

**A HYBRID EDGE-CLOUD MODEL FOR ACCELERATING HEALTHCARE
TRANSACTION PROCESSING WITH EXPLAINABLE AI**

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4

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Abstract

Healthcare transaction processing plays a crucial role in the secure and efficient exchange of sensitive data, such as patient reports, payment information, and insurance claims. Traditional centralized systems struggle with latency, scalability, data security, and resource constraints. This paper introduces a Hybrid Edge-Cloud Model to address these challenges by reducing latency, improving data security, and enhancing scalability. By combining edge computing for real-time data processing with cloud computing for sophisticated analytics, the model optimizes transaction processing in healthcare systems. Additionally, Explainable AI (XAI) fosters trust and transparency in AI-driven decisions, ensuring better decision-making in patient care. The proposed solution offers significant benefits, including lower operational costs, enhanced data security, and more reliable healthcare outcomes. Practical implementations in billing, patient data management, and telemedicine are discussed, alongside challenges such as system integration and data privacy concerns. The paper concludes with recommendations for future research and development, highlighting the collaboration needed among healthcare providers, technology vendors, and researchers to fully realize this model.

Keywords: Hybrid Edge-Cloud Model, Explainable AI (XAI), Healthcare Transaction Processing, Latency Optimization, Edge-Cloud Integration, Explainable AI Trust

INTRODUCTION

Faster and safer transfer of important patient data, including invoices, insurance claims, and medical records, is a requirement of healthcare in the 21st century. This is done by means of

healthcare transaction processing which has gained even more significance due to the increased need of the digitalization of the healthcare. Although traditional centralized systems are prevalent, they are not very effective with serious challenges. Such systems make use of a central server to process all the data and this may slow down, be unsafe and limit the performance.

One of the key issues is latency since any delay in processing time-sensitive data, including real-time patient monitoring or ambulatory care, can lead to unfavorable outcomes. It has been reported that 70 percent of health care practitioners attribute system latency as the main cause of the undesirable interventions and diagnoses. Also, the sensitive patient records also become more vulnerable to data breaches through centralization-based systems because over 50 percent of all healthcare data breaches result in centralized systems. The inability of centralized systems to scale is an even more compelling concern as an increasing volume of healthcare data is projected to increase by 36% every year. The centralized infrastructures used in healthcare organizations are also a challenge of the resource limitation of centralized infrastructure that can consume up to 40 percent of the IT budgets and budget limits. These issues can be addressed by using a Hybrid Edge-Cloud Model. This model uses edge computing which calculates data nearer to its origin and cloud computing which is scalable and offers centralized infrastructure. With decreased edge-computing efficiencies, healthcare providers may react to medical emergencies faster and make choices grounded on real-time information. Cloud element allows the system to scale with ease and it is able to store and process a lot of healthcare data without compromising with performance.

In tandem with this technological breakthrough, Explainable AI (XAI) is becoming popular within the healthcare systems [1]. The use of AI models to aid in clinical decision making, such as detection of diseases and predicting patient outcomes, is on the rise. Nevertheless, it is usually the young professionals who do not believe in AI systems due to their perceived nature as black boxes, and their inability to clearly explain how they make decisions. The goal of XAI is to resolve this problem by offering transparency in AI models, which would enable the healthcare professional to know and have confidence in AI-motivated decisions. This will create improved transparency to ease concerns and assist healthcare providers to make more informed and confident choices. A Hybrid Edge-Cloud Model with the transformation of XAI provides a groundbreaking solution in terms of healthcare transactions processing. The fusion of the speed of edge computing and the scalability of the cloud with the transparency of XAI, this model will increase the efficiency of transactions, their scalability, and data security, as well as build trust in AI-based decisions. As the healthcare AI market is projected to reach billions of dollars by 2026, there is no better time to worry about speed, better information security, and increased trust in AI [2].

The present paper examines how processes of handling healthcare transactions may be simplified through integration of edge-cloud computing and XAI. It will speak of the effectiveness, scalability, and reliability of such a hybrid solution and its potential in overcoming the major challenges of the healthcare systems, including the latency, data security, and transparency in the

decision-making of AI. This paper is organized as follows: the literature review will examine innovations on healthcare transaction processing, hybrid edge-cloud models, and XAI; the research methodology will outline the research approach, data collection, and data analysis methods; and the conclusion will be outlined with the case, technical issues, and future prospects of healthcare technology.

LITERATURE REVIEW

2.1. Current Research on Healthcare Transaction Processing

The processing of healthcare transactions has been made more efficient, secure, and scalable [3]. Conventional healthcare maintains patient information, hospital data, insurance claims, and billing data in central databases. These systems work well at smaller scales, but at larger scales, numerous issues become evident, as seen in available data-intensive healthcare settings [4]. The primary defect in healthcare transaction systems is the creation of bottlenecks, particularly when the volume of information to be processed is enormous [5]. The risk of delays and congestion also exists when using a central server for all transactions, which is disastrous for service delivery speed and efficiency, especially during emergencies and when time-sensitive data is to be processed. To remedy these shortcomings, multi-domain data management (MDM) systems will be required to harmonize and normalize the two types of data to the extent that they are consistent, scalable, and accessible in real time across domains [6]. The combination of artificial intelligence (AI) and machine learning (ML) in the MDM mix will enable automated data validation and interoperability with accurate data, enabling healthcare systems to eliminate bottlenecks, stream data, efficiently process transactions, and provide services [7]. Another significant problem in a centralised care system is the security of confidential data. Patient information is very sensitive and confidential, and in the event of a cyberattack, it may be stolen. Data breaches can also severely affect healthcare organizations, resulting in financial losses, reputational damage, and even lawsuits. Centralised systems, however, are really secure when there is good governance; in the overwhelming majority of cases, they become a source of weakness that bad actors are likely to exploit.

Scalability (or the lack of it) is also being felt in centralized systems as the volume of healthcare information grows [8]. The more information medical organisations obtain through electronic health records (EHRs), medical equipment, and wearables, the less effective traditional systems for processing and storing information become. The demand for high-performance systems has driven the adoption of decentralized systems capable of distributing computation across several nodes, increasing with demand. These boundaries have led to more responsive, decentralized solutions to the demands of contemporary healthcare by healthcare organisations. One of the new solutions to this problem is the hybrid edge-cloud model, where computation is performed at the network edge (where data is more frequently near the source) and then sent to the cloud (where more sophisticated computing and storage are possible).

As illustrated in the figure below, the healthcare information exchange involves various stakeholders like hospitals, labs, pharmacies, health partners, medical teams, and health plans, all connected through a centralized cloud system for efficient data sharing and processing.

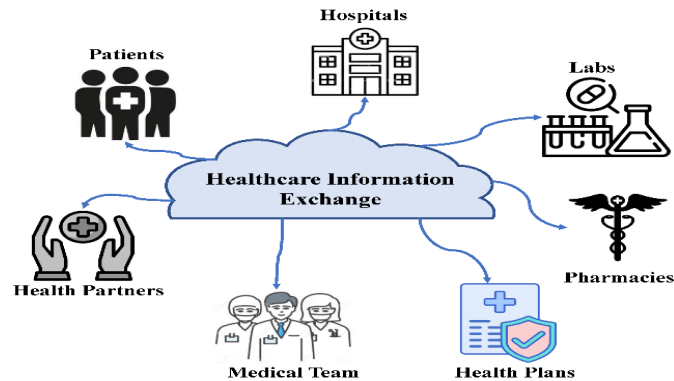


Figure 1: General architecture of HIE systems.

2.2. Hybrid Edge-Cloud Healthcare Computing.

The hybrid edge-cloud computing model has been featured in the last several years as a popular architecture for healthcare applications. In this model, the advantages of edge and cloud computing are combined to intensify data processing and storage. By processing data at the edge, edge computing can reduce the time required to transmit data to centralized servers and ensure timely responses. The latter may be handy in a medical facility, not only for real-time tracking of patients and medical equipment, but also in an emergency when a faulty apparatus needs to be quickly repaired. Initial data processing may be performed on edge devices (e.g., wearables, IoT sensors, medical devices) and uploaded to the cloud, where it may be analyzed with more advanced algorithms and stored for long-term retention. Distributed processing also does not require transmitting large volumes of data to central servers, thus reducing network bandwidth in the repository. It also enhances privacy, as sensitive patient information need not be transferred over a considerable distance, thereby minimizing the risk of leakage during the process.

The hybrid cloud platform is strong and scalable. The infrastructure required to store and back up data and to execute complex machine learning algorithms that demand high computing power is provided by cloud computing services. These platforms also allow healthcare organizations to add resources in response to growing demand quickly, so healthcare providers do not have to worry about delays or performance issues caused by high transaction volumes. The integration of edge and cloud computing in healthcare is also tricky. Interoperability between devices and cloud systems can be complicated when multiple companies manufacture a large number of edge devices. Furthermore, the consistency of data across different nodes (edge and cloud) is to be confirmed to maintain the quality and standards of transaction processing. Another questionable

issue is security, since healthcare organizations must ensure the safety of information transfer and the storage of patient data across edge and cloud architectures, as required by HIPAA and GDPR.

