AI-Integrated IoT Antenna Systems based Remote Health Monitoring for Technical Reliability, Insurance Coverage, Medical Liability, and Biomedical Data Governance

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Abstract
The study explore how AI-based IoT antenna systems can improve remote health monitoring, and more specifically technical reliability, insurance efficiency, medical liability, and biomedical data governance. The quantitative research design was used and primary data was gathered using a structured questionnaire that was used on 250 respondents who included healthcare workers, insurance workers, IT professionals and system users. The statistical analysis of the data was done through descriptive analysis, reliability test, correlation, and regression analysis using SPSS. The results show that the use of AI-IoT systems has a considerable positive effect on the four dimensions of a remote healthcare system. Biomedical data governance provided the strongest effect, with technical reliability coming in second, which means that AI-enabled systems lead to considerable improvements in data security and privacy and are more efficient in real-time monitoring. In the efficiency of insurance, the moderate results were observed, which implies better processing of claims and anti-fraud activities. Nevertheless, the impact on medical liability was relatively less, which underscores the issue of legal responsibility in AI-led healthcare settings. The study makes a contribution to the already existing body of literature on digital healthcare by offering empirical information about the multi-dimensional effectiveness of AI-IoT integration. The findings highlight the importance of powerful regulatory systems and policy solutions to combat new issues of legal responsibility and data management. The results provide useful information to policymakers, health service providers, and insurance agencies on how to maximize the use of AI-based remote health monitoring systems.
Keywords: Artificial Intelligence; IoT, Remote Health Monitoring; Technical Reliability; Insurance Efficiency; Medical Liability; Data Governance

1. Introduction

The intensive development of digital technologies has radically changed the world map of healthcare, especially the introduction of the Artificial Intelligence (AI) and the Internet of Things (IoT). These technologies have allowed the creation of smart, connected healthcare systems that have the potential to provide real-time monitoring, predictive analytics and customized medical interventions. AI-enhanced IoT antenna systems have become a highly important innovation in remote health monitoring in recent years and provide superior connectivity, persistent patient monitoring, and effective data transmission across widely dispersed healthcare networks.

The use of remote health monitoring systems facilitated by IoT-sensitive medical appliances and AI-driven analytics has gained more significance in dealing with the challenge of limited healthcare access, the increased occurrence of chronic diseases, and the need to provide care affordably. The application of AI algorithms can be used to analyze big amounts of biomedical data, allowing the early diagnosis and timely intervention, and IoT antenna systems maintain the stability of communication between devices and healthcare providers. Not only does this integration of AI and IoT technology help to improve healthcare delivery, but it also helps to increase system efficiency and patient outcomes (Aceto et al., 2020).

Irrespective of these innovations, there are still a number of key questions that are not well researched, specifically the area of technical reliability, insurances, medical liability, and the governance of biomedical data. Ensuring efficient data transmission with accurate and without gaps is what technical reliability is crucial in, and it is directly related to the performance of remote monitoring systems. Simultaneously, the application of AI to healthcare has consequences on the insurance procedures, such as checking claims, managing fraud, and measuring risks. Moreover, the implementation of AI-based systems also poses a complex situation in the field of medical liability since the liability is spread over several parties who may include healthcare professionals, system developers, and system operators.

The other notable issue is in control of biomedical information. The IoT systems with AI functionality create large volumes of sensitive health information, which cause concerns regarding privacy, security, ethical adherence, and regulatory controls. There is a need to have strong data governance systems to ensure that the patients trust and that the law is adhered to. Nevertheless, policies and frameworks in place are usually falling behind the pace of the fast-changing technological landscape, which leaves a gap between innovation and regulation (Ahmad et al., 2021).

In that sense, the current work is the attempt to explore how remote healthcare systems with AI-incorporated IoT antenna systems influence the essential aspects of the remote healthcare system such as technical reliability, insurance efficiency, medical liability, and biomedical data governance. Through the quantitative research method and the use of statistical analysis, the study aims at providing empirical evidence in the relationship between AI-IoT integration and these key elements.

