

Blockchain in Psychological Health: The Future of Medical Records

¹Dr. Cuddapah Anitha, ²Dr. Rita Rani, ³Prof. Ved Srinivas,

Received: 23-October-2022

⁴Ms. Seva Rangnekar, ⁵Dr. Omkar Harishchandra Dalvi

Revised: 26-November-2022

¹Associate Professor, Department of CSSE, Mohan Babu University, Erstwhile
SreeVidyanikethan Engineering College, Tirupati, Andhra Pradesh

Accepted: 28-December-2022

ORCID: 0000-0002-3502-266X

²Senior Consultant Radiation Oncologist & Palliative Care Incharge,
Centre Principal investigator NCDIR,

Mahavir Cancer Sansthan and Research Centre, Patna, Bihar

Orcid id: 0000-0001-6730-5421

³Assistant Professor, Public Policy, Thiagarajar School of Management,
Madurai, Tamil Nadu.

Orcid id : 0000-0002-8190-1032

Assistant Professor,

⁴Chetana's Institute of Management & Research, Mumbai, Maharashtra
Assistant Professor,

⁵Chetana's Institute of Management & Research, Mumbai, Maharashtra

Orcid id :0000-0001-6043-9494

ABSTRACT

Purpose-Electronic health records (EHRs) have replaced paper medical records due to their convenience, safety, and ability to lessen data duplication. Poor interoperability and unsolved privacy concerns are still difficulties with EHRs, though. Blockchain, a distributed ledger protocol made up of encrypted blocks of data grouped in chains, could be used to address the interoperability and confidentiality issues plaguing EHRs. In this paper, we explain what electronic health records (EHRs) are and how blockchain technology works, and we offer a blockchain-based future that will improve EHR interoperability and privacy.

Methodology-There was a total of 424 health care workers from hospitals in the Andhra Pradesh included in the study's quantitative analysis, which included descriptive statistics, a t test, and an analysis of variance.

Findings-Efficient data management, equitable access, and reliable systems are all topics the study examines. To this aim, we propose the continued need for research in health informatics, data sciences, and ethics in order to implement blockchain-based EHRs.

Social implications-Concerns around blockchain's carbon footprint, inequitable access to healthcare, and patient mistrust all need to be addressed in any blockchain-based EHR plan.

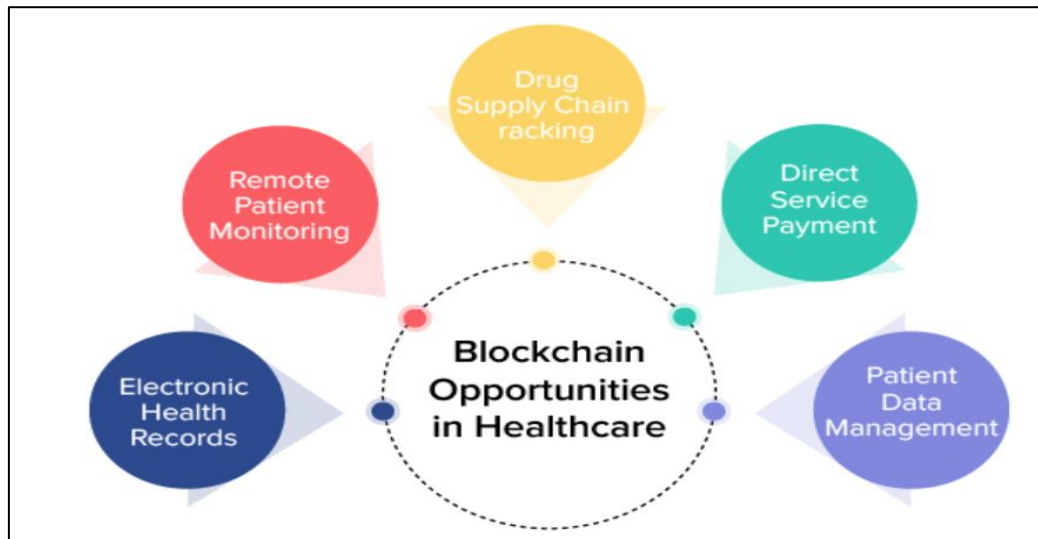
Originality-With the advent of blockchain technology, the groundwork is being laid for a completely new approach to healthcare. This study contributes to the literature on the use of blockchain technology in future healthcare because there are currently too few case studies examining the intersection of blockchain and contemporary medical practice.