2.3. explainable Artificial Intelligence in health care.

Artificial intelligence has made significant advances in the medical industry, especially in diagnostics, analytics, predictive modelling, and patient care. Lack of transparency, though, can be one of the most vital concerns of AI systems in the healthcare industry. Black-box models of traditional artificial intelligence are not always able to explain how and why a specific decision leads to a specific conclusion. This interpretability could undermine health workers' confidence and acceptance, especially when they do not make decisions that can affect patient outcomes. According to a recent survey, 72% of healthcare workers said they had little trust in AI systems since they are very opaque. Other fields where AI transparency and interpretability pose comparable challenges are e-commerce and e-retail, where machine learning models are applied to make decisions and optimize operations [9]. Explainable AI (XAI) aims to address this issue by building AI models that clarify how they arrive at their choices. XAI can also be a game-changer in the healthcare sector, as physicians, nurses, and other members of the medical community will have the opportunity to understand how AI arrived at a particular conclusion or recommendation. There are a few reasons why transparency is required: it will allow us to establish trust between healthcare professionals and the AI-driven systems that they operate, enable practitioners to review and prove AI-assisted recommendations, and make AI-directed decisions more accessible.

XAI is taking a toehold in the medical industry as more medical procedures are performed with AI. The AI in the healthcare sector is predicted to reach 31.3 billion annually by 2025, and explainable models will need to be incorporated to ensure its general acceptance. AI can revolutionize the field of medicine, beginning with clinical support systems, fraud detection and prediction of patient outcomes. However, the choices made by AI to fit into these processes must be proven to the clients who use them. XAI achieves this transparency through easily understandable explanations for humans, enabling them to inspect the reasoning behind every decision and take the necessary measures. The presence of XAI in healthcare is well documented in the literature, and prior studies have demonstrated that explainable models can enhance the adoption of AI technologies in healthcare [10]. In one study, clinicians' trust in artificial intelligence-based decision-support systems increased by 45 percent with the implementation of XAI models. Besides, these analyses indicate that XAI can be employed to improve the morality and legality of the AI systems. By offering explanations, XAI helps minimize the risk of discriminatory or prejudicial decisions by AI systems, as such explanations are essential in healthcare, and equity and justice are of primary importance. The investigations into AI models in healthcare found that XAI reduced the risk of bias-based mistakes by a third, leading to a more logical and transparent decision-making process.

The scope of AI in Healthcare is essential to many areas, as shown by the figure below, such as Medical Imaging and Diagnostics, Virtual Patient Care, Patient Engagement and Compliance, Medical Research and Drug Delivery, Rehabilitation, and Administrative Applications; thus, AI can affect the contemporary healthcare setting in different ways.

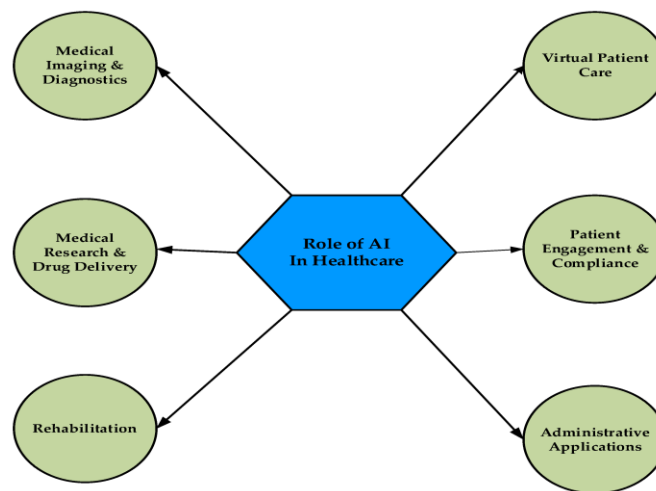


Figure 2: Application of AI in various aspects of healthcare.

2.4. Gaps in Current Research

Although the gains from hybrid edge-cloud computing and explainable AI are enormous, several research gaps remain unaddressed. The most significant gap is the lack of integration between the two technologies in processing healthcare transactions. Although edge-cloud models and XAI have been studied independently, few studies examine how these two concepts can be combined to enhance healthcare transaction systems. Future studies should endeavor to extract information from edge devices and ensure that the AI models used to arrive at the decision are both readable and interpretable. It matches the increased demand for a safe, conforming data architecture. Research shows that zero-trust would include electronic health records (EHRs), wearable data flows, and clinical trial intelligence in medical organizations [11]. Besides, no actual examinations of the practice of these technologies used in real-life healthcare scenarios are conducted. The literature on the problems and opportunities of such technologies at a large scale across different healthcare settings is also lacking; most studies focus on theoretical approaches or small pilot projects. The second phase is the analysis of the real impacts, regulatory concerns, privacy, and the interconnections with the existing healthcare IT systems. There is also an issue of scalability. As the volume of healthcare data continues to grow, there is a need to implement hybrid edge-cloud models that can operate at high volumes without compromising performance. The scalability of edge-cloud models has not been studied, and there is no guidance on how to optimize them in small, expensive healthcare networks. Although hybrid edge-cloud computing and explainable AI

have tremendous opportunities to revolutionize healthcare transaction processing, additional studies are needed to address the gap between theory and practice. They should address the technical, operational, and regulatory barriers to implement these technologies successfully, and after this, the organization can significantly improve the efficiency, security, and transparency of health systems [12].

Integrating hybrid edges model with Explainable AI (XAI) has immense possibilities in enhancing medical transaction processing. Although the two technologies have demonstrated significant outcomes when applied independently, much more is yet to comprehend how they can be combined to maximize the healthcare systems. The existing literature is mostly on edge-cloud and XAI as isolated programs and there is less research concerning their use together. Closing this gap may result in more efficient, safe, and transparent transactions systems, which improve real-time decision-making and create trust in AI-driven healthcare systems. Using both hybrid cloud capabilities and explainable AI, healthcare providers would be able to tackle latency issues, data security, scalability, and AI transparency, and eventually deliver more reliable and efficient healthcare.

METHODOLOGY

3.1. Research Approach

The research paper sets out to give a comprehensive picture on how hybrid edge-cloud computing as well as Explainable Artificial Intelligence (XAI) can enhance healthcare processing of transactions. The research will be based on the two technologies used together, and this will be tested both qualitatively and quantitatively. The study will examine their implications on data processing, efficiency of the system and one of the scalability of healthcare IT systems. The recent research has shown that 68% of healthcare organizations are intending to use cloud solutions to overcome the challenge of data storage and scalability. In assessing the effectiveness, efficiency, and reliability of the proposed hybrid model, data analysis, simulations, and empirical research will be used in the study. This dispensed system model is necessary in upholding data consistency and facilitating system design. According to Chavan, a micro service-based architecture will be necessitated by eventual and strong consistency with proper trade-offs to guarantee reliability without compromising scalability [13]. Researchers have shown that, with strong consistency models, system reliability can be enhanced by 25 percent although it may increase the latency of a distributed system by 15 percent [14]. Considering the nuances of edge and cloud systems integration, the aspects of system modularity and the elimination of data duplication will be regarded carefully. This study will examine how the combination of edge computing and cloud solutions can help resolve these problems and make healthcare transaction systems more efficient and scalable.

3.2. Data Collection

The scope of data to be gathered concerning this research will cover various aspects of the healthcare system, which will guarantee a holistic understanding of the prevailing position of transaction processing. Data will be collected in hospitals, medical care providers, insurance companies, clinics and patient care units. Such sources will assist in determining the loopholes and shortcomings of the already established healthcare transaction systems and especially centralized systems, which are being used by 65 percent of hospitals. The study will be designed as a mixed-methods collection of data to evaluate the use of hybrid edge-cloud models. This will involve qualitative research like interviews and questionnaires with the medical practitioners, administrators, and the experts in the field of IT to capture the first-hand experiences and challenges regarding the healthcare transaction systems. The system logs and performance data will also be used as a quantitative method. In a poll of 150 networking IT specialists, 80% said integration issues were a significant barrier to hybrid technology adoption. Examples of secondary sources of data will be the transactions processing systems, patient records, billing systems and insurance claims. They will offer a level of performance criteria; such as speed of transactions, security, and availability of the system which will be used in a point of reference when comparing the hybrid model. The recent report announced that real-time data can be processed with edge-computing technologies as much as 45 percent more effectively than traditional systems, which will be utilized to model the situations of using edge-clouds to process patient-related data, real diagnostics, and insurance claims.