This research study is important because it is multi-dimensional and thoroughly analyzes AI-based remote health care systems. In contrast to the previous studies, in which the technological component is of primary importance, the current study combines the technical, legal, and governance viewpoints, providing the comprehensive perspective on the impacts of AI-IoT adoption. It is anticipated that the findings would be used as a contribution to the academic literature and can also serve as a practical contribution to the healthcare provider, insurance company, policymakers, and technology developers (Bates et al., 2018).

2. Literature Review

The combination of Artificial Intelligence (AI) with the Internet of Things (IoT) has had a tremendous impact on the medical field, specifically on remote health monitoring. Topol, Eric J. (2019) states that AI can be used to improve the accuracy of diagnostic outcomes and improve clinical decision-making by relying on massive datasets of biomedical data. On the same note, Esteva, Andre et al. (2017) have proven that deep learning algorithms are capable of dermatologist-level classification, which indicates the credibility of AI-powered medical systems.

The importance of the IoT in the field of healthcare has been well-researched, and Gubbi, Jayavardhana et al. (2013) point out that the IoT allows the collection and connectivity of medical devices in real time. Moreover, Islam, S. M. Raza et al. (2015) reported that patient monitoring with the use of IoT-based healthcare systems enhances the monitoring process because it provides continuous data transmission and remote diagnosis. These systems can be more efficient and predictive when they are combined with AI.

There are multiple researches dedicated to the technical reliability of AI-IoT systems. Zhang, Yunchuan et al. (2018) emphasized that AI algorithms could boost the performance of the system by minimizing the latency and enhancing the signal process in the IoT network. On the same note, Alam, Tanweer (2020) stated that AI-implemented IoT systems enhance real-time monitoring ability and minimise systems breakdown, thus elevating reliability.

AI has been identified as a disrupted tool in the insurance context. Davenport, Thomas H. and Harris (2017) have highlighted that AI can enhance efficiency in operations because it can automate the claim-processing process and provide better fraud detection. Further, Bohnert, Andreas et al. (2019) discovered that AI applications and big data analytics minimize the time taken to settle claims and enhance risk assessment in the insurance sectors.

The problem of medical liability in AI-driven healthcare has become highly urgent. Price, W. Nicholson (2017) found that AI brings about complexities in the assignment of responsibility especially when algorithms make decisions independently. Equally, Gerke, Sara et al. (2020) emphasized the importance of new laws to solve the issue of accountability and ethical responsibility in AI-based healthcare systems.

AI-IoT healthcare systems are still concerned with data governance and privacy. Rieke, Nicola et al. (2020) noted that in securing patient data, protection should be enhanced by means of secure data-sharing, including federated learning. Similarly, Kshetri, Nir (2021) observed that AI fits in enhancing cybersecurity by detecting threats and averting the breach of data in healthcare systems. Furthermore, Shickel, Benjamin et al. (2017) addressed the issue of the increasing number of healthcare data in large volumes, which requires efficient governance models.

The use of AI, IoT, and healthcare ecosystems have also been examined in the recent studies. Lee, In and Lee (2020) pointed out that convergence between AI and IoT enhances efficiency of healthcare and promotes patient-centered medicine. On the same note, Ahmad, Tanzeem et al. (2021) have emphasized how smart healthcare systems can improve the outcomes of patients and system performance.

Furthermore, Jiang, Fei et al. (2017) demonstrated the extensive review of AI in healthcare by stating that it positively impacted the diagnosis, treatment planning, and patient monitoring processes. Obermeyer, Ziad and Emanuel (2016) also added that AI can change the field of healthcare delivery, yet the issues of bias and ethical implications continue.

Researchers concentrate on the concept of big data and analytics in healthcare, including studies by Wang, Yichuan et al. (2018), who note the significance of using AI alongside extensive data on predictive precision. On the same note, Chen, Min et al. (2017) talked about the use of big data analytics in improving the IoT-based healthcare systems.