Keywords: blockchain, healthcare, future, psychological, records

1. INTRODUCTION

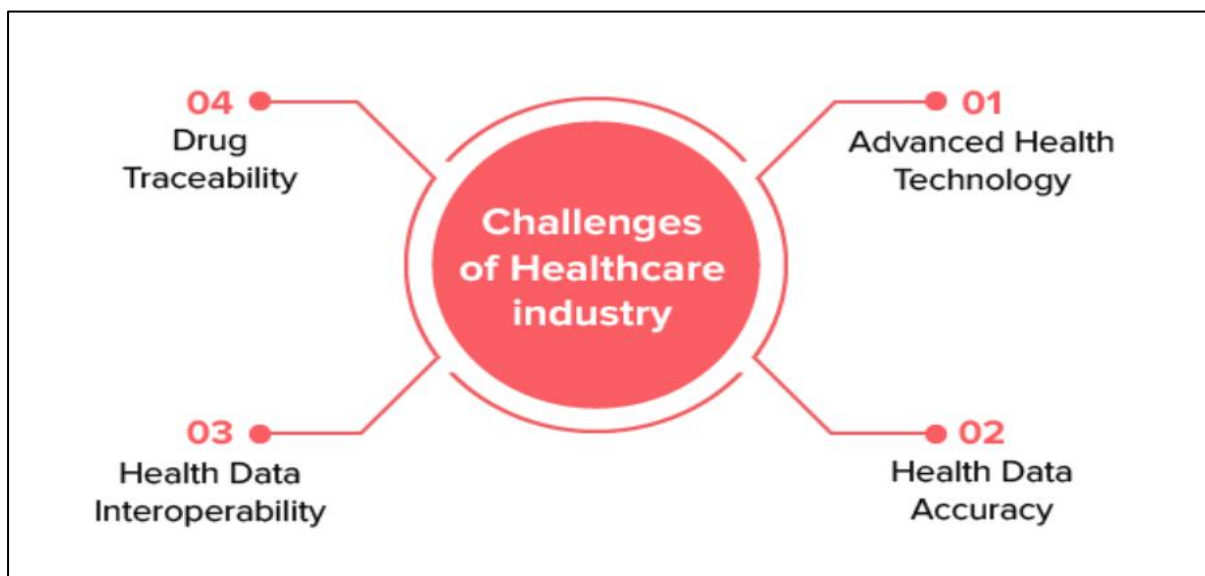
Numerous data are created, accessed, and transmitted on a regular basis in the healthcare industry, making it a clinical domain that is particularly data-intensive (Shi, He, Li, Kumar, & Khurram, 2020). The sensitive nature of the data and restricting considerations, such as security and privacy, make it extremely difficult to store and distribute this massive volume of data. Clinical environments and the healthcare industry as a whole rely heavily on SSS data-sharing for diagnosis and shared clinical decision making (Conoscenti, Vetro, & De Martin, 2016). It is crucial that clinicians have a way to quickly and easily send their patients' healthcare records to the appropriate authority, making data sharing a common practice (Abouelmehdi, Beni-Hssane, Khaloufi, & Saadi, 2017). To ensure that all parties involved in a patient's treatment have accurate and up-to-date information, it is crucial that primary care physicians and other specialists have access to the patient's clinical data (Ismail & Materwala, 2020). On the other hand, telemedicine and electronic healthcare are rapidly growing fields in which

patients' medical records are electronically transmitted to a remote doctor for second medical opinion(Chukwu & Garg, 2020).Through the use of shared clinical information, medical professionals can diagnose and treat patients remotely in these virtual clinics(Tariq, Qamar, Asim, & Khan, 2020). Due to the sensitive nature of patient data, ensuring its security, confidentiality, and privacy is a top priority in all such therapeutic agreements(Sangpetch & Sangpetch, 2016).



Therefore, it is crucial to facilitate safe, secure, and scalable data interchange in order to ensure healthy, meaningful clinical discussions with regards to remote patient cases(Dorri, Kanhere, & Jurdak, 2017). In order to increase diagnostic accuracy and treatment efficacy, clinical communication benefits from the secure and reliable transfer of data by soliciting the opinions of a panel of clinical specialists(Brunese, Mercaldo, Reginelli, & Santone, 2019).

In addition, several different interoperability issues arise frequently in this field. For instance, there can be significant operational difficulties associated with the safe, secure, and effective transfer of clinical data across different healthcare institutes & research organisations (Zhang, Xue, & Huang, 2016). The entities involved in such clinical data exchanges need to have a meaningful, trustworthy, and healthy working relationship with one another.



Issues that may arise include the private and sensitive nature of clinical data, data sharing agreements and protocols, the difficulty of patient matching algorithms, and ethical and regulatory restrictions (Kshetri, 2017). There are a number of crucial issues that must be settled amicably before any practical interchange of clinical data can take place, including the following. Over the past few years, scientists have attempted to develop tools for clinical practitioners that use the IoT, AI, ML & computer vision to better diagnose and treat chronic diseases.

2. REVIEW OF LITERATURE

Several research have demonstrated how blockchain technology may improve healthcare data exchange and aid in other diagnostic applications (Dinev, Albano, Xu, D'Atri, & Hart, 2016). Example use cases for the Healthcare Data Gateway approach include utilising a private blockchain to track and store individual patients' clinical data (Brunese et al., 2019). The patients in this model of individualised healthcare have complete control over their own private blockchain containing their health records and summary information. However, another study used a private Ethereum protocol blockchain to ensure not just the privacy but also the reliability of medical sensors, as well as removing the inherent dangers of remote patient monitoring (Al-Muhtadi, Shahzad, Saleem, Jameel, & Orgun, 2019). Their blockchain-based approach can allow for trustworthy real-time remote monitoring, which will help doctors monitor their patients' health from afar and keep accurate records of their care (Brunese et al., 2019).