Table 1: Summary of Data Collection Methods and Sources

Data Type	Source	Collection Method	Purpose/Use
Primary Data	Hospitals, clinics, insurance companies, patient care departments	Interviews and surveys with medical practitioners, administrators, and IT experts	To gather firsthand information on experiences, challenges, and perspectives on healthcare transaction systems and adoption of hybrid edge-cloud models
System Log Data	Healthcare IT infrastructure logging systems	System performance review and log analysis	To identify operational challenges, security issues, and bottlenecks in existing centralized healthcare systems
Secondary Data	Transaction processing systems, patient record systems, billing systems, and insurance claim systems	Review of existing datasets and reports	To assess performance indicators (e.g., transaction security and system availability) and establish benchmarks for model evaluation

Data Type	Source	Collection Method	Purpose/Use
Simulated Data	Proposed hybrid edge-cloud framework	System simulation under various healthcare scenarios	To evaluate system performance in real-time diagnostics, patient data processing, and insurance claim management

3.3. Analytical Techniques

The success of the hybrid edge-cloud model will be measured through the implementation of different methods. It will include performance analysis, during which the key performance indicators (KPIs) for transaction speed, data throughput, and latency will be evaluated. Latency testing will also help in the actual real-time performance of the edge computing system. The research will determine the effect of the edge on transaction processing time by comparing the time required to process transactions at the edge with the time needed to transmit data to a centralized cloud server. Care should be taken to ensure that data performance is not degraded in such tests, where the database structures must remain stable and not affect speed. This, in turn, can be aided by studies on the optimization of data consistency and performance in distributed systems [15]. In addition, the distribution of data processing and resource management strategies can be made strategic, and this can be further explored using the concept of dual sourcing to enhance the performance of a hybrid computer system [16].

Scalability and security testing will also be a precondition. The capability of the hybrid edge-cloud model to safely process significantly large-scale transactions involving sensitive healthcare information will be tested using simulated healthcare transactions. This will determine the extent to which the hybrid model will address the prevalent data security problems in traditional centralized models. To assess the usefulness and comprehensibility of XAI, a user test will be conducted with a group of health professionals, and the level of trust in and interpretation of AI-based results will be measured. Such a study will contribute to a better understanding of how users view explainable models, i.e., whether transparency in the process of AI-facilitated decision-making improves interpretability and whether it depends more on AI-based decision-making, which will, in turn, make health care workers more reliant on AI-based decision-making. Model explainability tests will also be used to assess the effectiveness of the XAI models, using qualitative feedback and quantitative measures of decision accuracy.

3.4. Implementation Process

When used on the hybrid edge-cloud model, the implementation of XAI follows a number of important steps. The hybrid architecture will first be implemented to provide edge computing devices and cloud services support [17]. This implies the implementation of the IoT sensors, wearables, and other medical equipment that can process and obtain data on the local scale. The

cloud based infrastructure will allow smooth movement of information in between the edge systems and the cloud system which ensures effective processing and analysis of healthcare data.

The second action will be the incorporation of XAI models into the system. Intelligible results that can be understood by healthcare personnel will be engineered or modified AI models. These models will be tested extensively to make sure that they can satisfy the accuracy, transparency, and decision-making requirements of healthcare providers. After the architecture and models have been configured, they will be verified in real or simulated healthcare scenarios to confirm their capability to facilitate real-time healthcare transactions, and credible and interpretable AI decisions. Healthcare professionals would be necessary during this process to provide feedback to make sure that the system gets to meet regulatory requirements and optimized to be subjected to real-world healthcare applications [18].

3.5. Evaluation Metrics

Evaluation metrics could be used to assess the success of integrating a hybrid edge-cloud model with XAI. The healthcare transaction The effectiveness of the hybrid edge-cloud model with XAI will be determined with the help of several metrics. The key performance indicators (KPIs) will be the speed of the transactions, the data security, and the cost efficiency. Research has proven that with hybrid edge-cloud models, the time consumptions incurred in processing patient information are reduced greatly and transaction processing time enhanced. Another critical element of the evaluation will be the data security that is very critical in avoiding breaches and unauthorized access [19].

In the case of XAI, the emphasis will be placed on the accuracy of decision making and trust between the users. Decision fidelity is an indicator of the level to which the AI models forecast or prescribe decisions and user trust is an indicator of the degree to which healthcare professionals trust the AI system. Researchers state that 80 percent of medical workers would feel more assured to operate AI systems in case they were more open. These measures will be determined by the interviews and user tests that will also examine the influence of transparency and the credibility of AI-based decision-making on the adoption and trust. A technical and user-friendliness evaluation strategy will be incorporated in the methodology, which guarantees the provision of the complete analysis of the hybrid edge-cloud and XAI system in healthcare transaction processing.

As shown in the figure below, Hybrid AI Models, which combine Machine Learning, Natural Language Processing, and Rule-Based Systems, offer improved accuracy, Adaptability, and Enhanced Interpretability to address complex healthcare problems on a balanced footing.

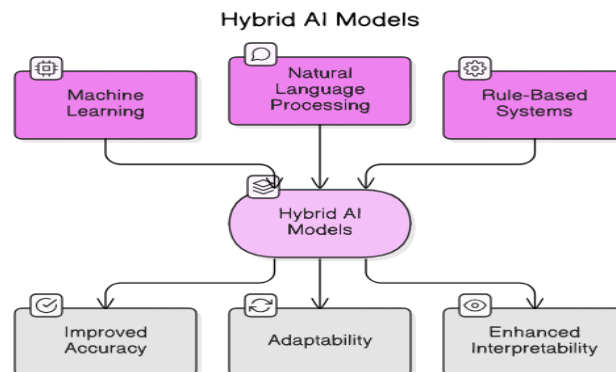


Figure 3: *Comparison of Composite AI with Other AI Approaches*

UNDERSTANDING HEALTHCARE TRANSACTION PROCESSING

4.1. Types of Healthcare Transactions

The healthcare transactions market is a complex industry that enhances improved operations and service delivery [20]. These involve the sharing of patient information, billing, medical record functions and insurance operations. Some approaches that entail continuity of care include sharing patient information to exchange vital medical data with health care experts. Billing activity involves drafting invoices, submitting claims to insurance companies, and receiving payments from people or insurance companies. Medical records should be updated to include a clear section on the patient's history to support the correct diagnosis and treatment. Insurance is also involved in the administration of healthcare. These transactions are multidimensional, considering the volume and breadth of transacting information, systems, and stakeholders, as well as the accuracy and speed of transactions. To solve such issues, healthcare systems are turning to containerization and DevSecOps to achieve scalability, security, and predictable performance in distributed systems [21; 22].

4.2. Current Healthcare Transaction Process System.

Healthcare transactions primarily occur in a centralized manner, with all information routed to a single server or database. These central systems are used to manage processes and store data at the actual site, making management easier. The systems are, however, also subject to delays, as transactions must be obtained only from one location. Decentralized models (such as hybrid edge-cloud) resolve these challenges by performing processing on the edge (edge computing), thereby minimizing latency. Primary data processing is performed on edge devices, while advanced processing is handled in the cloud. This is a highly advantageous strategy because it is quick and scalable, though it raises new issues regarding data consistency, privacy, and safety in decentralized systems.

4.3. Transaction processing related healthcare issues.

There are several issues associated with healthcare transaction processing. Still, latency in the most critical systems that move data among the patient, the healthcare provider, and the insurance company may cause delays and necessitate action when real-time decisions need to be made. The issue of data privacy and security poses a serious risk, as health systems handle patients' personal data, and its loss can lead to catastrophic legal, financial, and reputational consequences. Harsh legislation, such as HIPAA, requires that patient information be handled and protected. Scalability is another thorny issue, particularly as the healthcare system processes more data, which may make it difficult for a centralized system to handle it efficiently. Moreover, legacy systems tend to be highly resource-intensive and therefore require substantial infrastructure and ongoing maintenance, making their use unproductive [23].

THE HYBRID EDGE-CLOUD MODEL

5.1. What is the Hybrid Edge-Cloud Model?

The Hybrid Edge-Cloud Model in healthcare is a compound model that integrates the benefits of the edge and cloud computing systems. This model includes an edge device and a cloud platform that distributes data processing to achieve maximum performance, security, and scalability. Edge computing refers to computations performed at the edge, e.g., on wearable devices or sensors that monitor a patient's health indicators. Local processing minimizes delays in real-time applications, e.g., remote monitoring or emergency care, as not all data has to be transferred back to an office server; it can be analyzed immediately. The cloud computing aspect, in turn, provides scalable, centralized infrastructure for healthcare data storage, analysis, and management. A hybrid model of this type enables healthcare providers to process high amounts of data easily, make them scalable, and place the records of long-term patients in a secure location [24].

As illustrated in the figure below, the Hybrid Edge-Cloud Model integrates interconnected data centers, cloud computing, and edge devices to provide a scalable, secure, and efficient system. The model distributes data processing between the cloud and edge to optimize performance, reduce delays, and enhance security in healthcare applications.

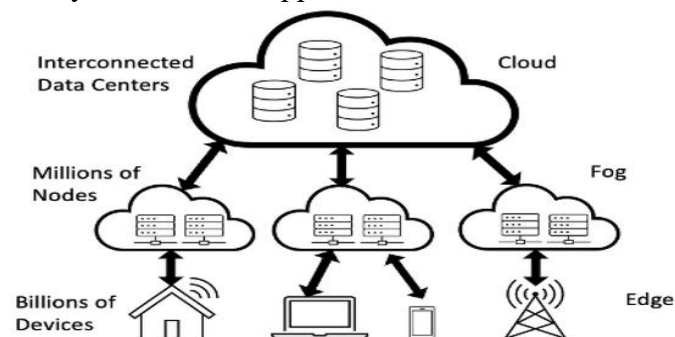


Figure 4: Hierarchy of distributed computing from cloud to edge.