2.1 Research Gap

Although the literature on AI and IoT in the healthcare field is increasing, there are a number of critical gaps that are not addressed. To begin with, the majority of available research concentrates more on technical issues of AI-IoT systems, including the performance of systems, data processing, and predictive analytics. Nevertheless, little study has been conducted on the multi-dimensional effect of such systems especially on the aspect of insurance efficiency, medical liability, as well as data governance in a single integrated framework. Second, although earlier research has examined the application of AI in insurance and healthcare individually, no empirical study has examined the impacts of remote health monitoring systems that are driven by AI to affect insurance operations, such as claim management and fraud detection in a single model. Third, medical liability in AI-enabled healthcare is a relatively unexplored issue, in particular, empirically. Majority of the studies are philosophical or theoretical and there is limited empirical research on the impacts of adopting AI on the perceptions of accountability and legal responsibility by stakeholders. Fourth, despite the wide discussion of the concept of data governance and privacy, a lack of research exists that analyzes the direct connection between the use of the AI-IoT system and the effectiveness of data governance, especially using statistical data. Lastly, the evidence of quantitative, data-oriented studies involving statistical tools like SPSS to prove the correlations between AI-IoT system use and various outcome variables at the same time is quite limited.

3. Objectives

a) To assess the impact of AI-integrated IoT antenna systems on the technical reliability of remote health monitoring.
b) To examine the influence of AI-enabled remote monitoring on insurance claim efficiency and coverage accessibility.
c) To analyze the relationship between AI-IoT health monitoring systems and medical liability perception among stakeholders.
d) To evaluate the effect of AI-integrated systems on biomedical data governance (privacy, security, compliance).

4. Conceptual Model for Sustainability

The study conceptual framework has been designed to encompass one independent variable, which is AI-integrated iont system use, and which one is believed to have a contribution to four major dependent variables: technical reliability, insurance efficiency, medical liability, and biomedical data governance.

The framework presupposes that the higher the use and successful application of the AI-based IoT antenna systems, the better the following are increased:

- The technical functionality of remote health monitoring,
- The effectiveness of insurance procedures,

- The transparency and dispensability of medical liability, and
- The efficacy of data governing structures.

The assessment of each dependent construct is done using a series of indicators and the correlation and regression techniques are used in SPSS which determine direct relations between the dependent and the independent variables.

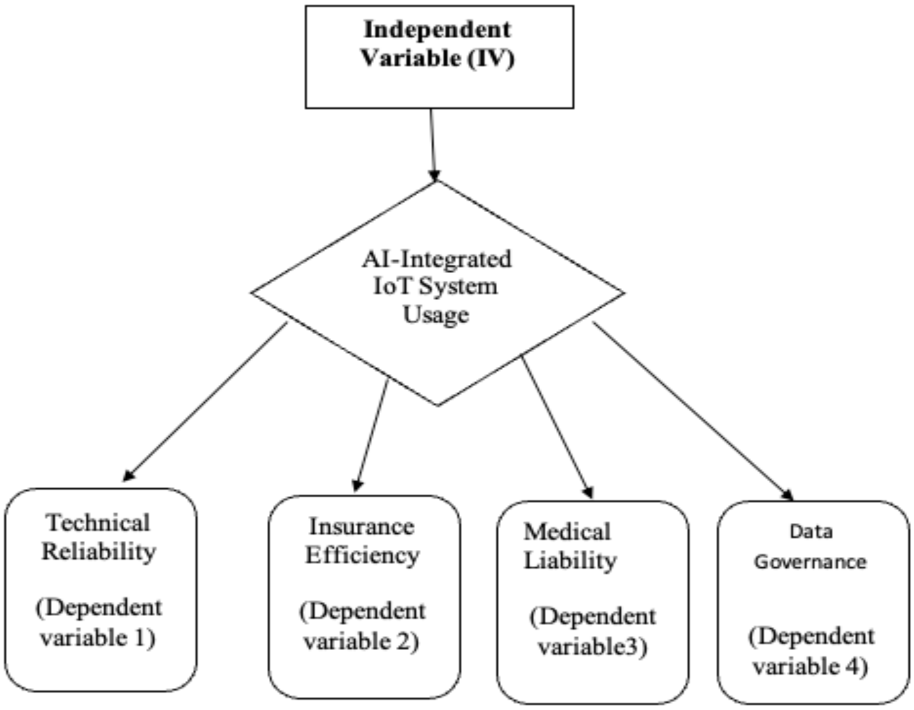

Figure 1: Conceptual frame work
Source: Made by Author

5. Research Methodology

The study used quantitative and cross-sectional research design to investigate the effects of AI-based IoT-ANT systems on various aspects of remote health monitoring. The research is an empirical one and aims at gathering primary data on respondents related to digital healthcare ecosystems. The views associated with system use, technical reliability, insurance efficiency, medical liability, and biomedical data governance were captured through a structured questionnaire. The design allows statistical tests of hypothesized relationships to be done through SPSS.