Similarly, another study showed how encrypted health records might be stored safely by using blockchain technology (a distributed ledger that any user on the network can view). In this approach, a blockchain-based electronic health record is created by making the encrypted healthcare data publicly available (Zhang et al., 2016). With their proposed system, patients are given greater access to their clinical data, allowing them to not only view and monitor their information at will, but also add to and share it with their care providers (Conoscenti et al., 2016). In another piece of research, researchers advocated for a blockchain- and cloud-based framework for the storage and distribution of individual patients' health records (Chowdhury, Colman, Kabir, Han, & Sarda, 2018). With the help of the proposed approach, sensitive patient medical records may be stored and transmitted securely. The proposed method is one of a kind since it eliminates the need for a mediator by giving patients full access and control over their own medical records (Sánchez-Corcuera et al., 2019).

Recently, a blockchain architecture was introduced that makes use of parallel computing and simulated medical systems in order to evaluate the current state of patient healthcare. The suggested method uses parallel executions to evaluate the patient's state, diagnosis, and treatment process as a whole, and to study the associated therapeutic processes and using simulations to aid in medical decision making. The diagnostic precision and therapeutic efficacy of the proposed system have been studied in both actual and simulated healthcare settings. According to the findings reported in this study Ranjan, M. P. et al., (2015), it is possible to distinguish human affective states with a high level of accuracy by using visual and gesture modalities. According to the findings of Chowdhry et al. (2018), retirement-specific self-esteem, regretfulness, leisure time activities, and family structure were significantly higher in unemployed retirees. On the other hand, goal-directedness and social support were significant predictors of psychological well-being in reemployed retirees. The findings of the study suggested that retirees who found new work have improved psychological well-being. Azaria, Ekblaw, Vieira, & Lippman, (2016) developed BloCHIE, a one-of-a-kind network based on blockchain technology for the sharing of healthcare information (Shi et al., 2020). The purpose of the research conducted by M, A. M. and Mustafa, D. K. M. (2021) is to determine the prevalence of learning difficulties among children who have a hearing impairment, as well as the effect that these learning impairments have on the ability to communicate through sign language. The proposed system assesses the need for the sharing of healthcare data, primarily private healthcare information and medical records electronically & also deals with other types of data by employing blockchain across numerous sources. They combined on-chain and off-chain verification procedures into the platform to ensure that it met the necessary standards for authenticity and confidentiality. Clinical professionals and healthcare organisations can dramatically improve data sharing, privacy, and security by adopting blockchain technology as a tool. Similar mechanisms for safeguarding patient

data, resolving significant data security issues, and rolling out a blockchain software system across a hospital network were provided by Singh and Madaan (2022).

Research Gap:

Blockchain is one of the most promising emerging technologies of our time, and its popularity is only expected to expand in tandem with the proliferation of connected devices. Statista reported in September 2015 that there has been a dramatic growth in blockchain-related investments worldwide beginning in 2014. This suggests that in the years to come, blockchain technology may be expected to develop, grow, and reach new heights at an accelerated rate.

Objectives of the study

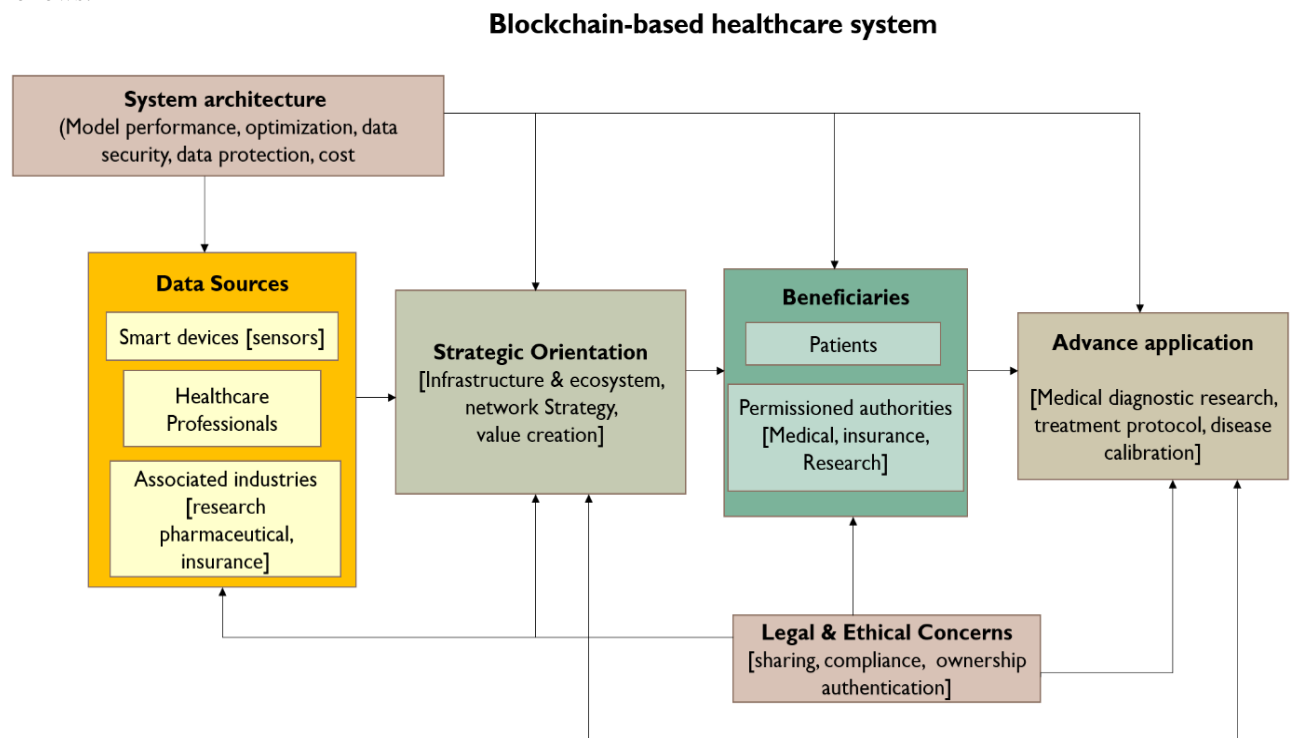
- To identify factors influencing future of blockchain technology in healthcare sector.
- To quantitatively assess factors influencing future of blockchain technology in healthcare sector.

