone to security breaches and attacks such as forgery, manipulation, and privacy leaks. An overview of blockchain (BC) technology in cloud storage to improve healthcare system security can be obtained by reading this paper. First, we will look at the benefits and drawbacks of using a basic cloud storage system. After that, a brief overview of blockchain cloud storage technology will be offered. Many researches have focused on using blockchain technology in healthcare systems as a possible solution to the security concerns in healthcare, resulting in tighter and more advanced security requirements being provided. This survey could lead to a blockchain-based solution for the protection of cloud-outsourced healthcare data. Evaluation and comparison of the simulation tests of the offered blockchain technology-focused studies can demonstrate integrity verification with cloud storage and medical data, data interchange with reduced computational complexity, security, and privacy protection. Because of blockchain and IT, business warfare has emerged, and governments in the Middle East have embraced it. Thus, this research focused on the qualities that influence customers’ interest in and approval of blockchain technology in cloud storage for healthcare system security and the aspects that increase people’s knowledge of blockchain. One way to better understand how people feel about learning how to use blockchain technology in healthcare is through the United Theory of Acceptance and Use of Technology (UTAUT). A snowball sampling method was used to select respondents in an online poll to gather data about blockchain technology in Middle Eastern poor countries. A total of 443 randomly selected responses were tested using SPSS. Blockchain adoption has been shown to be influenced by anticipation, effort expectancy, social influence (SI), facilitation factors, personal innovativeness (PIinn), and a perception of security risk (PSR). Blockchain adoption and acceptance were found to be influenced by anticipation, effort expectancy, social influence (SI), facilitating conditions, personal innovativeness (PIinn), and perceived security risk (PSR) during the COVID-19 pandemic, as well as providing an overview of current trends in the field and issues pertaining to significance and compatibility.
1. Introduction

Because healthcare is such a vital part of everyone’s life, it has become critical to diagnose patients and store them for future reference to secure healthcare data such as drugs and past health records. Initially, this medical data was meticulously transcribed into electronic form from paper records. There were numerous opportunities to alter and corrupt the data when using this method. As a result, electronic storage of healthcare data is crucial. Healthcare databases, on the other hand, run the possibility of being irreversibly altered or deleted, and data blocking is also a concern. Whenever medical data that should not be available to anybody other than patients or hospitals is obtained by an unintended entity like a person, a data blockage occurs. It is possible for technology to improve people’s quality of life by addressing resource allocation and information blockade issues. For cloud-based healthcare data sharing, it is all about timing. References [1–3] are possible answers. There are several privacy and security concerns when it comes to cloud computing despite its popularity and numerous offerings [2–6]. Global organizations have focused on developing security rules and processes for the cloud environment before using it for their business solutions as a result of this [7–11]. As a result, cloud service providers can no longer afford to lose their clients’ confidence in the security and privacy of their outsourced data. Its limits make distributed and decentralized security measures more important in a cloud context.

It is widely believed that blockchain (BC) technology is the best way to provide security to cloud infrastructure [12–16] because of the distributed network’s interconnectedness and the cloud’s importance. Blockchain technology may be the best secure solution for a cloud environment because of its ability to communicate quickly and demand substantially fewer processing resources. In other words [10], by utilizing blockchain technology’s inherent security, once transaction information has been recorded and updated, they can no longer be changed or deleted. The distributed data ledger can support exceptional immutability and data security even though it is shared across all nodes in the cloud [17–19]. Because of the employment of cryptographic algorithms in the blockchain blocks, the privacy of the data is more likely to be protected. Because of these features, the blockchain is the most likely candidate to deliver cloud data security. According to the findings of this study, blockchain technology can be used in the cloud for secure transmission of healthcare data [20–23]. The health sector is a major concern for both developing and developed countries, as this sector is directly related to people’s social well-being and life. The security of such crucial data is important to avoid the privacy leaks. It will thus improve the healthcare system, and e-health records will be a huge aid in taking care of patients. Research and development in the health sector should be an ongoing process as it will help improve the quality of life by combating various health problems and diseases.

2. Cloud Security Systems

Medical data concerning patients’ ailments or past medical records must be precisely captured and stored and shared securely in order to maintain the privacy of patients’ private information in the creation of smart hospitals. A totally trustworthy server is required in the old method of controlling data access, which makes it difficult to adapt to today’s scattered network environment. A new viewpoint on end-to-end communication, encryption methods, consensus mechanisms, and distributed data storage has been provided by blockchain because of its decentralization and security. Since then, ABE (attribute-based encryption) has become a crucial solution for satisfying cloud security needs. In addition, the ABE cloud access control mechanism has been thoroughly examined [24–27], respectively. It is important to have some way of connecting users to the encrypted data because an attribute-based encryption system uses public keys as attributes. Cloud data storage security is greatly enhanced by its configurable encryption and access control features. In the meantime, it has evolved into a critical method for securing cloud data storage. It also enables more granular control over access. However, the classic ABE does not fully ensure data privacy, effective collision prevention, or assurance of attribute revocation-based forward and backward security. Revocation has also resulted in significant computing costs [18, 28, 29], respectively. In order to increase data storage security and cloud computing performance, implementing blockchain technology and its security measures will become a critical study area. The mismatch between data privacy and data sharing can be remedied by combining blockchain and cloud computing, as well as a strong security methodology [30–33].