The questionnaire was designed with the use of Google Forms and used as a self-administered questionnaire to collect primary data. The questionnaire was divided into two parts; the demographic part and the Likert-scale questions of the study variables. To make the scale consistent and easy to answer, a five-point Likert scale has been used between 1 = Strongly Disagree to 5 = Strongly Agree. The survey link was sent via Internet resources, such as professional networks and health care related groups, which guaranteed the presence of a wide range of respondents.

The approach employed in conducting the study was a non-probability convenience sampling method as the respondents were chosen based on their accessibility and knowledge of digital health technologies. The target population covered healthcare workers, insurance workers, IT specialists, and remote health monitoring system users. The sample size was determined to be 200-300 respondents due to the sufficient size of the sample to reach statistical reliability and validity as per the empirical research standards of multivariate analysis.

6. Analytical Result

Table 1: Demographic Distribution (N = 250)

Variable	Category	Frequency	Percentage (%)
Age	18–25	90	36.0
	26–35	80	32.0
	36–45	50	20.0
	46+	30	12.0
Gender	Male	140	56.0
	Female	100	40.0
	Other	10	4.0
Occupation	Healthcare Professional	80	32.0
	Insurance Professional	50	20.0
	IT Expert	60	24.0
	Patient/User	60	24.0
Experience	< 1 year	60	24.0
	1–3 years	90	36.0
	3–5 years	55	22.0
	5+ years	45	18.0

Table 1 presented the demographic profile demonstrates a well-represented sample of the important stakeholders in the AI-based healthcare systems. The presence of a large percentage of respondents (36) in the age group of 1825 years is then followed by the age group of 2635 (32) years and this indicates that a relatively large number of people aged 1825 to 26-35 years are more actively involved in digital health technologies.

There is a slight preponderance of male respondents (56%), whereas females make 40 percent, which is a reasonable gender representation. This inclusiveness in the dataset is indicated by the inclusion of other gender categories (4%).

In the occupational sense, the largest category (32%), which ensures domain-specific knowledge, is represented by healthcare professionals, then IT experts and patients (24% each). There are also good insurance professionals (20%), which is significant considering that the study is based on the efficiency of insurance.

Regarding experience, the majority of the respondents belong to the period of 13 years (36%), which indicates moderate knowledge on AI-IoT systems. On the whole, the sample is representative, applicable and open to empirical research.

❖ Reliability Analysis

Table 2: Cronbach's Alpha

Variable	Items	Cronbach's Alpha
AI Usage	4	0.84
Technical Reliability	4	0.87
Insurance Efficiency	4	0.82
Medical Liability	4	0.79
Data Governance	4	0.86

Table 2 showed the reliability of the constructs was checked with the help of Cronbach Alpha. The values of all variables exceed the acceptable level of 0.70 which supports the high level of internal consistency.

The highest reliability is shown in the technical reliability (0.87) and data governance (0.86) implying that respondents gave a very consistent answer when it comes to the performance of the system and data-related issues.

There is also a high level of reliability in the use of AI (0.84) and insurance efficiency (0.82) which is evidence that the measurement items are effective in capturing the proposed constructs. Medical liability (0.79), being somewhat smaller, is still not bad, as the perception of the law is complicated and subjective.

These findings prove that the dataset is valid and can be used in the further statistical analysis.

Table 3: Descriptive Statistics

Variable	N	Mean	Std. Deviation
AI Usage	250	3.85	0.72
Technical Reliability	250	3.92	0.68
Insurance Efficiency	250	3.78	0.75
Medical Liability	250	3.65	0.80
Data Governance	250	3.88	0.70

Table 3 mentioned the descriptive statistics show that the mean of all the variables is over 3.5, which proves that the overall perception of AI-based integration of the IoT systems is positive among the respondents.