Hypothesis of the study

- **H01:** There is no significant relationship among factors influencing future of blockchain technology in healthcare sector.
- **Ha1:** There is significant relationship among factors influencing future of blockchain technology in healthcare sector.
- **H02:** There is no significant relationship to quantitatively assess among factors influencing future of blockchain technology in healthcare sector.
- **Ha2:** There is significant relationship to quantitatively assess among factors influencing future of blockchain technology in healthcare sector.

3. RESEARCH METHODOLOGY

The study is primary and descriptive in nature. The responses obtained from 424 personnel working in hospital at Andhra Pradesh. The responses obtained through structured questionnaire. The SPSS software used to analyse descriptive statistics, t test, ANOVA analysis. The model for blockchain technology in healthcare industry are as follows:



4. RESULT AND DISCUSSION

Table 1: Age distribution

Age	Frequency	Percentage
18-24	86	20.28%
25-34	93	21.93%
35-44	102	24.05%
45-54	98	23.11%
Above 55	45	10.61%

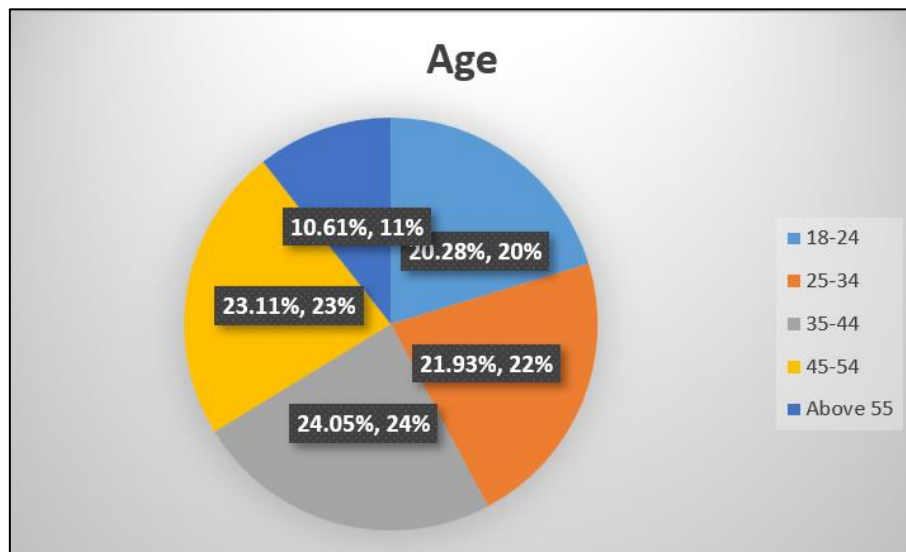


Table 1 stated the age distribution analysis and documented that majority of personnel as respondents having age category of 35-44 (n=102, 24.05%) following by 45-54 years (n=98,23.11%). Above 55 age (n=45, 10.61%) respondents found to be least in the study.

Table 2: Gender

Gender	Frequency	Percentage
Male	277	65.33%
Female	147	34.66%

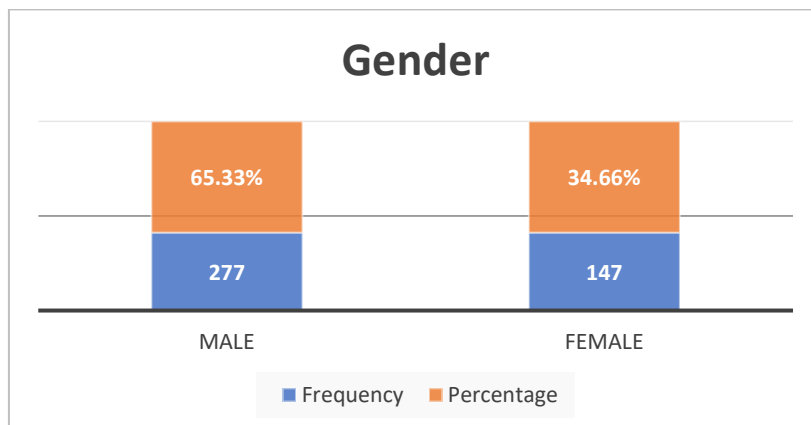


Table 2 stated the gender analysis and depicted that majority of respondents found to be male (n=277, 65.33%) in the study. Only few females (n=147, 34.66%) found participative in the study.