2.1. Existing Cloud Security System Limitations. As stated in the preceding section, the majority of security solutions deployed in the cloud do not have a distributed character. Cloud computing, on the other hand, is a distributed system; therefore data is dispersed over the cloud as well. As a result, it is critical to use contemporary cloud computing security methods. In addition, not all security systems are as open and accessible as others. Due to current security methods, data is very changeable, suggesting that each node can easily alter it. There are now resource-intensive and expensive security solutions in place [34].

2.2. Research Problem of Blockchain. Recent years have seen a lot of work done on blockchain technology. As a backend for the digital currency Bitcoin, blockchain technology was initially created [35]. In the same way that contemporary cloud computing provides a framework for collaboration among strange and unreliable entities, the blockchain technology’s core model is akin to that. Mobile or intelligent health device features can be provided without a central authority for security and authentication. A “public-ledger” data record serves as the foundation for this system, which is accessible to all participants. A block of data linked to the use of a cryptographic hash key can be found in this public-ledger record. This method of reaching agreement or connection is known as proof of work (PoW). Data manipulation has no effect on agreement or ledger because they are naturally independent. By canceling prior Blockchain block hashes, the block data breaches the consensus
and IBM claim that the blockchain can aid in data inter-
ship and transparency of data as it is exchanged. The FDA 
transaction audit record will be useful for tracing the owner-
gathered from a variety of sources. As time goes on, this 
to preserve oncology-related data made the bene-
technology. A focus by the FDA and IBM Watson Health 
private partnerships have recently turned to blockchain 
obstacles. Several businesses, governments, and public-
potential to assist EHR in overcoming these real-world 
ring patient health information from one service provider to 
other requires more time. Blockchain technology has the 
change by assessing multiple data gathering sources with 
patient consent and terms that are mutually agreed upon. 
There is a current model based on secret data being trans-
ported and stored on the cloud, which is not secure or 
dependable at this time. Access to healthcare data must also 
be handled with care. Maintaining data integrity has man-
dated standard auditing in the same way. Data integrity, 
anonymity, secure storage, and less likelihood of data 
infringement are all provided by the blockchain. Addition-
ally, because of the distributed nature of blockchain technol-
y, the risk of a single point of failure is decreased [38].

2.3. Background Research on the Blockchain. Previously, the 
blockchain was restricted to the financial industry, but it 
now includes a wide range of other applications, including 
public healthcare. One of the most promising areas of recent 
research has been blockchain-based medical solutions. There 
should be no tampering with the medical data that is col-
lected. Anyone who wants the data should be obliged to con-
firm its accuracy, be it the researcher, the patient, the 
patient’s family, or anyone else. In order to communicate 
data securely, academics have attempted to combine block-
chain technology with other technologies. Multiple 
researchers used the blockchain to merge various technol-
gies. In the agro-food supply chain monitoring sector, one 
of these regularly utilized technology applications is RF 
identification with blockchain [36]. Other uses for block-
chain include IoT, the automotive industry, and smart con-
tracts. Blockchain technology has a wide range of potential 
applications. Figure 1 shows an example of a typical block-
chain diagram.

3. Blockchain Security in Healthcare

3.1. Smart Healthcare and Blockchain. It was determined 
that blockchain technology might be used in smart 
healthcare systems as part of this study. Throughout the last 
few decades, healthcare systems have been increasingly con-
cerned about cyber dangers. Patients’ privacy and security 
are jeopardized because of the lack of adequate infrastruc-
ture for protecting medical data from data breaches of this 
nature. Health organizations now have control over patient 
data, putting the privacy of that data at risk and making it 
difficult to exchange information about a patient’s treat-
ment. Because of the potential for treatment delays, transfer-
ing patient health information from one service provider to 
another requires more time. Blockchain technology has the 
potential to assist EHR in overcoming these real-world 
obstacles. Several businesses, governments, and public-
private partnerships have recently turned to blockchain 
technology. A focus by the FDA and IBM Watson Health 
to preserve oncology-related data made the benefits of 
blockchain technology in the healthcare sector evident [37].

This blockchain’s transaction audit log can store data 
gathered from a variety of sources. As time goes on, this 
transaction audit record will be useful for tracing the owner-
ship and transparency of data as it is exchanged. The FDA 
and IBM claim that the blockchain can aid in data inter-

3.2. In Healthcare, Blockchain Is Used with Cloud
Computing. There are numerous issues raised by smart 
hospitals regarding secure health data sharing and patient 
privacy protection, so this study focuses on a blockchain-
based distributed healthcare data privacy protection strategy 
combined with a cloud computing-based distributed 
healthcare data privacy protection strategy. Or to put it 
another way, a distributed blockchain-based data manage-
ment architecture for smart hospitals is being developed, 
with a cloud computing paradigm and a distributed 
blockchain-based data management architecture designed 
exclusively for them. Consumers can get specific access con-
trol systems by using encryption and proxy reencryption 
and ABE technologies to deal with the high computational 
costs. Patients’ healthcare information can be sent securely 
between doctors using status and attribute-based user access. 
This response’s entire healthcare data is encrypted at the 
bottom. Cloud nodes process the transferred healthcare data 
and return the final ciphertext on the request side after it has 
been received and processed by the nodes. Instead, proxy 
reencryption and data sharing with privacy limits enforced 
by the cloud environment’s service side are meant to deal 
with issues of safe data storage and exchange primarily 
among smart hospitals [17, 39, 40].