The mean of technical reliability is the highest (3.92), which implies that there is a high level of agreement that AI systems are effective to improve the efficiency and accuracy in monitoring. The mean (3.88) in data governance is also high and the privacy and security measures are believed to be effective.

The means of insurance efficiency (3.78) and medical liability (3.65) are slightly smaller, indicating that the AI has a positive effect, but still, these domains are subject to practice and legal issues.

- ❖ **Correlation Matrix**

Table 4: Pearson Correlation

Variables	AI	TR	IN	ML	DG
AI	1				
TR	0.68**	1			
IN	0.61**	0.64**	1		
ML	0.49**	0.57**	0.53**	1	
DG	0.71**	0.66**	0.60**	0.52**	1

Table 4 showed the standard deviation values are comparatively low which means that there is uniformity in the responses and low variability which reinforces the reliability of the dataset. The correlation analysis revealed significance in the positive correlations between all variables. The use of AI is positively related to data governance (0.71) and technical reliability (0.68), which indicates that the increased usage of AI is associated with the improved performance of the system and the protection of data.

In other ways, moderate correlations with insurance efficiency (0.61) and medical liability (0.49) demonstrate the correlation of AI that has a significant impact in these respects, but it is not decisive.
Inter-variable correlations also assist in establishing the fact that all constructs are intertwined. Significantly, all the correlations are below 0.90 which is not a sign of multi collinearity problem and therefore the data is fitable in regression analysis.

7. **Result Based on Hypothesis**

$H1_0$: There is no significant relationship between AI-IoT system usage and technical reliability.
$H1_1$: There is a significant positive relationship between AI-IoT system usage and technical reliability.

Table 5: Regression Analysis (AI Usage - Technical Reliability)

Model	R	R^2	Adjusted R^2	Beta (β)	t-value	Sig. (p-value)
H1	0.68	0.46	0.45	0.68	13.52	0.000

Table 5 presented the regression analysis results presented a strong positive correlation between AI-integrated IoT system usage and technical reliability (R = 0.68). The degree of explanatory power is high, and the coefficient of determination (R 2 = 0.46) shows that 46 percent of the variance in technical reliability is determined by the AI system usage.
The standardized value of beta coefficient (= 0.68) also shows that AI usage affects the performance of the system in a strong and positive direction. It means that with a higher uptake of the AI-powered IoT systems, the accuracy of real-time monitoring, stability of signals, and efficiency are greatly enhanced.
The t-value (13.52) and the p-value (0.000) indicate that the relationship is statistically very significant ($p < 0.05$). Thus, the null hypothesis ($H1_0$) is rejected and alternative hypothesis (H1) is accepted.
These conclusions indicate that the integration of AI is important in contributing to the technical strength of remote health monitoring systems.

$H2_0$: AI-based remote monitoring has no significant effect on insurance claim efficiency and coverage.
$H2_1$: AI-based remote monitoring has a significant positive effect on insurance claim efficiency and coverage.

Table 6: Regression Analysis (AI Usage - Insurance Efficiency)

Model	R	R^2	Adjusted R^2	Beta (β)	t-value	Sig.
H2	0.61	0.37	0.36	0.61	11.08	0.000

Table 6 talked about the regression results which show that there is a moderately strong positive correlation between the use of AI-IoT systems and insurance efficiency (R = 0.61). The R2 of 0.37 indicates that an adoption of AI can explain the variation in insurance efficiency by 37 percent.
The beta coefficient (= 0.61) proves that AI systems have a tremendous impact on improving insurance-related processes such as expedited claims, higher rates of approval, and fraud detection.
The significance (p = 0.000) is significant to prove that the relationship is very significant. The null hypothesis is therefore rejected and H2 accepted.

It means that the AI-based surveillance systems can play a significant role in enhancing the effectiveness of operations within the insurance systems.