Table 3: Marital Status

Marital Status	Frequency	Percentage
Single	123	29.00%
Married	229	54.00%
Others	72	17%

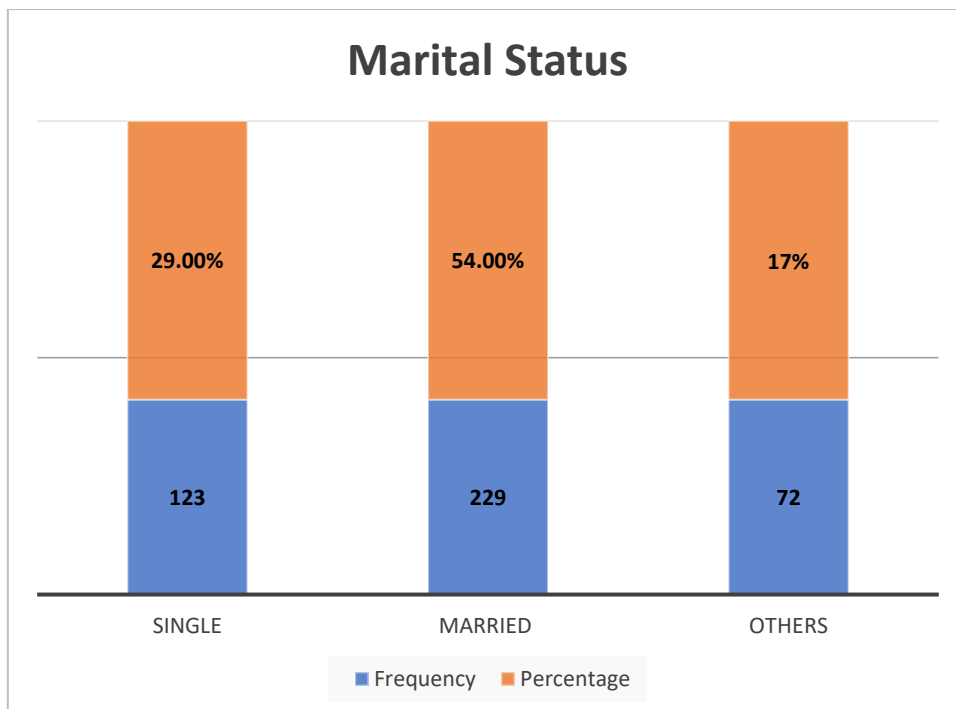


Table 3 stated the marital status analysis and depicted that majority of respondents found to be married (n=229, 54%) in the study followed by single (n=123, 29%). Only Others (n=72, 17%) found least participative in the study.

Table 4: Educational Qualification

Educational Qualification	Frequency	Percentage
10 th	7	1.65%
12 th	26	6.13%
Graduation	172	40.56%
PG & Higher	123	29.00%
Professional degree	96	22.64%

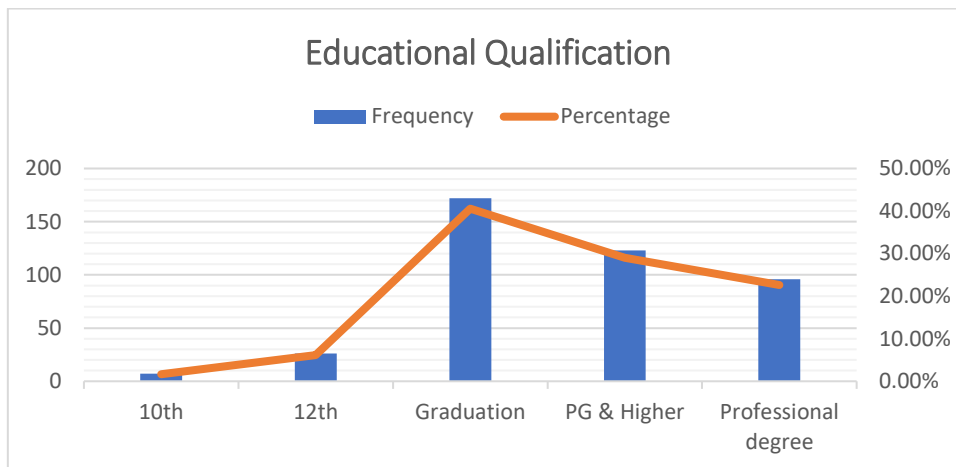


Table 4 stated the educational distribution analysis and documented that majority of personnel as respondents having educational qualification as graduate (n=172, 40.56%) following by PG and Higher (n=123, 29%). 10th (n=7, 1.65%) respondents found to be least in the study.