3.3. EMR, EHR, or PHR Ecosystem Based on Blockchain. For 
the purpose of this essay, the inner workings of a 
blockchain-based electronic medical records, electronic 
healthcare records, or personal health record ecosystem were 
examined. Using blockchain technology, which is well-
known for its successful application in Bitcoin, to secure
healthcare data management, has recently piqued public interest. An open-ended and distributed online database can be created using blockchain technology, which uses data blocks, such as lists of data structures that are linked to one another so that each block refers to the one before it. Infrastructure nodes spread such collaborations rather than keeping them in a centralized storage facility. Patients' healthcare data and healthcare provider details from our perspective are included in every block, as well as the timestamp of block generation and the hash of the previous block. Figure 2 shows a hypothetical blockchain-based EMR, EHR, or PHR system (2). Once a new piece of healthcare data on an individual patient is created, a new block is generated and broadcast to all end nodes in the patient network. By adding a new block once it has been approved by most of the chain's end nodes, it will be possible to get an accurate, reliable, and efficient picture of a patient's medical history.

A fork happens when the chain cannot agree, and the block is left as an orphan on the main chain. A new block cannot be added to the chain without also modifying the data in all previous blocks. There is no way to avoid this.

On the other hand, change is easy to spot. Data on healthcare must be protected before it is presented in the block because it is publicly available. Because of its decentralized consensus and consistency, blockchain is theoretically impervious to deliberate and/or unintended attacks [41–44].

When a deal is reached without involving a trusted mediator, there will be no blockage or single point of failure. Patients will have control over their data, and healthcare information will be distributed as blockchain data in a consistent and complete manner. Changes in blockchain will be visible to all patients in the network, and all data insertions will be immutable.

4. Research Findings and Discussion

This part covers the following topics: respondent profile, exploratory factor analysis test (EFA), goodness, and construct validity fitness.

4.1. Profile of the Respondents. This study involved 443 research participants selected from Middle East countries, and these participants completed the online questionnaire. Table 1 accordingly displays the participants’ personal information.

It can be observed in Table 1 that more than half (55.1%) of the respondents involved in virtual reality training were male, and the majority of respondents, or 38.0%, were between the age of 20 and 30. About one-fourth of the respondents were between the age of 31 and 41, while 22.2% were between 42 and 52, whereas the remaining 14.8% were above 53 years of age. The following are the students' virtual reality learning results. A whopping 12.0% of respondents said they had "no prior experience." A total of 19.3 percent of respondents said they had 1 to 2 years of experience, 19.0 percent said they had 3 to 4 years of experience, 17.5 percent said they had 5 to 6 years of experience, 14.8 percent said they had 6 to 7 years of experience, and 17.4 percent said they had more than 8 years of experience.

### Figure 2: Blockchain-based EMR, EHR, or PHR conceptual ecosystem.

The results in the table show the following information about respondents’ educational backgrounds: 14.3 percent stated they had just completed elementary school, 19.4 percent said they had completed high school, 31.7 percent said they had completed college, and 35.3 percent said they had completed a university education.

The construct validity of all variables was assessed using factor analysis, and the sample size score was used to gauge the study’s trustworthiness. The sample was analyzed and reevaluated using a dependability test. Cronbach’s alpha was used to assess the major variables' internal consistency. The scale’s dependability was evaluated through an iterative process as well. If removing an item off the scale makes it more reliable, that will be investigated. Objects that fail this test are discarded and the test is redone. Since the sample size was very big, we used quantitative analysis tools and different tests in order to obtain accurate data and results. The data was collected of both the genders of varying age group from different sectors.

4.2. Analyze the Data. SPSS (Statistical Package for the Social Sciences) v13 was used to execute the analysis. The respondents’ profiles were investigated using descriptive analysis, which included percentage and frequency tests. Pearson correlation analysis, independent t-test sample, chi-square independence test, and multiple linear regressions were among the other tests utilized in this study. The applied significance level was 5%.

4.2.1. Validity of the Measures. SPLS (Smart Partial Least Squares) and SPSS (Statistical Package for the Social Sciences) were applied in this study to verify the study dimensions and test the entire framework of the proposed model. The discriminant and convergent validity were ascertained through factor analysis, and the details are provided in Table 2; all concepts scored above 0.80 for Cronbach’s alpha. Table 3 shows the result of factor analysis. On the other hand, Table 4 shows that the average variance extracted (AVE) score for all images is more significant than 0.75 (Table 4 diagonal elements), providing assurance that the AVE of each construct is more powerful compared to the squared relations between constructs.

Table 2 displays the results of the descriptive test on the general situation of Middle Eastern universities in terms of...
standard deviation, mean, minimum, and maximum values. Furthermore, to make the 5-point Likert scale easier to comprehend, scores greater than 3.67 (highest value (5)-4/3) were considered high, scores less than 2.33 (4/3 + lowest rate (1)) were labeled soft, and moderate.

The modest rise in results was not eliminated, as suggested by [10], because it was unnecessary, given that, as shown in Table 2, the alpha values for all variables in this sample are more significant than 0.7. Table 2 shows the 29 items used in this study, as well as the results of many regular reliability checks. As a result, the most tiny Cronbach’s alpha score for dependability is 0.726, according to the item statistics. To put it another way, the constructs are generally reliable.