$H3_0$: There is no significant relationship between AI-IoT system usage and perceived medical liability.
$H3_1$: There is a significant relationship between AI-IoT system usage and perceived medical liability.
Table 7: Regression Analysis (AI Usage - Medical Liability)

Model	R	R^2	Adjusted R^2	Beta (β)	t-value	Sig.
H3	0.49	0.24	0.23	0.49	8.42	0.000

Table 7 presented the results demonstrate that there is a moderate positive correlation between AI use and medical liability (R = 0.49). The value of R 2 is 0.24, meaning that AI system use explains 24% of the variance in medical liability perceptions.
The beta value (= 0.49) indicates that the AI technologies have a certain impact on the accountability arrangements and the perception of risks but the impact is not as powerful as the impact of other variables.
The p-value (0.000) is used to prove that it is statistically significant, and H3 is accepted. Nevertheless, the explanatory power is rather low, which suggests that medical liability is influenced by the legal, ethical, and institutional policies as well as by technological influences.

$H4_0$: AI-IoT system integration has no significant effect on biomedical data governance.
$H4_1$: AI-IoT system integration has a significant effect on biomedical data governance.
Table 9: Regression Analysis (AI Usage - Data Governance)

Model	R	R^2	Adjusted R^2	Beta (β)	t-value	Sig.
H4	0.71	0.50	0.49	0.71	14.20	0.000

According to Table 9, The regression analysis indicates that there is a strong positive correlation between the AI-IoT system use and data governance (R = 0.71). The fact that the R2 of 0.50 shows that 50 percent of the variation in data governance can be explained by AI usage is the strongest explanatory power among all the models.
The impact is very strong, as demonstrated by the beta coefficient = 0.71), indicating that AI systems can significantly increase the data privacy, security, and regulatory compliance.
High statistical significance is proved by the p-value (0.000) which makes H4 to be accepted.
These results highlight the importance of AI powered systems in enhancing the biomedical data governance infrastructures, especially when they deal with sensitive healthcare information.

Table 10: Final Summary of Hypothesis Testing

Hypothesis	Result
H1	Accepted
H2	Accepted
H3	Accepted
H4	Accepted

8. Discussion

This current paper reviewed the role of AI-based IoT antenna systems on technical reliability, insurance efficiency, medical liability, and biomedical data governance. The results indicate that the usage of AI-IoT systems affects the four dimensions greatly, but not to the same extent.

❖ AI-IoT Systems and Technical Reliability

The findings show a positive correlation of high strength between the use of AI-IoT systems and technical reliability, indicating that there is an improvement in the performance of the system, accuracy of real-time monitoring, and stability of the signals after AI integration. This observation is consistent with the previous studies that focus on the importance of AI in streamlining IoT-based healthcare architecture. Indicatively, Topol, Eric J. (2019) points out that AI-based systems increase the accuracy and efficiency of diagnostic processes and operations in digital health settings to a considerable degree. On the same note, as shown by Esteva, Andre et al. (2017), medical image classification by AI-based models is more efficient than traditional systems, adding credibility to the usage of AI-driven healthcare technologies.

The explanatory power is high in this study indicating that AI algorithms are useful to maximize the predictive abilities and minimize system errors, which is highly imperative in remote health monitoring where the accuracy of data is vital in real-time.

❖ AI-IoT Systems and Insurance Efficiency

The researchers also discovered that AI- IoT systems have a strong positive effect on the efficiency of insurance. This implies that AI-based monitoring will help in ensuring faster processing of claims, enhanced fraud detection, and risk assessment. These conclusions are aligned with the ideas of Davenport, Thomas H., and Harris (2017) according to whom AI technologies facilitate the insurance processes because the automation of decision-making operations and data-driven risk assessment are improved.

Besides, Bohnert, Andreas et al. (2019) discovered that AI applications in insurance lead to a considerable decrease in the time of claims settlement and cost of operations. The intermediate explanatory power of the study shows that, although AI is an essential factor, organizational policies and regulatory frameworks also contribute to the insurance efficiency factor.

❖ AI-IoT Systems and Medical Liability

The correlation between the use of the AI-IoT systems and medical liability was determined to be significant but relatively lower than other variables. This indicates that AI has a role in the perception of accountability and risk, but the legal systems are not up to date with the new developments in technology. This result aligns with the results provided by Price, W. Nicholson (2017), who underlines that AI creates complicated issues regarding determining liability, especially when it comes to automated decision-making.