Table 5: Annual income

Annual income	Frequency	Percentage
Up to 1,00,000	83	19.57%
1,00,001 - 2,00,000	109	25.70%
2,00,001 - 5,00,000	98	23.11%
5,00,001 – 10,00,000	79	18.63%
Above 10,00,000	55	13%

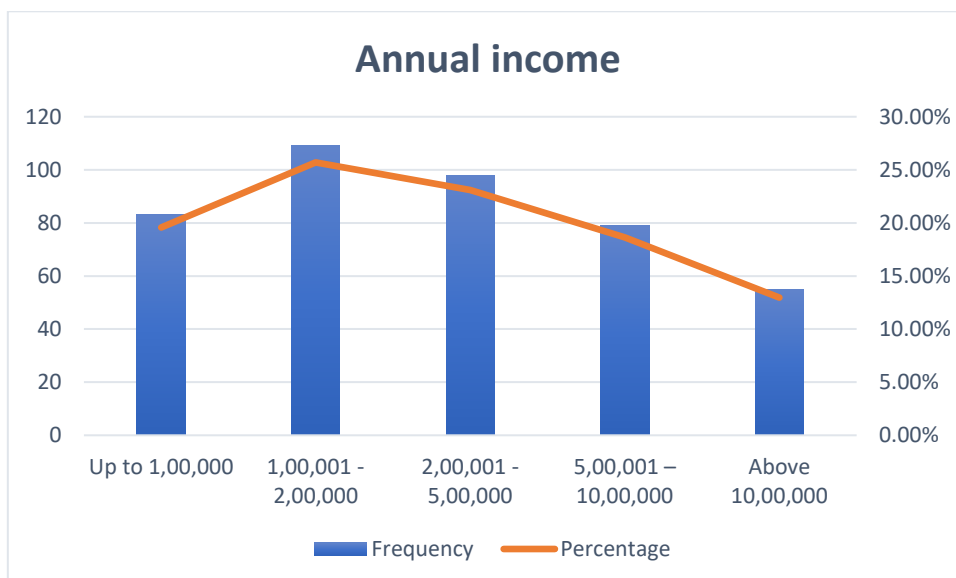


Table 5 stated the annual income analysis and documented that majority of personnel as respondents having annual income as 1,00,001 - 2,00,000 (n=109, 25.70%) following by 2,00,001 - 5,00,000 (n=98, 23.11%). Above 10,00,000 (n=55, 13%) respondents found to be least in the study.

Table 6: Reliability Test

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.902	0.954	8

Cronbach's alpha was calculated for this collection of questions using SPSS 23, and the value was found to be 0.902, which is excellent (a value of Cronbach's alpha above 0.7). For the questionnaire's final set of 8 questions. Therefore, there are internal consistency found among variables.

Table 7: Descriptive Statistics

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Privacy	424	1	5	4.39	.644
Internet of medical Things	424	1	5	4.36	.641
Interoperability	424	1	5	4.34	.717
Standardization	424	1	5	4.32	.649
Managing Storage Capacity	424	1	5	4.18	.813
Scalability	424	1	5	4.40	.607
Regulation	424	1	5	4.25	.738
Security	424	1	5	4.28	.717
Valid N (listwise)	424				

Table 7 stated the descriptive statistics of the study and stated that Scalability (Mean=4.40, Standard deviation=.607) is the prime factor considered as future of blockchain in health care industry followed by Privacy (Mean=4.39, Standard deviation=.644). Managing storage capacity (Mean=4.18, Standard deviation=.813) is the least factor considered in the study.

Table 8: One-Sample Statistics

One-Sample Statistics				
	N	Mean	Std. Deviation	Std. Error Mean
Privacy	424	4.39	.644	.031
Internet of medical Things	424	4.36	.641	.031
Interoperability	424	4.34	.717	.035
Standardization	424	4.32	.649	.032
Managing Storage Capacity	424	4.18	.813	.039
Scalability	424	4.40	.607	.029
Regulation	424	4.25	.738	.036
Security	424	4.28	.717	.035

Table 8 stated the one sample statistics of the study and stated that Scalability (Mean=4.40, Standard deviation=.607 and Standard error=.029) is the prime factor considered as future of blockchain in health care industry followed by Privacy (Mean=4.39, Standard deviation=.644 and Standard error=.031). Managing storage capacity (Mean=4.18, Standard deviation=.813 and Standard error=.039) is the least factor considered in the study.

Table 9: One-Sample Test

One-Sample Test						
	Test Value = 0					
	t	Df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Privacy	140.091	423	.000	4.316	4.25	4.38
Internet of medical Things	137.019	423	.000	4.361	4.30	4.42
Interoperability	124.709	423	.000	4.342	4.27	4.41
Standardization	139.758	423	.000	4.406	4.34	4.47
Managing Storage Capacity	105.958	423	.000	4.184	4.11	4.26
Scalability	149.286	423	.000	4.403	4.35	4.46
Regulation	118.422	423	.000	4.245	4.17	4.32
Security	122.952	423	.000	4.278	4.21	4.35

Table 9 stated the t test statistics of the study and stated that Scalability (t=149.286) is the prime factor considered as future of blockchain in health care industry followed by Privacy (t=140.091). Managing storage capacity (t=105.958) is the least factor considered in the study.