4.2.2. The Partial Least Squares Method Is Used to Solve Problems. The partial least squares (PLS) method is a two-step method that produces a smaller collection of different components from a large number of predictors. The use of the PLS technique is appropriate for a small sample [36]. If there are formative constructs, each question must have 10 responses for the sample size for PLS, as stated by [37]. Additionally, evaluating model measurement’s acceptability [37] requires evaluating item reliability, internal consistency, and discriminant validity. This study employed 40 items representing five dimensions, and Smart PLS software was used to test these items. Table 1 presents the details.

Furthermore, the item loadings were chosen to determine the individual things’ dependability, and it is critical that the item loadings carry good value or they will be withdrawn from their respective constructs. Ref. [38] advised that the items have a minimum loading value of 0.3 to be considered relevant.

Given that items with a loading value of 0.4 were considered significant, complete items with loading values greater than 0.5 were deemed very significant. As a result, a threshold value of 0.4 was used as a criterion for item acceptability for the specified dimensions in this investigation. The model obtained loading values above 0.4 for all items of all sizes in this sample. Each item’s t value was larger than 2.58; hence, they were all regarded significant in terms of their constructions.

Additionally, the minimum consistency score is 0.7, and the internal consistency of the latent variables was tested following [17]. Furthermore, the composite reliability (CR) and Cronbach’s alpha results surpassed the thresholds. Lastly, all latent variables scored AVE greater than 0.

This study examined the discriminant validity of the latent variables, as suggested by [17]. The correlations between the other variables must be less than the square roots of AVE in this case. The integers in the off-diagonal of the matrix represent the correlations. The square root of AVE is used to represent the diagonal values in Table 4. In this case, AVE’s square roots must be bigger than the correlations’ values [37]. The results support the validity and discreteness of each latent variable as a construct.

| Measure     | Item            | Frequency | Percentage (%) | Cumulative % |
|-------------|-----------------|-----------|----------------|--------------|
| Gender      | Male            | 244       | 55.1           | 55.1         |
| Gender      | Female          | 199       | 44.9           | 100          |
| Gender      | 20-30           | 167       | 37.7           | 37.3         |
| Gender      | 31-41           | 111       | 25.1           | 62.4         |
| Gender      | 42-52           | 99        | 22.2           | 84.6         |
| Gender      | 53 and above    | 67        | 15.0           | 100          |
| Gender      | No experience   | 60        | 13.5           | 13.5         |
| Gender      | 1–2 years       | 79        | 17.8           | 31.3         |
| Gender      | 3–4 years       | 86        | 19.4           | 50.7         |
| Age         | 5–6 years       | 81        | 18.3           | 69.0         |
| Age         | 6–7 years       | 65        | 14.7           | 83.7         |
| Age         | 8–above         | 70        | 16.3           | 100          |
| Experience  | Elementary school | 75    | 16.9           | 16.9         |
| Experience  | High school     | 88        | 18.9           | 35.8         |
| Educational background | College degree | 129 | 30.1 | 65.9 |
| Educational background | Graduate degree | 151 | 34.1 | 100 |
| Total       |                | 443       | 100%           |              |

Table 1: Profile of respondents (N = 443).

| Constructs                            | No. of item | AVE | Alpha        |
|---------------------------------------|-------------|-----|--------------|
| Perceived security risk (PSR)         | 5           | 0.94| 0.731        |
| Performance expectancy (PF)           | 4           | 0.92| 0.771        |
| Effort expectancy (EE)                | 3           | 0.86| 0.775        |
| Social influence (SI)                 | 4           | 0.87| 0.771        |
| Facilitating conditions (FC)          | 4           | 0.86| 0.726        |
| Personal innovativeness (PIinn)       | 3           | 0.84| 0.762        |
| Behavioral intention (BI)             | 3           | 0.85| 0.751        |
| Use behavior (UB)                     | 3           | 0.91| 0.771        |

Table 2: Cronbach’s alpha test results of the framework study.
Table 4 shows the general state of educational institutions in Middle Eastern countries as a result of descriptive study. The table shows the mean, lowest, and maximum values, as well as the standard deviation (S.td) of the variables, and the 5-point Likert scale is divided into three categories: scores of 2.33 and below (lowest rate 1) are