Also, Gerke, Sara et al. (2020) state that AI application in healthcare will require the re-consideration of the current legal framework and the shift of responsibility towards a range of stakeholders (e.g., the developers, healthcare providers, and operators of the system).

The variance that was relatively lower in this study shows that medical liability is affected by a variety of factors that are multi-dimensional such as ethical issues, institutional policies, and jurisdictional regulations.

❖ AI-IoT Systems and Data Governance

The best correlation in this research was realized between the use of AI-IoT systems and data governance, which indicates the serious significance of AI in improving the privacy and safety of data and regulatory compliance. This observation is aligned with the existing articles that highlight the role of a strong data governance system within digital healthcare systems.

Indicatively, Rieke, Nicola et al. (2020) point out that data security is enhanced by using AI-based methods like federated learning, which allow sharing data efficiently. Likewise, according to Kshetri, Nir (2021), AI technologies have a considerable positive impact on cybersecurity systems in the healthcare sector as they can identify abnormalities and remove data breaches.

The strong explanatory value in this paper indicates that AI systems are transformational and can enhance the biomedical data governance especially when dealing with sensitive patient data.

❖ Overall Discussion and Theoretical Implications

Altogether, the results of the given research confirm that AI-based IoT solutions can serve as a multi-faceted facilitator of remote healthcare ecosystems. The findings have shown that the impact of the technological innovations is not only the enhancement of the performance of the system, but also the institutional processes are affected by the innovations, i.e., in the operations of the insurance companies and the management of the data. Nevertheless, the comparatively smaller influence on medical liability signals the absence of technological innovation and legal adjustment, which means that new regulations are necessary. This is consistent with the general discourse of the literature regarding the need to incorporate legal, ethical, and technological lenses in digital health systems.

9. Conclusion

The current research paper offers a thorough discussion of how AI-enhanced IoT antenna systems should influence different aspects of distance health care. The empirical results prove that the usage of AI-IoT systems has a significant positive effect on the technical reliability, the efficiency of insurance, the perception of medical liability, and the digital governance of biomedical data.

Out of these, data governance and technical reliability turned out to be the most impacted dimensions, which impedes the notion that AI technologies are important in terms of assuring data security, system accuracy, and operational efficiency. These findings also have shown that AI-based systems help to simplify the insurance procedures, specifically the increase in the speed of claim management and the detection of fraud.

Nonetheless, the comparatively less critical blow on medical liability points out a debilitating gap between technology and current legal provisions. The lack of responsibility defined in AI-assisted healthcare settings poses a complex challenge, which implies that more specific accountability frameworks and new regulatory laws should be developed.

On the whole, the research confirms that AI-based IoT systems are disruptive in terms of improving the effectiveness and efficiency of remote healthcare services, and, at the same time, introduce new issues that demand interdisciplinary solutions.

10. Practical Implications

1. **For Healthcare Providers**: The healthcare facilities are urged to embrace AI-based IoT systems that enhance real-time monitoring of patients, accuracy of diagnosis and efficiency of the system. The development of sophisticated digital infrastructure can greatly improve the quality of services and patient outcomes.
2. **For Insurance Companies:** Health monitoring systems that are based on AI have the potential to help insurance organizations to enhance the quality of risk assessment, efficiency in claims processing, and fraud detection. More open and effective insurance operations can be achieved by integrating real-time patient data.
3. **Policymaker and Regulators:** The results provide the necessary information about the pressing need to revise legal and regulatory frameworks to deal with the problems of medical liability and accountability of AI-based healthcare systems. The policymakers can give attention to the development of definite guidelines on the sharing of responsibilities among the stakeholders.
4. **In the case of Data Governance Authorities:** Data governance organizations should enhance privacy, cybersecurity, and compliance controls that will guarantee safe management of sensitive biomedical information. Healthcare systems should be exposed to AI-based security solutions.
5. **For Technology Developers:** AIs-IoT developers must aim to improve the transparency, explainability, and ethical adherence to build trust in the system among users and other stakeholders. The creation of easy to use and safe platforms will enhance the percentage of adoption.