Table 10: ANOVA Analysis

ANOVA						
		Sum of Squares	Df	Mean Square	F	Sig.
Internet of medical Things	Between Groups	50.451	3	16.817	57.266	.000
	Within Groups	123.339	420	.294		
	Total	173.790	423			
Interoperability	Between Groups	37.608	3	12.536	29.283	.000
	Within Groups	179.805	420	.428		
	Total	217.413	423			
Standardization	Between Groups	41.288	3	13.763	42.212	.000
	Within Groups	136.938	420	.326		
	Total	178.226	423			
Managing Storage Capacity	Between Groups	53.718	3	17.906	33.287	.000
	Within Groups	225.933	420	.538		
	Total	279.651	423			
Scalability	Between Groups	37.842	3	12.614	44.823	.000
	Within Groups	118.194	420	.281		
	Total	156.035	423			
Regulation	Between Groups	40.543	3	13.514	29.882	.000
	Within Groups	189.948	420	.452		

	Total	230.491	423			
Security	Between Groups	33.830	3	11.277	25.834	.000
	Within Groups	183.331	420	.437		
	Total	217.160	423			
Privacy	Between Groups	33.830	3	11.277	25.834	.000
	Within Groups	183.331	420	.437		
	Total	217.160	423			

Table 10 stated the ANOVA analysis and documented that in all variables the significance value is less than .005. Therefore, all the variables under study are positively influence on the future of blockchain technology in healthcare industry.

Hypothesis Testing:

By application of t test, ANOVA Analysis stated that the null hypothesis is rejected (There is no significant relationship amongfactors influencing future of blockchain technology in healthcare sector; there is no significant relationship to quantitatively assess amongfactors influencing future of blockchain technology in healthcare sector) and alternative hypothesis (There is significant relationship amongfactors influencing future of blockchain technology in healthcare sector; There is significant relationship to quantitatively assess amongfactors influencing future of blockchain technology in healthcare sector) is accepted.

5. CONCLUSION AND IMPLICATIOZS

There may be impetus to adopt blockchain in healthcare in the near future, despite healthcare's occasional lag behind other industries in receiving new breakthroughs, because of the possible data's integrity. One or more key areas may emerge as priorities for blockchain-based management of electronic health records. Smart contracts have many potential uses in the healthcare industry, and the examples given above should convince us to use them. An immutable chain of blocks provided by smart contracts would account for individualised care outside of existing clinical frameworks. To prevent duplication in the parent centralised system, converging clinical systems could use a blockchain smart contract to prevent the creation of identical records. One way in which blockchain technology can be useful to scientists is by providing immutable, time-stamped versions of research. Similar to how smart contracts give patients agency over their data, a blockchain-based record of documentation might provide researchers with a permanent archive of their findings. Blockchain technology is essential in the vast pharmaceutical sector.

Many people, including doctors, nurses, hospitals, universities, healthcare organisations, government agencies, and biomedical researchers, will benefit fromthe practical application of blockchain technology in the healthcare domain because it will allow them to more safely and confidently disseminate the massive amounts of data, share clinical knowledge, and communicate recommendations while guaranteeing the privacy of all parties involved. If blockchain technology could be successfully implemented in healthcare clinical settings, it would undoubtedly pave the way for new research pathways that would help progress scientific research. At the same time, the collection, storage, and interchange of such clinical data in a secure, scalable, and interoperable manner is essential for precision medicine applications, which will help in the discovery of new methods for diagnosing and treating disease. Neural-control systems may benefit from blockchain technology, and the digital representation of a person's brain may be kept there. Few businesses have even committed to a role for blockchain technology while neurotechnology is still in its early stages of development.

REFERENCES

1. Abouelmehdi, K., Beni-Hssane, A., Khaloufi, H., &Saadi, M. (2017). Big data security and privacy in healthcare: A Review. *Procedia Computer Science*, 113, 73–80. <https://doi.org/10.1016/j.procs.2017.08.292>