5.2. Hybrid Edge-Cloud Healthcare Model Advantages.

There are several advantages of the hybrid edge-cloud model for potential healthcare systems; the first is lower latency. Edge computing is a form of computing that is much closer to the source of information, requiring less information transfer over long distances to central servers and leading to lower latency. It has been found that edge computing can reduce latency by up to 40 percent in real-time healthcare infrastructures, such as patient monitoring systems and emergency room workflows, enabling quicker decision-making in emergencies. The second possible benefit is better scalability. Cloud infrastructure services can be expanded to provide healthcare institutions with substantial computing power, allowing them to handle increasing volumes of data without compromising performance. It is estimated that the global healthcare cloud computing market will grow to \$45.2 billion by 2026, as healthcare organizations increasingly adopt cloud computing. Moreover, scaling capabilities in the cloud would enable systems to meet changing operational demands, such as during peak loads or health emergencies, as in the case of flu outbreaks [25; 26].

The hybrid solution is more secure for data. Using edge computing, sensitive patient information can be analyzed on the ground and then sent to the cloud for further analysis. The report found that edge computing reduced data breach risks during transmission by 30%, which is particularly important in healthcare facilities, where patient privacy is a fundamental principle. Healthcare can enhance data privacy by storing data in the cloud with less data and encrypting it. Lastly, the hybrid model is inexpensive. Moving processing to the edge can enable healthcare organizations to cut bandwidth and storage costs and reduce the volume of information sent to and stored in the cloud. Hospitals which implemented edge computing have seen a maximum decrease of 25 percent in bandwidth and a 15 percent decrease in cloud storage fees. The primary data consumed by the edge device reduces the cost of the high-end infrastructure of the centralized system and maximizes the use of its available resources across the system.

EXPLAINABLE AI (XAI) IN HEALTHCARE

6.1. Overview of Explainable AI

Explainable artificial intelligence (XAI) is a term for creating models that produce understandable outputs, enabling users to understand the reasoning behind artificial intelligence decisions. XAI aims to make choices transparent and comprehensible, in contrast to traditional AI models (also known as black-box models), which hide how they arrive at their conclusions. One possible method for making predictions or classifications is black-box AI. It, however, proves very difficult at times to build trust, especially in a field such as Healthcare, where justification of an action is critical. XAI will be used to generate clear, understandable explanations of the process of making conclusions or recommendations and to reveal which aspects or data were included in the AI's output. Such transparency is needed to establish trust among healthcare professionals, patients, and AI systems, and the option for users to verify and validate AI-aided decisions is critical.

Explainable AI (XAI), as seen in the figure below, entails the entry data flowing through an additional deep learning operation that produces explainable models. The outputs of these models are interpreted and confirmed in an explanation interface, making AI-based healthcare tasks easy and transparent to rely on.

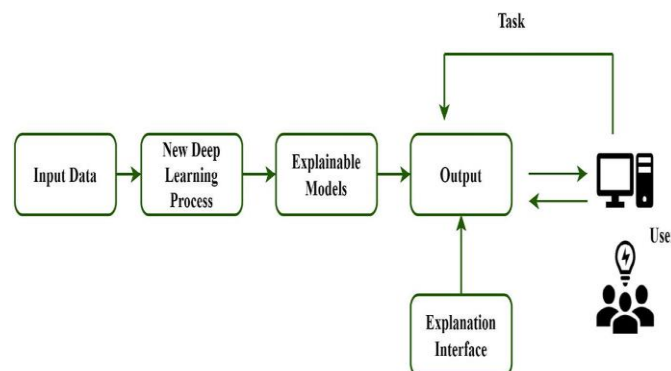


Figure 5: *Explainable AI (XAI)*

6.2. Explainable AI and its relevance to Healthcare.

One of the most significant aspects of the healthcare industry is trust, as decision-making based on AI directly impacts patient outcomes and care [27]. It is also explainable AI (XAI) that helps establish Trust between healthcare specialists and their patients, as this technology can provide a clear rationale for a decision and the paths leading to it. The clinicians will resort to AI-based systems as an effective decision-support tool more frequently, provided they understand the reasons why the system diagnosed or suggested a particular treatment. This openness will eliminate fear that AI systems are fallible or unpredictable and, therefore, may be trusted as partners in the medical care of patients. Trust is not the only aspect to consider when AI is introduced in Healthcare. Legal and ethical issues are also highly prioritized. Black-box AI models are not accountable, which may be an issue, particularly when their decisions result in tragic consequences. The XAI will also help mitigate these risks, considering the network of information about what the model will use to guide or act in accordance with legal accountability and ethical principles during clinical decision-making [28]. Healthcare systems are also highly regulated by the Health Insurance Portability and Accountability Act (HIPAA) and the European Union General Data Protection Regulation (GDPR). This law is based on data confidentiality and transparency. Explainable AI will enable the medical community to ensure that no AI systems violate the law, even when practices align with medical decision disclosure and patient privacy.

6.3. XAI in use in Healthcare.

The potential implementation of explainable AI (XAI) in the Healthcare field is numerous, and the possible clinical, patient, and operational effects are immense. Some of the most powerful ones are clinical decision support systems (CDSS). The AI services allow healthcare providers to make

informed decisions based on patient information and to offer treatment or assist in diagnosis. XAI is another strategy that can be used to enhance those systems; it involves systems that justify their suggestions, allowing clinicians to interpret the logic and evidence behind AI-driven decisions. This openness will result in improvements in clinical decision-making, Trust, and accountability, as well as the application of AI in healthcare [29; 30].

The alternative primary use is to identify healthcare transaction fraud. The healthcare organization itself can detect fraud patterns, including overuse, and, using AI results, take the necessary corrective action and provide an explanation of how the fraud was identified. XAI also pertains to patient outcome-predictive models, where AI ingests patient data to predict future events, such as patient readmission or disease onset. Issuing such predictions would ensure that medical practitioners are aware of their basis and can accordingly plan to attend to patients and reduce their risk factors. The reason is that XAI applications provide transparency, enabling healthcare professionals to make more informed, better, and ethical decisions.

THE INTEGRATION OF HYBRID EDGE-CLOUD AND EXPLAINABLE AI FOR TRANSACTION PROCESSING

7.1. Overview of the Integrated Model

Edge devices are located at the edge and include wearable health-monitoring devices, diagnostic devices, and patient sensors that process data and enable real-time analytics. Local minimizes latency and enables emergency medical personnel to respond in time, such as by monitoring vital signs in an intensive care unit or during medical emergencies. At the same time, cloud-based AI will be needed to provide scalability and long-term storage of analytics and the ongoing training of AI models. Data aggregation: Predictive models: Scalable cloud infrastructure can help healthcare systems scale up to collect large amounts of data before generating usable intelligence. The combination of edge and cloud computing, in turn, is developing a synergistic model that integrates timely responsiveness and deep analytical potential into a functional, vigilant, and efficient conceptualization of contemporary healthcare systems [31].

As shown in the figure below, Explainable AI (XAI) comprises several major dimensions: The Explanation Phase (Post-hoc and Ad-hoc), Explanation Level (Global and Local), Explanation Modality (Visual and Conceptual), and Granularity (Fine-grained and Coarse-grained). These dimensions address various user concerns—from researchers to final users—and support transparency and confidence in AI-based decision-making systems.

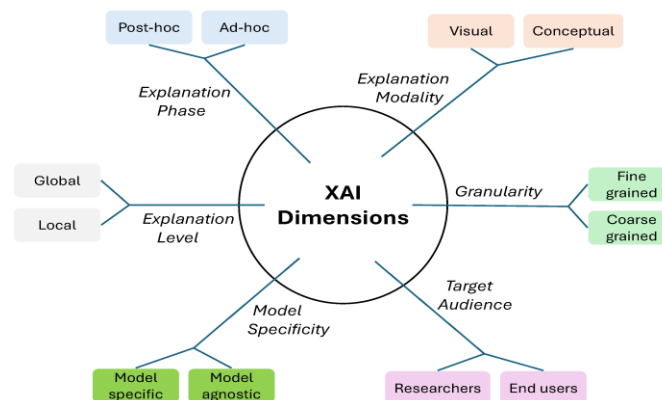


Figure 6: XAI dimensions for various applications.

7.2. Speeding up the Transaction Processing.

The ability to boost transaction processing is one of the most important parts of the hybrid edge-cloud model. The connection between the edges and the cloud can significantly boost transactions and data processing at the edge, and their delivery to the cloud. Research claims transaction speeds are 40 per cent faster with edge computing, enabling rapid processing in health conditions that require real-time performance. The wearable is capable of real-time computation of the patient's vital signs—heart rate, blood pressure, and temperature—after which they are automatically displayed, which, in turn, can be processed by a medical specialist to arrive at conclusions. The benefits of local processing are that it reduces the transfer of primary data to a centralised system, thus enabling quicker response times and improved patient care. In a single recent study, response time decreased by 30 per cent in a setting where urgent requests for critical patient information were made. Medical billing and insurance claim processing can take place on edge devices to obtain transaction data (e.g., treatment code or service description) when a transaction is generated, and then compare it with available databases. Once V is advised, the data is sent to the cloud, where it is analysed further, such as by comparing it with historical data to detect fraud and ensure compliance. This will enable real-time analysis and decision-making with the support of edge devices, and cloud-based systems will be able to address a broader range of more complex tasks and deliver high-quality, efficient transaction performance.