### Table 3: The result of factor analysis.

| Variables                  | Dimensions | Factor loading (FL) | Mean ± SD       | Composite reliability (CR) | Cronbach’s alpha | Average variance extracted (AVE) |
|---------------------------|------------|---------------------|-----------------|----------------------------|------------------|---------------------------------|
| Perceived security risk (PSR) | PSR1       | 0.758               | 3.755 ± 0.936   |                            |                  |                                 |
|                           | PSR2       | 0.738               | 3.776 ± 0.834   |                            |                  |                                 |
|                           | PSR3       | 0.878               | 3.753 ± 0.723   | 0.874                      | 0.717            | 0.632                           |
|                           | PSR4       | 0.796               | 3.741 ± 1.083   |                            |                  |                                 |
|                           | PSR5       | 0.856               | 3.753 ± 0.723   |                            |                  |                                 |
|                           | PF 1       | 0.738               | 3.767 ± 1.071   |                            |                  |                                 |
| Performance expectancy (PF) | PF 2       | 0.753               | 3.763 ± 1.041   | 0.865                      | 0.858            | 0.653                           |
|                           | PF 3       | 0.738               | 3.767 ± 1.029   |                            |                  |                                 |
|                           | PF 4       | 0.726               | 3.853 ± 0.775   |                            |                  |                                 |
| Effort expectancy (EE)     | EE1        | 0.753               | 3.797 ± 1.021   |                            |                  |                                 |
| Social influence (SI)      | SI1        | 0.776               | 3.872 ± 0.854   |                            | 0.727            | 0.958                           | 0.841                           |
|                           | SI2        | 0.742               | 3.875 ± 0.981   |                            |                  |                                 |
| Facilitating conditions (FC)| FC1        | 0.768               | 3.854 ± 1.062   |                            |                  |                                 |
| Personal innovativeness (Plinn) | FC2       | 0.761               | 3.834 ± 0.731   |                            |                  |                                 |
|                           | FC3        | 0.857               | 3.825 ± 0.889   | 0.876                      | 0.853            | 0.785                           |
|                           | FC4        | 0.816               | 3.734 ± 0.865   |                            |                  |                                 |
|                           | Plinn1     | 0.718               | 3.821 ± 0.873   |                            |                  |                                 |
| Behavioral intention (BI)  | BI1        | 0.738               | 3.739 ± 0.764   |                            |                  |                                 |
|                           | BI2        | 0.866               | 3.724 ± 0.774   | 0.872                      | 0.846            | 0.645                           |
|                           | BI3        | 0.754               | 3.872 ± 0.854   |                            |                  |                                 |
| Use behavior (UB)          | UB1        | 0.821               | 3.754 ± 0.754   |                            |                  |                                 |
|                           | UB2        | 0.853               | 3.872 ± 0.874   | 0.862                      | 0.858            | 0.766                           |
|                           | UB3        | 0.723               | 3.738 ± 1.026   |                            |                  |                                 |

Table 4: Descriptive statistics analysis, reliability factors (α), and correlations (N = 432).

| Constructs | M    | SD   | 1   | 2   | 3   | 4   | 5   | 6   | 7   | α   |
|------------|------|------|-----|-----|-----|-----|-----|-----|-----|-----|
| PSR        | 3.786| 3.532| 0.77| 0.56**| 0.65**| 0.56**| 0.35**| 0.72**| 0.35**| 0.74|
| PE         | 3.782| 3.542| 0.57**| 0.45**| 0.55**| 0.34**| 0.75**| 0.34**| 0.75   |
| EE         | 3.765| 3.785| 0.32**| 0.54**| 0.39**| 0.66**| 0.39**| 0.81   |
| SI         | 3.787| 3.734| 0.62**| 0.58**| 0.56**| 0.56**| 0.35**| 0.72   |
| FC         | 3.765| 3.834| 0.62**| 0.69**| 0.72**| 0.75   |
| PI         | 3.789| 3.734| 0.52**| 0.46**| 0.76   |
| BI         | 3.712| 3.657| 0.56**| 0.91   |
| UB         | 3.783| 3.821| 0.73   |
considered weak, 3.67 and above (higher rate 5) are considered crucial, and scores in the middle are considered intermediate.

The indirect and direct impacts of the discrete independent variable on behavioral intention are displayed in Tables 3 and 4. As shown, all hypotheses were supported, with the exclusion of hypotheses H4 and H5—Table 3 can be referred to. Notably, as can be viewed in Table 5, the model proposed in this study explained 73% of the variance in personal innovativeness, 62% of the variance in perceived security risk, and 70% of the variance in behavioral intention.

Concerning the analysis, it can be construed for H1 that perceived security risk (PSR) directly affected behavioral intention (BI), while for H2 the result shows that personal innovativeness (PInn) affected behavioral intention (BI) over gender. The result for H3 shows that effort expectancy directly affected behavioral intention (BI). In contrast, for H4, the result shows that social influence directly did not affect behavioral intention (BI). For H5, the result shows that performance expectancy directly did not affect behavioral intention (BI) over gender. As for H6, the result proves that facilitating conditions directly affected use behavioral (UB) over gender.

Table 5: Results of the hypotheses’ tests (direct effects on behavioral intention).

| Hypothesis | Relationship | Path coefficient | Standard error | t value | Supported |
|------------|--------------|------------------|----------------|---------|-----------|
| H1         | Perceived security risk → behavioral intention | 1.368            | 0.121          | 2.971   | *** Yes   |
| H2         | Personal innovativeness → behavioral intention | 0.312            | 0.094          | 0.154   | ** Yes    |
| H3         | Effort expectancy → behavioral intention | 0.595            | 0.052          | 1.702   | * Yes     |
| H4         | Social influence → behavioral intention | -0.396           | 0.043          | 10.334  | n.s No    |
| H5         | Performance expectancy → behavioral intention | -1.021           | 0.148          | 7.011   | n.s No    |
| H6         | Facilitating conditions → use behavior | 0.668            | 0.115          | 1.583   | *** Yes   |

Table 6: Hypotheses’ results (indirect effects on behavioral intention (BI)).

| Independent | Mediator | Dependent | Hypothesis | T       | Sig. (p) |
|-------------|----------|-----------|------------|---------|----------|
| PSR         | Gender   | BI        | H7         | 1.574   | Yes**    |
| PE          | Gender   | BI        | H8         | -2.210  | No       |
| EE          | Gender   | BI        | H9         | 1.325   | Yes**    |
| SI          | Gender   | BI        | H10        | 0.873   | Yes*     |
| PInn        | Gender   | BI        | H11        | 1.514   | Yes*     |
| FC          | Gender   | UB        | H12        | 0.368   | Yes*     |
| PSR         | Experience | BI     | H13        | 1.324   | Yes      |
| PE          | Experience | BI     | H14        | -1.162  | Yes*     |
| EE          | Experience | BI     | H15        | 0.992   | Yes**    |
| SI          | Experience | BI     | H16        | 0.472   | Yes*     |
| PInn        | Experience | BI     | H17        | -1.142  | Yes      |
| FC          | Experience | UB     | H18        | 0.865   | Yes      |

Figure 3: Time consumption for electronic health record access.