2. Al-Muhtadi, J., Shahzad, B., Saleem, K., Jameel, W., & Orgun, M. A. (2019). Cybersecurity and privacy issues for socially integrated mobile healthcare applications operating in a multi-cloud environment. *Health Informatics Journal*, 25(2), 315–329. <https://doi.org/10.1177/1460458217706184>
3. Azaria, A., Ekblaw, A., Vieira, T., & Lippman, A. (2016). MedRec: Using blockchain for medical data access and permission management. *Proceedings - 2016 2nd International Conference on Open and Big Data, OBD 2016*, 25–30. <https://doi.org/10.1109/OBD.2016.11>
4. Brunese, L., Mercaldo, F., Reginelli, A., & Santone, A. (2019). A blockchain based proposal for protecting healthcare systems through formal methods. *Procedia Computer Science*, 159, 1787–1794. <https://doi.org/10.1016/j.procs.2019.09.350>
5. Chowdhury, M. J. M., Colman, A., Kabir, M. A., Han, J., & Sarda, P. (2018). Blockchain Versus Database: A Critical Analysis. *Proceedings - 17th IEEE International Conference on Trust, Security and Privacy in Computing and Communications and 12th IEEE International Conference on Big Data Science and Engineering, Trustcom/BigDataSE 2018*, 1348–1353. <https://doi.org/10.1109/TrustCom/BigDataSE.2018.00186>
6. Chukwu, E., & Garg, L. (2020). A systematic review of blockchain in healthcare: Frameworks, prototypes, and implementations. *IEEE Access*, 8, 21196–21214. <https://doi.org/10.1109/ACCESS.2020.2969881>
7. Conoscenti, M., Vetro, A., & De Martin, J. C. (2016). Blockchain for the Internet of Things: A systematic literature review. *Proceedings of IEEE/ACS International Conference on Computer Systems and Applications, AICCSA*, 0. <https://doi.org/10.1109/AICCSA.2016.7945805>
8. Chowdhry, D. R., & Shekhawat, K. (2018). An Evaluative Analysis of Psychological Well-Being Determinants Among Retires and Reemployed Retired Army Personnel's. *Kaav International Journal of Arts, Humanities & Social Science*, 5(2), 42-49. <https://www.kaavpublications.org/abstracts/an-evaluative-analysis-of-psychological-well-being-determinants-among-retires-and-reemployed-retired-army-personnels>
9. Dinev, T., Albano, V., Xu, H., D'Atri, A., & Hart, P. (2016). Individuals' Attitudes Towards Electronic Health Records: A Privacy Calculus Perspective. https://doi.org/10.1007/978-3-319-23294-2_2
10. Dorri, A., Kanhere, S. S., & Jurdak, R. (2017). Towards an optimized blockchain for IoT. *Proceedings - 2017 IEEE/ACM 2nd International Conference on Internet-of-Things Design and Implementation, IoTDI 2017 (Part of CPS Week)*, 173–178. <https://doi.org/10.1145/3054977.3055003>
11. Ismail, L., & Materwala, H. (2020). Blockchain paradigm for healthcare: Performance evaluation. *Symmetry*, 12(8). <https://doi.org/10.3390/SYM12081200>
12. Kshetri, N. (2017). Blockchain's roles in strengthening cybersecurity and protecting privacy. *Telecommunications Policy*, 41(10), 1027–1038. <https://doi.org/10.1016/j.telpol.2017.09.003>
13. M, A. M., & Mustafa, D. K. M. (2021). Learning Disabilities among Children with Hearing Impairment and Its Impact on Their Sign Language. *Kaav International Journal of Arts, Humanities & Social Science*, 8(4), 8-11. <https://www.kaavpublications.org/abstracts/learning-disabilities-among-children-with-hearing-impairment-and-its-impact-on-their-sign-language>
14. Ranjan, M. P., & Bajpai, D. A. (2015). Emotion Detection Through Face & Body Gesture For Technology Enabled Learning. *Kaav International Journal of Science, Engineering & Technology*, 2(1), 50. <https://www.kaavpublications.org/abstracts/emotion-detection-through-face-body-gesture-for-technology-enabled-learning>
15. Sánchez-Corcuera, R., Nuñez-Marcos, A., Sesma-Solance, J., Bilbao-Jayo, A., Mulero, R., Zulaika, U., ... Almeida, A. (2019). Smart cities survey: Technologies, application domains and challenges for the cities of the future. *International Journal of Distributed Sensor Networks*, 15(6). <https://doi.org/10.1177/1550147719853984>
16. Sangpetch, O., & Sangpetch, A. (2016). Internet of Things Technologies for HealthCare, 71–76. <https://doi.org/10.1007/978-3-319-51234-1>
17. Shi, S., He, D., Li, L., Kumar, N., & Khurram, M. (2020). Applications of blockchain in ensuring the security and privacy of electronic health record systems: A survey Shuyun. *Computers & Security*, 1(January), 1–20.

18. Singh, A., &Madaan, G. (2022). Blockchain Technology in Electronic Healthcare Systems. In Blockchain Technology in Corporate Governance: Transforming Business and Industries (pp. 1–23). Scrivener Publishing LLC. <https://doi.org/10.1002/9781119865247>
19. Tariq, N., Qamar, A., Asim, M., & Khan, F. A. (2020). Blockchain and smart healthcare security: A survey. *Procedia Computer Science*, 175(2019), 615–620. <https://doi.org/10.1016/j.procs.2020.07.089>
20. Zhang, J., Xue, N., & Huang, X. (2016). A Secure System for Pervasive Social Network-Based Healthcare. *IEEE Access*, 4(c), 9239–9250. <https://doi.org/10.1109/ACCESS.2016.2645904>
21. <https://www.mobileappdaily.com/blockchain-in-healthcare>