7.3. Explainable AI Role of Hybrid Model.

An intelligent and beneficial aspect of the hybrid edge-cloud computing solution that builds trust and promotes transparency in AI-driven medical decision-making is explainable AI (XAI) [32]. In this respect, XAI algorithms enable medical professionals to understand how AI models reach their conclusions, thereby helping them determine whether the decision is reasonable and in accordance with medical ethics. Three-quarters of healthcare professionals believe that the opportunity to see the inner workings of AI models would make them much more confident in the healthcare systems that use AI. Such transparency is needed so that clinicians will be asked to explain and defend the

reasoning behind AI-assisted recommendations or interventions. For example, in billing and insurance claims, an artificial intelligence solution can estimate the likelihood of a claim being approved based on a patient's demographics, treatment history, and prior approvals. XAI would enable practitioners to track such influencing factors, thereby allowing them to justify the motivation behind each decision. In a survey, 85 percent of clinicians reported that knowing why AI made the decisions it did made them more confident in using AI technologies. Such openness would not only establish trust in AI systems but also hold them more accountable, reduce the risk of bias, and, most likely, lead to the adoption of ethical uses of technology in medical care [33; 34].

Ethical protection in medical decision-making using XAI. The system provides interpretable AI models that help healthcare practitioners identify biases or failures in AI-based reasoning, especially those directly related to patient care. As an example, an AI system creates a treatment plan. Next, it will be identified with the XAI, which elements the model has taken into account, and the choice will not contradict clinical guidelines. Research indicates that 60% of AI-enabled healthcare systems with XAI have reduced bias-related errors in patient treatment. It is not discriminatory to any patient. The risks of trust, responsibility, and equity in AI-enabled medical transactions, which are highly sensitive to medical outcomes, can be reduced by incorporating XAI into the hybrid edge-cloud model, especially in black-box AI.

Table 2: Role of Explainable AI (XAI) in the Hybrid Edge-Cloud Healthcare Model

Role/Function	Description	Example/Application	Expected Impact
Transparency and Interpretability	XAI algorithms make AI-driven decisions understandable to medical practitioners, clarifying how models reach conclusions.	In insurance claim processing, XAI reveals how patient demographics, treatment history, and prior approvals influence claim outcomes.	Enhances clinician trust and allows justification of AI-assisted recommendations.
Accountability and Ethical Compliance	Provides visibility into AI reasoning, ensuring medical decisions align with ethical and clinical standards.	XAI helps validate that treatment recommendations conform to medical guidelines.	Ensures responsible use of AI and adherence to professional ethics.
Bias Detection and Fairness	Enables identification of biases or unfair patterns in AI decision-making.	Detects and corrects discriminatory outcomes in diagnosis or patient prioritization.	Promotes equity and minimizes discrimination in healthcare delivery.

Role/Function	Description	Example/Application	Expected Impact
Trust and Acceptance of AI Systems	Improves confidence among healthcare providers by making AI operations explainable.	Clinicians can review AI logic before adopting its recommendations.	Encourages wider adoption and reliance on AI-supported decision-making.
Risk Reduction in “Black-Box” AI	Reduces uncertainty and risk by allowing insight into complex AI models.	Helps in validating AI behavior in critical patient-care applications.	Minimizes errors and promotes safer deployment of AI in healthcare.

CASE STUDIES AND REAL-WORLD APPLICATIONS

8.1. Use Case 1: Real-Time Healthcare Billing and Insurance Claims

Billing and insurance claims processing will generally be slow and prone to error, and in most cases require extensive verification, which, in turn, slows reimbursements and imposes an administrative burden. According to a recent study, 25 percent of healthcare claims are not processed on time due to manual verification, placing a significant administrative burden. Such issues may be effectively solved through a hybrid edge-cloud computing model with explainable artificial intelligence (XAI), which can offer much more useful responses more quickly. Information such as patient bills and treatment records can be processed in real time with low latency in most cloud-edge computing environments, thereby enabling faster decision-making. In real-time applications, edge computing can also reduce processing time by 40+, speeding up claim approvals and decisions. Meanwhile, cloud computing is a form of data storage system that uses large volumes of claim data and performs more advanced analytical processes to detect abnormalities or fraud. It is presumed that AI systems that can do so will reduce the cost of fraud detection by 20 per cent, as they will be more effective at detecting anomalies. These systems, as well as XAI, will ensure that the claims validation process is automated and that there is an accurate explanation of how the AI reached specific conclusions or why the specified claims were accepted, declined, or sent back for further analysis. This openness fosters trust among healthcare providers, insurance companies, patients and optimizes efficiency and accountability in financial dealings. Edge devices process the minors, and the data read — patent data and service code — are checked. Automated systems have been shown to help reduce human error by up to 30 percent in the billing subprocess, to help provide the are processed coprocessor correctly treatment, pre-test accuracy implemented on the machine such as these to verify who the patient is and whether they are entitled to receive it in order to improve the process by demonstrating the logic behind each claim made and makes the process less subject to refusal and error possible. XAI captures can calculate past billing and live-edge information and detect anomalies or fraud. For example, take a statement

made in a distant location, and the patient's medical history shows that the patient never visited that location. That system might then signal the need for further analysis [35].

The cloud is examined once the claims are verified. The roles addressed in this review are patient history review, compliance, and payment processing. Cloud is scalable to 10 petabytes of healthcare data in 1 year, enabling the processing of numerous claims without performance loss. Cloud computing can be scaled to accommodate the massive number of claims in a healthcare network. The hybrid model assists in reducing the time spent validating and authorizing claims, goals, and specifications by analyzing real-time edges. Such speed will be more efficient and minimize errors, as even complex models can be executed on large databases with edge computing in the cloud, reducing the time spent verifying claims by 30 percent and providing real-time outcomes so a decision can be made. This hybrid system would ease financial burdens on health personnel and administrators, and improve cash flow [36].

8.2. Use Case 2: Patient Decision Support Systems.

Patient data determines the quality and timeliness of healthcare delivery. By integrating edge and cloud computing, edge computing would enable the healthcare institution to perform real-time analyses, and cloud computing would allow the study to be conducted over the long term. Wearable sensors are also peripheral devices that a critical care setting needs to use, as they can measure vital signs in real time, e.g., heart rate, blood pressure, oxygen levels, etc. AI models that operate on the edge can analyze this data in real time and report that something may be wrong (e.g., an irregular heartbeat or a declining oxygen level), requiring emergency treatment. It is also worth noting that real-time patient monitoring and response can greatly enhance patient safety and provide medical assistance, thereby improving patient outcomes [37]. The cloud enables long-term storage and processing of large volumes of information—the cloud archives history for analysis — unlike edge computing, which supports real-time decision-making. Cloud-based AI models enable healthcare recipients to identify long-term trends, forecast future health outcomes and health risks, and prescribe preventive measures. Clinical decision support systems (CDSS) are supplemented with real-time edge insights to enable further analysis in the cloud. For example, suppose the patient's health information suggests a greater risk of heart disease. In that case, the system may recommend a course of action from among millions of treatment options for discussion with health experts using XAI.

As illustrated in the figure below, cloud computing in healthcare has several key use cases, including telemedicine & remote patient care, workflow automation, accurate data-driven diagnostics, EHR management, and drug discovery & research. These applications showcase the wide-ranging benefits of cloud technology in improving healthcare services and outcomes.

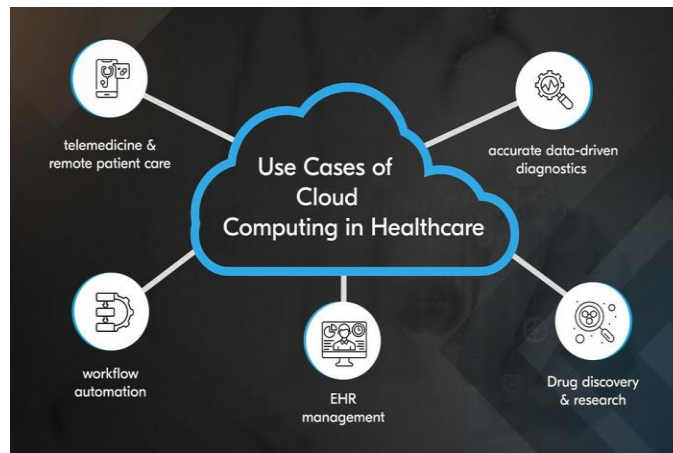


Figure 7: Cloud Computing in Healthcare

8.3. Use Case 3: Remote Healthcare and Telemedicine.

Telemedicine has also advanced rapidly in rural areas and other underserved regions with significant populations lacking access to healthcare services. The hybrid edge-cloud system will enhance telehealth functionality by enabling the patient and healthcare expert to communicate instantly and analyze large amounts of data. This will result in low latency, a predictable data flow, fluent interaction during remote consultations, and enhanced quality and access to healthcare. [38].

