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Development of A Hybrid Model For Real-Time Business Intelligence Decision-Making In Healthcare

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ABSTRACT

The increasing volume, variety, and velocity of healthcare data have created significant opportunities for data-driven decision-making while simultaneously exposing limitations in conventional Business Intelligence (BI) systems. Healthcare organizations often rely on fragmented information systems, delayed reporting processes, and historical data, which can limit the ability of healthcare professionals and managers to respond promptly to emerging clinical, operational, and administrative situations. This study proposes the development of a hybrid model for real-time Business Intelligence decision-making in the healthcare sector. The proposed model integrates real-time data acquisition, data integration, business intelligence, predictive analytics, and decision-support mechanisms to provide timely and actionable insights to healthcare decision-makers. The hybrid architecture is designed to integrate data from diverse sources, including electronic health records, hospital information systems, laboratory systems, administrative databases, and healthcare monitoring devices. A Design Science Research approach is adopted to guide the requirements analysis, model design, prototype development, implementation, and evaluation of the proposed framework. The model combines descriptive and predictive analytics with real-time processing and visualization to support faster, evidence-based decision-making. The proposed approach is expected to improve decision-making speed, information availability, predictive capability, resource utilization, and operational efficiency within healthcare organizations. The study contributes a structured framework for integrating real-time Business Intelligence and advanced analytics into healthcare decision-support processes and provides a foundation for developing more responsive and data-driven healthcare management systems.

Keywords: Business Intelligence, Real-Time Analytics, Healthcare, Decision-Making, Hybrid Model, Data Analytics, Predictive Analytics, Decision Support Systems.

I. INTRODUCTION

Background of the Study

Business Intelligence (BI) has emerged as an important approach for transforming organizational data into meaningful information that supports evidence-based planning, monitoring, and decision-making. In healthcare, BI involves the application of data management technologies, analytical methods, reporting systems, dashboards, and decision-support tools to clinical, administrative, financial, and operational data. The growing digitalization of healthcare has expanded the role of BI from conventional reporting to the integration and analysis of heterogeneous data generated across different healthcare environments. The World Health Organization (WHO) recognizes effective health information systems as essential for generating reliable information to support evidence-informed decision-making and health-system management (World Health Organization [WHO], 2024a).

Healthcare organizations generate substantial volumes of data from electronic health records (EHRs), laboratory information systems, pharmacy systems, medical devices, patient-monitoring systems, financial databases, hospital management systems, and other digital platforms. When these data are effectively integrated, processed, and analyzed, BI can provide decision-makers with information concerning patient care, service utilization, resource consumption, financial performance, and organizational efficiency. Consequently, healthcare BI can be conceptualized as a decision-support mechanism that transforms raw data into descriptive, diagnostic, predictive, and potentially prescriptive insights.

The application of BI is particularly relevant to healthcare management because decisions concerning patients, personnel, facilities, equipment, finances, and supplies frequently depend on the availability of accurate and timely information. Recent evidence suggests that healthcare management systems supported by information technology, predictive analytics, and real-time data can enhance coordination, communication, prediction, early-warning capabilities, and resource



utilization (Grosman-Rimon et al., 2023). Thus, BI provides a foundation for moving healthcare organizations toward more systematic and data-driven decision-making.

Evolution from Traditional Reporting to Real-Time Analytics

Historically, healthcare BI systems have relied heavily on periodic reporting and retrospective analysis. Hospitals and other healthcare organizations commonly produce daily, weekly, monthly, or annual reports describing indicators such as patient admissions, bed occupancy, mortality, revenue, staff utilization, medication consumption, and service performance. Although historical reporting remains important for strategic planning and organizational evaluation, it may be inadequate when decisions must be made within minutes or hours.

The increasing digitalization of healthcare has created opportunities to move from periodic reporting toward continuous or real-time analytics. Real-time BI involves the acquisition, processing, analysis, and visualization of data with minimal delay between the occurrence of an event and the availability of relevant information to decision-makers. This capability allows healthcare organizations to monitor changing conditions and respond to emerging situations more rapidly.

Increasing Volume and Complexity of Healthcare Data

The rapid adoption of digital technologies has significantly increased the volume, variety, and complexity of healthcare data. Modern healthcare data are no longer limited to structured demographic and clinical records. They may include clinical notes, laboratory results, medical images, medication records, administrative information, financial transactions, patient-generated health data, and data generated continuously by connected medical devices.

The integration of EHR data with patient-generated health data illustrates the increasing complexity of the healthcare data environment. Ye et al. (2024) examined the role of artificial intelligence in integrating EHRs and patient-generated data for clinical decision support, demonstrating the growing importance of combining information from multiple healthcare data environments.

Importance of Timely Information for Clinical and Administrative Decisions

Timeliness is a fundamental characteristic of useful healthcare information because many clinical and administrative decisions have immediate or near-immediate consequences. Clinicians require current information concerning patient conditions, laboratory results, medications, and risk indicators, while healthcare managers require timely information concerning bed availability, staffing, patient flow, equipment, supplies, and service demand.