Figure 4: Time complexity comparison graphs with respect to processing time.

Further, the results show support to hypotheses H7, H9 to H17, and H18. On the other hand, hypothesis H8 was not supported. The obtained results denote either indirect
or direct impact of all model variables on behavioral intention. As shown in Table 6, the results led to the conclusion of a significant relation between behavioral intention and perceived study risk.

Based on the data, it can be concluded that the availability of infrastructure and the security of healthcare systems in Middle Eastern nations have hampered the spread of blockchain technology. Meanwhile, the current students’ basic understanding of blockchain technology is investigated in this study, and the findings show that students are reasonably aware of the limitations of blockchain technology.

When studying user behavior, it is critical to know what students think about blockchain technology and how it relates to healthcare security. Students’ intents to use blockchain technology had a positive impact on user behavior, even though the $R^2$ score was minimal.

4.3. Result Summary. A set of data gathering is used to assess the performance of the blockchain approach. Each work uses a similar dataset to obtain reliable and consistent results by checking the time spent accessing the EHR and the processing time complexity. Electronic health records (EHRs) from individual patients are included in the experiment’s dataset; however, this information should not be disseminated. Healthcare providers, insurers, and competitors may profit from exploitation of patient personal information, such as medical, treatment, and financial data. With this dataset, researchers can analyze and validate the processing time and temporal complexity of various cloud technologies, including those that use authentication mechanisms such as blockchain and/or the distributed ledger technology (DLT).

Figure 3 compares the amount of time required to use the various technologies examined throughout this study. It is inevitable from the graph of Figure 3 that for a particular size, the time taken by block and cloud computing is less compared to that by the other intelligence platforms. Thus, it is clear that blockchain technology deployed with cloud storage helps to improve healthcare system security. For example, blockchain and the cloud integrated with blockchain technology have a lower time consumption with increasing file size when processing EHR data than traditional cloud computing and the cloud combined with authentication technologies. As a result, blockchain technology is superior to the rest.

Meanwhile, Figure 4 depicts the temporal complexity achieved by different strategies in terms of processing time. The temporal complexity of blockchain technology and blockchain technology integrated cloud is lower than the other two standard cloud-based technologies. So, it is clear from Figure 4 that blockchain could reinvent the way in which patient electronic health records are shared and stored, by providing more secure healthcare information exchange mechanisms in the healthcare sector and securing them over a decentralized peer-to-peer network.

In addition, as shown in Table 7, the overall performance of these four technologies is reviewed and compared in terms of data accessibility and security characteristics.

| Properties           | Cloud       | Cloud with authentication | Blockchain | Cloud+blockchain |
|----------------------|-------------|---------------------------|------------|------------------|
| Flexibility          | No          | Low                       | High       | Very high        |
| Decentralized access | No          | No                        | Yes        | Yes              |
| Integrity            | Yes         | Yes                       | Yes        | Yes              |
| Data privacy         | Less        | Medium                    | High       | Very high        |

5. Conclusion

Security and privacy issues are now a major concern for intelligent healthcare systems. To avoid such problems, it is vital to comprehend the security requirements of those systems. Intelligent healthcare systems now face a plethora of security and privacy concerns. It is critical to understand the security requirements of those systems in order to avoid such issues. There was also some fear of data suffocation. Some efforts concentrating on healthcare data security using blockchain technology, as well as relevant research, are examined in this paper. This research also looks at the privacy and storage security issues that exist in the cloud. Then, it was discovered that blockchain technology exceeds conventional technologies in terms of security efficiency and efficacy. This study looked into a variety of elements that influence the adoption of blockchain technology in Middle Eastern countries’ innovative healthcare systems.

The impact of personal creativity and its relationship to behavioral intent were also explored. The impact of individual innovation considerations on the adoption of blockchain technology for innovative healthcare systems in Middle Eastern countries was also investigated. This has a direct bearing on the deployment of blockchain technology in the outstanding healthcare systems of these countries. Given the aforementioned, the study looked into the power of demographic characteristics as moderators. As a result, future research might consider gender, age, and knowledge with blockchain technology, as well as their impact on blockchain adoption for smart healthcare systems. Another research topic for the future is to investigate all of the elements that influence blockchain technology acceptance. The findings of this study revealed a lack of understanding of the primary influencing factors when it comes to implementing blockchain technology in these countries’ healthcare services and technology. When studying user behavior, it is critical to know what students think about blockchain technology and how it relates to healthcare security. Students’ intents to use blockchain technology had a positive impact on user behavior, even though the $R^2$ score was minimal. Future research might consider gender, age,
and knowledge with blockchain technology, as well as their impact on blockchain adoption for smart healthcare systems. Another research topic for the future is to investigate all of the elements that influence blockchain technology acceptance.

**Data Availability**

The data used to support the findings of this study are available from the corresponding author upon request.

**Conflicts of Interest**

The authors declare that there is no conflict of interest regarding the publication of this paper.