Edge devices can handle the video consultation, remote monitoring, and patient input data. Such machines scan patient data, such as heart rate and blood pressure, so that the medical practitioner can view the patient at a glance during an examination. AI-oriented tools can also help physicians diagnose issues in real time using the information they receive. The use of telemedicine is frequently multistage, with patients, remote care equipment, and healthcare providers being among the participants. Thus, there should be free exchange of information. The hybrid edge-cloud will also support successful communication between devices across the edge and cloud infrastructure, enabling healthcare professionals to access the latest patient data and make necessary decisions. Hybrid edge-cloud devices constantly track the health status (glucose, heart rate, breathing) of remote patients and those with chronic conditions. The edge devices' display screen alerts for urgent actions, and the data is saved in the cloud to enable tracking over time and further analysis. Cloud-based and on-edge AI models can identify health distinctions that suggest the need for preventive care.

TECHNICAL CONSIDERATIONS AND IMPLEMENTATION CHALLENGES

9.1. Integration Complexity

The problem with the hybrid edge-cloud service for healthcare facilities is technical issues during implementation [39]. Healthcare organizations can have multiple systems, devices, and platforms which do not always integrate. These systems need to be synchronized to facilitate the free flow

of data and real-time analysis, supporting edge and cloud computing. Healthcare transactions are sensitive information that must meet high standards under regulators such as HIPAA and GDPR. To adopt the hybrid model, healthcare institutions should centralize their edge and cloud systems and processes, and provide secure, compliant communication systems to support information exchange. To enable them to introduce edge computing and cloud computing, medical institutions may need to upgrade their infrastructure. This could involve investing in new hardware, software, and network architecture to facilitate the hybrid model.

9.2. Data Privacy and Security

The privacy and security of information are central issues in healthcare. Integrity assurance of patient information should be done at peripheral healthcare institutions and in the cloud. This would facilitate strong encryption, a safe data storage system, and access controls to prevent unauthorized use. One is to consider how peripheral devices and cloud systems can fulfil security requirements so that healthcare organizations do not violate privacy standards, including HIPAA and GDPR. Any change in data should be recorded and monitored to track progress toward success. To maintain information exchange between edge devices and the cloud, medical facilities can implement the latest security measures, such as secure APIs, encrypted connections (e.g., VPN or SSL/TLS), and multi-factor authentication, to protect patient information.

9.3. Dependability and Performance.

In a facility providing critical health care, resources and time are of the essence. Therefore, any lack of performance reliability could lead to disastrous consequences, such as failure to provide timely services. Medical applications (particularly those using real-time information, e.g., critical care or telemedicine at large) should run continuously. The edge devices will also ensure real-time processing even when the cloud connection is unavailable. However, the cloud cannot be deficient in long-term data storage or in the ability to run complex AI models. Healthcare transactions can be disastrous in the event of network problems. The latter risk may be addressed through a hybrid edge-cloud architecture that enables edge processing even when the network is unavailable. Besides, edge-to-cloud low-latency networks ensure that the most sensitive data is conveyed and that quicker decisions are made. Healthcare organizations should have backup systems both in the cloud and at the Edge. The local Edge backs up local data to mitigate network failures, and cloud redundancy helps prevent data loss in the event of infrastructure issues. These technical reasons and topics will help medical facilities install a hybrid edge-cloud solution that enables transactions to be handled safely and efficiently.

The Balanced Scorecard model comprises four perspectives — Financial, Customer, Internal Processes, and Innovation — as depicted in the figure below. This strategy enables organizations to quantify and harmonize their performance across various spheres, thereby sustaining growth and development in the healthcare and other sectors.

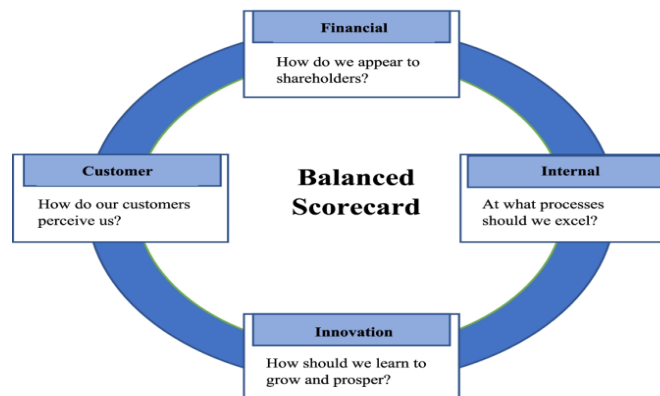


Figure 8: Balanced Scorecard Perspectives

DISCUSSION

10.1. Evaluation of the Proposed Model

The hybrid edge-cloud model is an effective way of reducing specific challenges in medical transaction processing. Along with reduced latency, edge computing will enable healthcare systems to make more decisions in real time by running them at the edge. For example, in real-time systems such as remote patient monitoring or emergency response, edge processing provides a 40x reduction in response time and, in turn, enables scaling and sufficient storage capacity to address the growing volume of healthcare data. It can also support the long-term storage and fast processing of a healthcare organization, with a capacity of up to 10 petabytes of data, expected to grow by 20-30 percent per year [40]. When combined, these technologies enable faster, healthier transactions in the healthcare industry, including real-time claim processing, patient data processing, and telemedicine.

There are advantages and disadvantages to using this model. The high financial, equipment, and experience demands of the infrastructure significantly hamper the implementation of edge and cloud systems, which are very complex. Implementation expenses for a hybrid edge-cloud system can range from 0 to 3 million dollars, depending on the size and scale of a healthcare plant. This may be demanding, especially for smaller health institutions, in terms of budgeting. It is also not cheap to install and is inaccessible to small health centres. Healthcare IT News (2023) survey of 60 per cent of small healthcare facilities claims cost limitations as one of the key reasons behind their non-adoption of modern technologies, such as hybrid edge clouds.

Other considerations to facilitate the model's success include system heterogeneity, data compatibility, and balancing processing across the local and cloud environments. For example, healthcare systems with interoperability issues: above all, healthcare providers (72 per cent) have listed the inability to coordinate the compatibility of various data systems and software as one of their most critical operational issues. In addition, performing edge and cloud data processing

involves trade-offs among performance, security, and reliability that can be difficult to manage, especially as data volumes grow. The hybrid edge-cloud is a scalable model that meets the growing needs of the healthcare industry and addresses key requirements, including faster transaction speeds, enhanced security, and improved decision-making. The model will cut transaction volume in half and enhance data security by encrypting all cloud and edge data.

The Hybrid Edge-Cloud Model in healthcare, as shown in the figure below, offers the following advantages: it enables real-time decision-making through edge computing and scalable cloud-based storage of patient data, leading to more efficient services, timely healthcare transactions, and improved patient care outcomes.

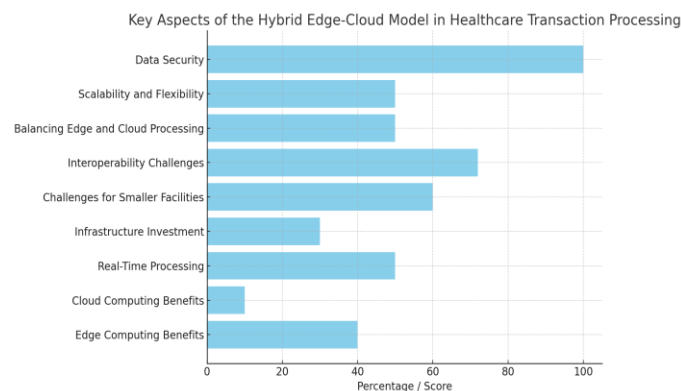


Figure 9: Key Aspects of the Hybrid Edge-Cloud Model in Healthcare Transaction Processing

10.2. Implication on Healthcare Outcomes.

The given hybrid edge-cloud idea has a good chance of enhancing outcomes and achieving the highest healthcare efficiency. Data processing and edge-edge-based processing enable healthcare providers to take more immediate action and respond faster, thereby reducing latency in life-threatening situations. The hybrid model can streamline healthcare, but business processes, such as patient monitoring, diagnostics, and billing, can improve transaction accuracy. Explainable AI (XAI) will keep people, including medical practitioners and patients, confident in the use of automated systems, as they are given the chance to make decisions. It also makes patients more active, as they will be better informed about the reasons for reasonable medical prescriptions. They will have a more robust training in decision-making, resulting in better patient satisfaction. The model, in the long run, enables scalability so that the healthcare system can accommodate the ever-increasing needs of patients with complex medical histories without scaling down. It can also be tailored to the global healthcare setting, offering solutions for developed and underserved regions. It also presupposes that providers will have the opportunity to optimize the system to respond to new challenges and to ensure long-term improvement in patient care.

10.3. Legal, ethical and regulatory.

The first two issues that should not be overlooked in adopting hybrid edge-cloud models are data security and privacy in healthcare. Healthcare organizations must have stringent measures of patient data confidentiality referred to in regulations like HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation). The hybrid model can solve these issues by integrating encryption and safe transmission protocols of information that is being processed at the edge and in the cloud.