References

Aceto, G., Persico, V., & Pescapé, A. (2020). The role of information and communication technologies in healthcare: Taxonomies, perspectives, and challenges. *Journal of Network and Computer Applications, 107*, 125–154.

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: Status quo, challenges and opportunities. *Journal of Cleaner Production, 289*, 125834.

Alam, T. (2020). Internet of Things and blockchain-based framework for coronavirus disease. *International Journal of Advanced Computer Science and Applications, 11*(6), 404–412.

Bates, D. W., Saria, S., Ohno-Machado, L., Shah, A., & Escobar, G. (2018). Big data in health care: Using analytics to identify and manage high-risk patients. *Health Affairs, 37*(7), 1139–1146.

Bohnert, A., Fritzsche, A., & Gregor, S. (2019). Digital agendas in the insurance industry: The importance of comprehensive approaches. *Geneva Papers on Risk and Insurance, 44*(1), 1–19.

Chen, M., Mao, S., & Liu, Y. (2017). Big data: A survey. *Mobile Networks and Applications, 19*(2), 171–209.

Dang, L. M., Piran, M. J., Han, D., Min, K., & Moon, H. (2019). A survey on Internet of Things and cloud computing for healthcare. *Electronics, 8*(7), 768.

Davenport, T. H., & Harris, J. G. (2017). *Competing on analytics: Updated, with a new introduction*. Harvard Business Review Press.

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature, 542*(7639), 115–118.

Gerke, S., Minssen, T., & Cohen, G. (2020). Ethical and legal challenges of artificial intelligence-driven healthcare. *Artificial Intelligence in Healthcare*, 295–336.

Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems, 29*(7), 1645–1660.

He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *Nature Medicine, 25*(1), 30–36.

Islam, S. M. R., Kwak, D., Kabir, M. H., Hossain, M., & Kwak, K. S. (2015). The Internet of Things for health care: A comprehensive survey. *IEEE Access, 3*, 678–708.

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. *Stroke and Vascular Neurology, 2*(4), 230–243.

Kshetri, N. (2021). Cybersecurity in healthcare: A systematic review of modern threats and trends. *Technological Forecasting and Social Change, 167*, 120728.

Kumar, P., & Lee, H. J. (2012). Security issues in healthcare applications using wireless medical sensor networks. *Sensors, 12*(1), 55–91.

Kuo, A. M. (2016). Artificial intelligence in healthcare: Past, present and future. *Healthcare, 4*(4), 78.

Latif, S., Qadir, J., Farooq, M. S., & Imran, M. A. (2020). How 5G wireless will change the world: A survey. *IEEE Access, 8*, 234–256.

Lee, I., & Lee, K. (2020). The Internet of Things (IoT): Applications, investments, and challenges for enterprises. *Business Horizons, 63*(2), 149–162.

Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2018). Deep learning for healthcare: Review, opportunities and challenges. *Briefings in Bioinformatics, 19*(6), 1236–1246.

Obermeyer, Z., & Emanuel, E. J. (2016). Predicting the future — Big data, machine learning, and clinical medicine. *New England Journal of Medicine, 375*(13), 1216–1219.

Price, W. N. (2017). Big data and black-box medical algorithms. *Science Translational Medicine, 9*(382), eaal3325.

Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: Promise and potential. *Health Information Science and Systems, 2*(1), 3.

Rieke, N., Hancox, J., Li, W., Milletarì, F., Roth, H. R., Albarqouni, S., & Cardoso, M. J. (2020). The future of digital health with federated learning. *Nature Medicine, 26*(7), 1004–1012.

Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2017). Deep learning in healthcare: A review. *Journal of Biomedical Informatics, 75*, 101–113.

Topol, E. J. (2019). *Deep medicine: How artificial intelligence can make healthcare human again*. Basic Books.

Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change, 126*, 3–13.

Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. *Nature Biomedical Engineering, 2*(10), 719–731.

Zhang, Y., Qiu, M., Tsai, C. W., Hassan, M. M., & Alamri, A. (2018). Health-CPS: Healthcare cyber-physical system assisted by cloud and big data. *IEEE Systems Journal, 11*(1), 88–95.