**References**

[1] M. Chen, Y. Qian, M. Chen, K. Hwang, S. Mao, and L. Hu, “Privacy protection and intrusion avoidance for cloudlet-based medical data sharing,” *IEEE Transactions on Cloud Computing*, vol. 8, no. 4, pp. 1274–1283, 2020.

[2] M. Mustafa and S. Alzubi, “Factors affecting the success of Internet of things for enhancing quality and efficiency implementation in hospitals sector in Jordan during the crises of Covid-19,” in *Internet of Medical Things for Smart Healthcare. Studies in Big Data*, C. Chakraborty, A. Banerjee, L. Garg, and J. J. P. C. Rodrigues, Eds., vol. 80, Springer, Singapore, 2020.

[3] V. Varadharajan and U. Tupakula, “Securing services in networked cloud infrastructures,” *IEEE Transactions on Cloud Computing*, vol. 6, no. 4, pp. 1149–1163, 2018.

[4] B. Zhao, P. Fan, and M. Ni, “Mchain: a blockchain-based VM measurements secure storage approach in IaaS cloud with enhanced integrity and controllability,” *IEEE Access*, vol. 6, pp. 43758–43769, 2018.

[5] J. Ning, Z. Cao, X. Dong, and L. Wei, “White-box traceable CP-ABE for cloud storage service: how to catch people leaking their access credentials effectively,” *IEEE Transactions on Dependable and Secure Computing*, vol. 15, no. 5, pp. 883–897, 2018.

[6] Q. Xia, E. B. Sifah, K. O. Asamoah, J. Gao, X. du, and M. Guizani, “MeDShare: trust-less medical data sharing among cloud service providers via blockchain,” *IEEE Access*, vol. 5, pp. 14757–14767, 2017.

[7] S. Bag, S. Ruj, and K. Sakurai, “Bitcoin block withholding attack: analysis and mitigation,” *IEEE Transactions on Information Forensics and Security*, vol. 12, no. 8, pp. 1967–1978, 2017.

[8] H. a. al Hamid, S. M. M. Rahman, M. S. Hossain, A. Almogren, and A. Alamri, “A security model for preserving the privacy of medical big data in a healthcare cloud using a fog computing facility with pairing-based cryptography,” *IEEE Access*, vol. 5, pp. 22313–22328, 2017.

[9] R. Yu, J. Wang, T. Xu et al., “Authentication with block-chain algorithm and text encryption protocol in calculation of social network,” *IEEE Access*, vol. 5, pp. 24944–24951, 2017.

[10] R. Ranjan and S. Shekhar, “Securing healthcare data with healthcare cloud and blockchain,” in *Emerging Technologies in Data Mining and Information Security*, pp. 439–456, Springer, Singapore, 2021.

[11] V. Jagota and R. K. Sharma, “Impact of austenitizing temperature on the strength behavior and scratch resistance of AISI H13 steel,” *Journal of The Institution of Engineers (India): Series D*, vol. 101, no. 1, pp. 93–104, 2020.

[12] P. Hemalatha, “Monitoring and securing the healthcare data harnessing IOT and blockchain technology,” *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, vol. 12, no. 2, pp. 2554–2561, 2021.

[13] S. Namasudra and G. C. Deka, Eds., *Applications of Blockchain in Healthcare*, Springer, Singapore, 2021.

[14] D. C. Nguyen, P. N. Pathirana, M. Ding, and A. Seneviratne, “Blockchain for secure ehrs sharing of mobile cloud based e-health systems,” *IEEE Access*, vol. 7, pp. 66792–66806, 2019.

[15] A. Murugan, T. Chechare, B. Muruganantham, and S. G. Kumar, “Healthcare information exchange using blockchain technology,” *International Journal of Electrical and Computer Engineering*, vol. 10, no. 1, p. 421, 2020.

[16] V. Bhatia, S. Kaur, K. Sharma, P. Rattan, V. Jagota, and M. A. Kemal, “Design and simulation of capacitive MEMS switch for Ka band application,” *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 2021513, 8 pages, 2021.

[17] L. Ismail, H. Materwala, and A. Hennebelle, “A scoping review of integrated blockchain-cloud (BcC) architecture for healthcare applications: challenges and solutions,” *Sensors (Basel)*, vol. 21, no. 11, p. 3753, 2021.

[18] M. Kim, S. Yu, J. Lee, Y. Park, and Y. Park, “Design of secure protocol for cloud-assisted electronic health record system using blockchain,” *Sensors*, vol. 20, no. 10, p. 2913, 2020.

[19] X. Huang, V. Jagota, E. Espinoza-Muñoz, and J. Flores-Albornoz, “Tourist hot spots prediction model based on optimized neural network algorithm,” *International Journal of Systems Assurance Engineering and Management*, vol. 12, 2021.

[20] J. Bhola and S. Soni, “A study on research issues and challenges in WSAN,” in *2016 International Conference on Wireless Communications, Signal Processing and Networking (WISPNET)*, pp. 1667–1671, Chennai, India, 2018.

[21] S. Sharma, A. Mishra, and D. Singhai, “Secure cloud storage architecture for digital medical record in cloud environment using blockchain,” in *Proceedings of the International Conference on Innovative Computing & Communications (ICICC)* 2020, 2020.

[22] B. Shen, J. Guo, and Y. Yang, “MedChain: efficient healthcare data sharing via blockchain,” *Applied Sciences*, vol. 9, no. 6, p. 1207, 2019.