XAI can be applied in medical fields to make sure that there is transparency in automated decision-making. XAI enables medical practitioners and patients to comprehend the reasoning behind clinical choices, whether it is a treatment prescription or a diagnosis. This clarity results in trust into AI systems, which is essential to their implementation in the healthcare field.

On ethical grounds, we have to prevent the occurrence of algorithmic bias and make AI models applied in the healthcare system fair and equitable. XAI can be used to alleviate the risks associated with bias decision-making by ensuring that AI models are more understandable and responsible. It is paramount to use AI systems in a responsible manner in healthcare facilities because the systems represent an important ethical concern and contribute to patient safety.

10.4. Automation: Future of healthcare transaction processing.

The hybrid edge-cloud model along with the XAI is the future of the processing of healthcare transactions with the prospect of changing the manner in which medical transactions are handled. To the extent that the healthcare industry is still digitalizing, these technologies will become key in facilitating the management of patient information, facilitating real-time optimization, and decision-making in a smarter, more automated way.

The further evolution of 5G networks can be regarded as one of the most influential aspects of the future of this model. Having high bandwidth and low latency, 5G will boost the real-time functionality of edge devices enabling employment of more data to be processed more rapidly. This will facilitate much more sophisticated decision-making and independent work with patients by incorporating AI-related robots into healthcare settings. It is the evolution of edge-cloud technologies, AI, connectivity that will enable the future of healthcare transaction processing to improve patient care and operational efficiency ultimately.

Table 3: Comparison of Model Efficiency Improvements Over Traditional Systems

Criteria	Hybrid Edge-Cloud Model	Traditional Centralized Systems
Latency	40x faster response time	Higher latency, slower processing
Data Security	Enhanced with encryption, local processing	Vulnerable to breaches, centralized storage
Scalability	Easily scalable, handles increasing data volume	Limited scalability, resource-intensive

Criteria	Hybrid Edge-Cloud Model	Traditional Centralized Systems
Transaction Speed	Faster real-time claim processing	Slower due to centralized data flow
Cost Efficiency	Reduced bandwidth and storage costs	High operational costs, especially for data management

FUTURE DIRECTIONS AND EMERGING TRENDS

11.1. Advancements in Edge and Cloud Computing

Edge and cloud computing technologies are rapidly advancing. These improvements also make 5G network development one of the most promising improvements, as it will provide more reliable connectivity to healthcare systems. Another aid to 5G will be edge devices that can handle much more data in real time and transfer it to the cloud without difficulty, thus shortening the time to respond to an emergency. Quantum computing is another area of hybrid process improvement, still young and advancing with more sophisticated AI models and greater efficiency.

11.2. The Emerging AI and XAI in Healthcare.

The medical industry is actively developing AI, and the fields of prediction and clinical decision support are improving. As AI models evolve, they will be able to give additional data on patient health and treatment results. However, the role of XAI increases as more complex models are developed, since there is a need to build transparency and design models that are intelligible enough to foster the required trust. XAI deployment will enhance healthcare decision-making and enable medical workers to gain insights into how AI makes diagnoses and prescriptions [41].

Explainable AI (XAI) has four purposes: to explain, justify, control, discover, and improve, as shown in the figure below. These functionalities make AI more transparent and increase the likelihood that healthcare professionals will accept and believe AI-based diagnoses and treatment advice, thereby supporting medical decision-making.

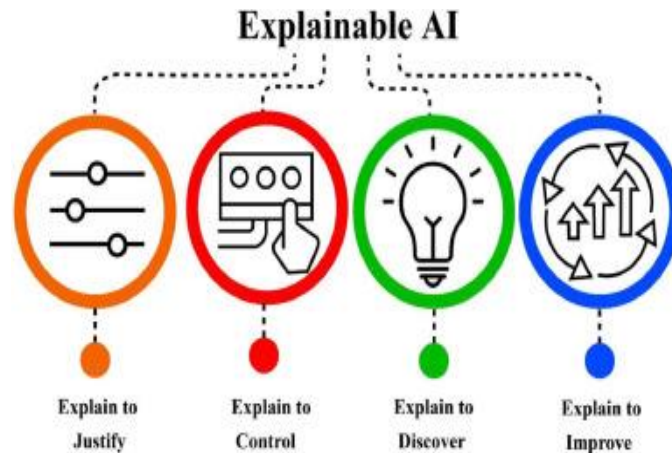


Figure 10: A review of Explainable Artificial Intelligence in healthcare

11.3. Potential of Wide Acceptance.

An edge-cloud AI is a form of hybrid AI that is scalable globally across healthcare portfolios. The model is a platform that has enhanced the effectiveness, scalability, and reliability of healthcare systems and organizations in both developed and developing nations, and has been sought after for solutions to care-delivery challenges. In particular, the hybrid framework can serve as a solution for instances where there are no centralized centers and real-time healthcare services are delivered through edge devices, cloud storage, and advanced analytics.

CONCLUSION

The new healthcare transaction processing models are the hybrid edge-cloud model and explainable artificial intelligence (XAI). This built-in model can be used to solve many critical issues in healthcare systems by facilitating real-time decisions at the edge and/or by enabling the processing and storage of large volumes of data in the cloud. It can enhance operational performance by minimizing latency and processing real-time data, both of which are critical in healthcare. The implemented cloud also enables healthcare systems to cope with the constantly increasing volume of data and ensures that work is a top priority. In addition, the hybrid model offers greater data security by handling more data at the edge, thereby minimizing exposure of sensitive data. The implementation of XAI will help build trust in the process of artificial intelligence-based decision-making and may contribute to its better disclosure. The overall image of AI-based healthcare systems is enhanced, thereby reducing their operational costs.

The implementation of a hybrid edge-cloud platform to enhance transaction processing and patient care is strongly advocated. This model will enable healthcare providers to address specific barriers in the traditional healthcare transaction system, i.e., latency, scalability, and data security issues. The hybrid model will address these questions, enable the efficient and safe collection of medical

data, and help the sphere during periods of high demand. In addition, it enables one to analyze adherence to regulations, patient confidentiality, and the ethical use of data.

The second wave of research needs to consider integration challenges and opportunities in cases where edge systems are connected with the cloud, as well as the possibility of interchangeable platforms and technologies. The second potential future research direction is to extend XAI to the healthcare field and focus on high-stakes situations where transparency is at issue. This integration of technology, scientific, and health care institutions will facilitate the normalization of cloud-based models, enabling the health care field to access these technologies' capabilities. The AinXAI-hybrid edge-cloud model can transform how healthcare transactions are conducted, as it is fast, efficient, and secure. Technologies will assist healthcare systems in improving work and patient outcomes. The future of healthcare depends on the above processes being implemented in a moral, scalable, and sustainable manner that will make a difference in the lives of healthcare providers and patients. This kind of innovation will make healthcare institutions leaders in healthcare payment and deliver quality care and services.

REFERENCES

- [1] Patel, A. U., Gu, Q., Esper, R., Maeser, D., & Maeser, N. (2024). The crucial role of interdisciplinary conferences in advancing explainable AI in healthcare. *BioMedInformatics*, 4(2), 1363-1383. <https://doi.org/10.3390/biomedinformatics4020075>
- [2] George, A. S., & George, A. H. (2024). Riding the wave: an exploration of emerging technologies reshaping modern industry. *Partners Universal International Innovation Journal*, 2(1), 15-38. <https://jscholarship.library.jhu.edu/items/23074d60-e70d-4bf7-bdef-1b09f3bc8272>
- [3] Cruz, G., Guimarães, T., Santos, M. F., & Machado, J. (2024). Decentralize healthcare marketplace. *Procedia Computer Science*, 231, 439-444. <https://doi.org/10.1016/j.procs.2023.12.231>
- [4] Vidhya, S., Siva Raja, P. M., & Sumithra, R. P. (2024). Blockchain-Enabled Decentralized Healthcare Data Exchange: Leveraging Novel Encryption Scheme, Smart Contracts, and Ring Signatures for Enhanced Data Security and Patient Privacy. *International Journal of Network Management*, 34(5), e2289.
- [5] Ali, A., Ali, H., Saeed, A., Ahmed Khan, A., Tin, T. T., Assam, M., ... & Mohamed, H. G. (2023). Blockchain-powered healthcare systems: enhancing scalability and security with hybrid deep learning. *Sensors*, 23(18), 7740. <https://doi.org/10.3390/s23187740>
- [6] Bonthu, C., & Goel, G. (2025). The role of multi-domain MDM in modern enterprise data strategies. *International Journal of Data Science and Machine Learning*, 5(1), 9. <https://doi.org/10.55640/ijdsml-05-01-09>