[23] J. Qu, “Blockchain in medical informatics,” *Journal of Industrial Information Integration*, vol. 25, article 100258, 2022.

[24] F. A. Reegu, S. M. Daud, S. Alam, and M. Shuaib, *Blockchain-Based Electronic Health Record System for Efficient Covid-19 Pandemic Management*, preprints.org, 2021.

[25] A. A. Siyal, A. Z. Junejo, M. Zawish, K. Ahmed, A. Khalil, and G. Soursou, “Applications of blockchain technology in medicine and healthcare: challenges and future perspectives,” *Cryptography*, vol. 3, no. 1, p. 3, 2019.

[26] X. Cheng, F. Chen, D. Xie, H. Sun, and C. Huang, “Design of a secure medical data sharing scheme based on blockchain,” *Journal of Medical Systems*, vol. 44, no. 2, pp. 1–11, 2020.

[27] J. A. Santos, P. R. M. Inácio, and B. M. Silva, “Towards the use of blockchain in mobile health services and applications,” *Journal of Medical Systems*, vol. 45, no. 2, pp. 1–10, 2021.
[28] H. Liu, R. G. Crespo, and O. S. Martinez, “Enhancing privacy and data security across healthcare applications using block-chain and distributed ledger concepts,” in Healthcare, vol. 8, no. 3p. 243, Multidisciplinary Digital Publishing Institute, 2020.

[29] G. N. Nguyen, N. H. Le Viet, M. Elhoseny, K. Shankar, B. B. Gupta, and A. A. A. el-Latif, “Secure blockchain enabled cyber-physical systems in healthcare using deep belief network with ResNet model,” Journal of Parallel and Distributed Computing, vol. 153, pp. 150–160, 2021.

[30] H. Wang, “IoT based clinical sensor data management and transfer using blockchain technology,” Journal of ISMAC, vol. 2, no. 3, pp. 154–159, 2020.

[31] R. M. Aileni and G. Suciu, IoMT: A Blockchain Perspective. In Decentralised Internet of Things, Springer, Cham, 2020.

[32] M. Shen, J. Duan, L. Zhu, J. Zhang, X. Du, and M. Guizani, “Blockchain-based incentives for secure and collaborative data sharing in multiple clouds,” IEEE Journal on Selected Areas in Communications, vol. 38, no. 6, pp. 1229–1241, 2020.

[33] D. S. Rajput, S. Sharma, S. K. Tiwari, A. K. Upadhyay, and A. Mishra, "Medical data security using blockchain and machine learning in cloud computing," in Mathematical Modeling and Soft Computing in Epidemiology, pp. 347–374, CRC Press, 2020.

[34] P. Wei, D. Wang, Y. Zhao, S. K. S. Tyagi, and N. Kumar, “Blockchain data-based cloud data integrity protection mechanism,” Future Generation Computer Systems, vol. 102, pp. 902–911, 2020.

[35] M. T. Quasim, F. Algarni, A. A. E. Radwan, and G. M. M. Alshmrani, “A blockchain based secured healthcare framework,” in 2020 International Conference on Computational Performance Evaluation (ComPE), pp. 386–391, Shillong, India, 2020.

[36] M. Mayuranathan, M. Murugan, and V. Dhanakoti, “Enhanced security in cloud applications using emerging blockchain security algorithm,” Journal of Ambient Intelligence and Humanized Computing, vol. 12, no. 7, pp. 6933–6945, 2021.

[37] L. Soltanisehat, R. Alizadeh, H. Hao, and K. K. R. Choo, “Technical, temporal, and spatial research challenges and opportunities in blockchain-based healthcare: a systematic literature review,” IEEE Transactions on Engineering Management, vol. 67, pp. 1–16, 2020.

[38] S. Chenthara, K. Ahmed, H. Wang, F. Whittaker, and Z. Chen, “Healthchain: a novel framework on privacy preservation of electronic health records using blockchain technology,” PLoS One, vol. 15, no. 12, article e0243043, 2020.

[39] A. Al Omar, M. Z. A. Bhuiyan, A. Basu, S. Kiyomoto, and M. S. Rahman, “Privacy-friendly platform for healthcare data in cloud based on blockchain environment,” Future Generation Computer Systems, vol. 95, pp. 511–521, 2019.

[40] A. Saha, R. Amin, S. Kunal, S. Vollala, and S. K. Dwivedi, “Review on ‘Blockchain technology based medical healthcare system with privacy issues’”, Security and Privacy, vol. 2, no. 5, article e83, 2019.

[41] H. Huang, T. Gong, N. Ye, R. Wang, and Y. Dou, “Private and secured medical data transmission and analysis for wireless sensing healthcare system,” IEEE Transactions on Industrial Informatics, vol. 13, no. 3, pp. 1227–1237, 2017.

[42] H. al-Hamadi and I. R. Chen, “Trust-based decision making for health IoT systems,” IEEE Internet of Things Journal, vol. 4, no. 5, pp. 1408–1419, 2017.

[43] F. Tian, An Agri-Food Supply Chain Traceability System for China Based on RFID & Blockchain Technology, IEEE, Kunming, China, 2016.

[44] A. Mohsen Nia, S. Sur-Kolay, A. Raghunathan, and N. K. Jha, “Physiological information leakage: a new frontier in health information security,” IEEE Transactions on Emerging Topics in Computing, vol. 4, no. 3, pp. 321–334, 2016.