- [7] Bonthu, C., Kumar, A., & Goel, G. (2025). Impact of AI and machine learning on master data management. *Journal of Information Systems Engineering and Management*. <https://www.iisem-journal.com/index.php/journal/article/view/5186>
- [8] Mazlan, A. A., Daud, S. M., Sam, S. M., Abas, H., Rasid, S. Z. A., & Yusof, M. F. (2020). Scalability challenges in healthcare blockchain system—a systematic review. *IEEE access*, 8, 23663-23673. <https://doi.org/10.1109/ACCESS.2020.2969230>
- [9] Brahmabhatt, R. (2025). Machine learning for dynamic pricing strategies in e-commerce and physical retail. *Utilitas Mathematica*. <https://utilitasmathematica.com/index.php/Index/article/view/2710>
- [10] Saraswat, D., Bhattacharya, P., Verma, A., Prasad, V. K., Tanwar, S., Sharma, G., ... & Sharma, R. (2022). Explainable AI for healthcare 5.0: opportunities and challenges. *IEEE Access*, 10, 84486-84517. <https://doi.org/10.1109/ACCESS.2022.3197671>
- [11] Chadha, K. S. (2025). Zero-trust data architecture for multi-hospital research: HIPAA-compliant unification of EHRs, wearable streams, and clinical trial analytics. *International Journal of Computational and Experimental Science and Engineering*, 12(3), 1–11. <https://ijcesen.com/index.php/ijcesen/article/view/3477/987>
- [12] Wenhua, Z., Qamar, F., Abdali, T. A. N., Hassan, R., Jafri, S. T. A., & Nguyen, Q. N. (2023). Blockchain technology: security issues, healthcare applications, challenges and future trends. *Electronics*, 12(3), 546. <https://doi.org/10.3390/electronics12030546>
- [13] Chavan, A. (2021). Eventual consistency vs. strong consistency: Making the right choice in microservices. *International Journal of Software and Applications*, 14(3), 45-56. <https://ijsra.net/content/eventual-consistency-vs-strong-consistency-making-right-choice-microservices>
- [14] Chavan, A. (2022). Importance of identifying and establishing context boundaries while migrating from monolith to microservices. *Helina*. [http://doi.org/10.47363/JEAST/2022\(4\)E168](http://doi.org/10.47363/JEAST/2022(4)E168)
- [15] Dhanagari, M. R. (2024). MongoDB and data consistency: Bridging the gap between performance and reliability. *Journal of Computer Science and Technology Studies*, 6(2), 183-198. <https://doi.org/10.32996/jcsts.2024.6.2.21>
- [16] Goel, G., & Bhramhabhatt, R. (2024). Dual sourcing strategies. *International Journal of Science and Research Archive*, 13(2), 2155. <https://doi.org/10.30574/ijsra.2024.13.2.2155>
- [17] Gao, X., He, P., Zhou, Y., & Qin, X. (2024). A smart healthcare system for remote areas based on the edge-cloud Continuum. *Electronics*, 13(21), 4152. <https://doi.org/10.3390/electronics13214152>
- [18] Karwa, K. (2023). AI-powered career coaching: Evaluating feedback tools for design students. *Indian Journal of Economics & Business*. <https://www.ashwinanokha.com/ijeb-v22-4-2023.php>

- [19] Karwa, K. (2024). Navigating the job market: Tailored career advice for design students. *International Journal of Emerging Business*, 23(2). <https://www.ashwinanokha.com/ijeb-v23-2-2024.php>
- [20] Al-Jaroodi, J., Mohamed, N., & Abukhousa, E. (2020). Health 4.0: on the way to realizing the healthcare of the future. *Ieee Access*, 8, 211189-211210. <https://doi.org/10.1109/ACCESS.2020.3038858>
- [21] Koneru, N. M. K. (2025). Containerization best practices: Using Docker and Kubernetes for enterprise applications. *Journal of Information Systems Engineering and Management*. <https://www.jisem-journal.com/index.php/journal/article/view/8905>
- [22] Konneru, N. M. K. (2021). Integrating security into CI/CD pipelines: A DevSecOps approach with SAST, DAST, and SCA tools. *International Journal of Science and Research Archive*. Retrieved from <https://ijsra.net/content/role-notification-scheduling-improving-patient>
- [23] Kumar, A. (2019). The convergence of predictive analytics in driving business intelligence and enhancing DevOps efficiency. *International Journal of Computational Engineering and Management*, 6(6), 118-142. Retrieved from <https://ijcem.in/wp-content/uploads/THE-CONVERGENCE-OF-PREDICTIVE-ANALYTICS-IN-DRIVING-BUSINESS-INTELLIGENCE-AND-ENHANCING-DEVOPS-EFFICIENCY.pdf>
- [24] Almaiah, M. A., Hajjej, F., Ali, A., Pasha, M. F., & Almomani, O. (2022). A novel hybrid trustworthy decentralized authentication and data preservation model for digital healthcare IoT based CPS. *Sensors*, 22(4), 1448. <https://doi.org/10.1016/j.aej.2022.09.031>
- [25] Malik, G. (2025). Business continuity & incident response. *Journal of Information Systems Engineering and Management*. <https://www.jisem-journal.com/index.php/journal/article/view/8891>
- [26] Malik, G. (2025). Business continuity & incident response. *Journal of Information Systems Engineering and Management*, 10(45s), 451–473. <https://www.jisem-journal.com/index.php/journal/article/view/8891>
- [27] Jermutus, E., Kneale, D., Thomas, J., & Michie, S. (2022). Influences on user trust in healthcare artificial intelligence: a systematic review. *Wellcome Open Research*, 7(65), 65. https://wellcomeopenresearch.org/articles/7-65/v1?utm_source=AuthorEmail&utm_campaign=WORArticleMilestone&utm_medium=Social
- [28] Nyati, S. (2018). Transforming telematics in fleet management: Innovations in asset tracking, efficiency, and communication. *International Journal of Science and Research (IJSR)*, 7(10), 1804-1810. Retrieved from <https://www.ijsr.net/getabstract.php?paperid=SR24203184230>

- [29] Pinnapareddy, N. R. (2025). Carbon conscious scheduling in Kubernetes to cut energy use and emissions. *International Journal of Computational and Experimental Science and Engineering*. <https://ijcesen.com/index.php/ijcesen/article/view/3785>
- [30] Pinnapareddy, N. R. (2025). Cloud cost optimization and sustainability in Kubernetes. *Journal of Information Systems Engineering and Management*. <https://www.jisem-journal.com/index.php/journal/article/view/8895>
- [31] Raju, R. K. (2017). Dynamic memory inference network for natural language inference. *International Journal of Science and Research (IJSR)*, 6(2). <https://www.ijsr.net/archive/v6i2/SR24926091431.pdf>
- [32] Alsadie, D. (2024). Artificial intelligence techniques for securing fog computing environments: trends, challenges, and future directions. *IEEE Access*. <https://doi.org/10.1109/ACCESS.2024.3463791>
- [33] Sardana, J. (2022). Scalable systems for healthcare communication: A design perspective. *International Journal of Science and Research Archive*. <https://doi.org/10.30574/ijsra.2022.7.2.0253>
- [34] Sardana, J. (2022). The role of notification scheduling in improving patient outcomes. *International Journal of Science and Research Archive*. Retrieved from <https://ijsra.net/content/role-notification-scheduling-improving-patient>
- [35] Singh, V. (2021). Generative AI in medical diagnostics: Utilizing generative models to create synthetic medical data for training diagnostic algorithms. *International Journal of Computer Engineering and Medical Technologies*. <https://ijcem.in/wp-content/uploads/GENERATIVE-AI-IN-MEDICAL-DIAGNOSTICS-UTILIZING-GENERATIVE-MODELS-TO-CREATE-SYNTHETIC-MEDICAL-DATA-FOR-TRAINING-DIAGNOSTIC-ALGORITHMS.pdf>
- [36] Singh, V. (2022). Advanced generative models for 3D multi-object scene generation: Exploring the use of cutting-edge generative models like diffusion models to synthesize complex 3D environments. [https://doi.org/10.47363/JAICC/2022\(1\)E224](https://doi.org/10.47363/JAICC/2022(1)E224)
- [37] Subham, K. (2025). Scalable SaaS implementation governance for enterprise sales operations. *International Journal of Computational and Experimental Science and Engineering*. <https://ijcesen.com/index.php/ijcesen/article/view/3782>
- [38] Sukhadiya, J., Pandya, H., & Singh, V. (2018). Comparison of Image Captioning Methods. *INTERNATIONAL JOURNAL OF ENGINEERING DEVELOPMENT AND RESEARCH*, 6(4), 43-48. <https://rjwave.org/ijedr/papers/IJEDR1804011.pdf>
- [39] Firouzi, F., Jiang, S., Chakrabarty, K., Farahani, B., Daneshmand, M., Song, J., & Mankodiya, K. (2022). Fusion of IoT, AI, edge-fog-cloud, and blockchain: Challenges, solutions, and a case study in healthcare and medicine. *IEEE Internet of Things Journal*, 10(5), 3686-3705. <https://doi.org/10.1109/IIOT.2022.3191881>

- [40] Angel, N. A., Ravindran, D., Vincent, P. D. R., Srinivasan, K., & Hu, Y. C. (2021). Recent advances in evolving computing paradigms: Cloud, edge, and fog technologies. *Sensors*, 22(1), 196. <https://doi.org/10.3390/s22010196>
- [41] Chen, Z., Liang, N., Zhang, H., Li, H., Yang, Y., Zong, X., ... & Shi, N. (2023). Harnessing the power of clinical decision support systems: challenges and opportunities. *Open Heart*, 10(2), e002432.