Information may be accurate but still have limited decision-making value when it becomes available too late. For example, knowing that hospital bed occupancy was 95% yesterday provides useful historical information, but knowing that occupancy is currently 95% and is predicted to reach full capacity within the next several hours provides a greater opportunity for preventive action.

Role of BI in Improving Healthcare Service Delivery, Resource Allocation, and Patient Outcomes

The role of BI in healthcare extends beyond the production of organizational reports. Properly designed BI systems can enable continuous monitoring of healthcare services, identification of operational inefficiencies, and analysis of resource utilization. Hospital managers can use BI to monitor indicators such as bed occupancy, patient waiting times, emergency department workload, staffing levels, medication and equipment inventories, admissions and discharges, readmission patterns, healthcare expenditure, and service utilization.

Grosman-Rimon et al. (2023) reported that healthcare management systems incorporating information technology, predictive analytics, and real-time data have the potential to improve integration, communication, coordination, prediction, early warning, and resource utilization. Similarly, Gomez-Cabello et al. (2024) identified applications of AI-based clinical decision-support systems in diagnosis, management, treatment recommendations, and complication prediction.

Problem Statement

Despite the increasing adoption of digital technologies and information systems in healthcare, significant challenges remain in transforming healthcare data into timely and actionable intelligence. Healthcare organizations frequently operate multiple information systems, experience inconsistent data quality, encounter interoperability limitations, and rely on reporting processes that may introduce delays between data generation and decision-making. WHO (2024a) identifies challenges related to data standardization, delays in receiving data, lack of integration and interoperability, and limited capacity to manage and use data effectively.

These challenges can reduce the ability of healthcare managers and professionals to obtain a comprehensive and current understanding of clinical and operational conditions. The major problems are discussed below.

Fragmented Healthcare Information Systems

Healthcare organizations commonly employ multiple information systems to support different functions. Clinical information may be maintained within EHR systems, laboratory results within laboratory information systems, medication information within pharmacy systems, and administrative and financial information within separate databases.

Although these systems may function effectively within their individual domains, the lack of integration can make it difficult to obtain a unified view of healthcare activities. Decision-makers may consequently need to access multiple systems and manually combine information before making decisions.



The problem becomes more complex when patient-generated information and data from connected devices are considered. Ye et al. (2024) highlight the importance and challenges of integrating EHR data with patient-generated data to support clinical decision-making. Fragmentation therefore represents a significant barrier to the development of comprehensive healthcare intelligence.

The proposed hybrid model addresses this problem by incorporating a data-integration layer capable of combining information from heterogeneous healthcare sources into a unified analytical environment.

Delays in Accessing Relevant Data

A second challenge concerns the time required to collect, process, analyze, and communicate healthcare information. Conventional reporting processes may involve data extraction, cleaning, aggregation, analysis, and report generation before information is presented to decision-makers.

Such delays can be problematic when healthcare conditions change rapidly. For example, an unexpected increase in emergency admissions may require immediate information concerning bed availability, staffing, laboratory capacity, patient flow, and medical supplies. A report generated several hours or days after the event may have limited value for immediate intervention.

WHO (2024a) identifies delays in receiving data as a barrier to effective health-information-system use. The proposed model therefore emphasizes real-time or near-real-time data acquisition and processing to reduce the time between the occurrence of an event and the availability of relevant decision-support information.

Poor Data Quality and Inconsistency

The effectiveness of BI depends substantially on the quality of the underlying data. Inaccurate, incomplete, duplicated, inconsistent, or outdated information can produce unreliable analytical results and potentially lead to inappropriate decisions.

Healthcare data-quality problems may arise from missing values, duplicate records, incorrect data entry, inconsistent terminology, different coding practices, incomplete documentation, outdated records, and errors during data transfer between systems.

WHO (2024b) emphasizes systematic data-quality assessment and improvement as an important component of strengthening health-information systems. Data-quality problems become even more significant when predictive analytics and AI are incorporated. Sáez et al. (2024) identify data variability, uncertainty, bias, and other factors as important considerations in developing trustworthy AI-based clinical decision-support systems.

Limited Interoperability Among Healthcare Systems

Interoperability refers to the ability of different information systems to exchange, interpret, and use information effectively. Limited interoperability can prevent healthcare organizations from combining information that is distributed across different systems.

For example, a laboratory system may contain important diagnostic information that cannot be readily integrated with the patient's EHR, pharmacy record, or administrative information. Consequently, decision-makers may have access to individual pieces of information without obtaining a complete representation of the situation.

WHO (2024a) identifies limited integration and interoperability as important barriers to effective health-information-system utilization. The WHO Digital Transformation Handbook for Primary Health Care further emphasizes interoperable, person-centred digital systems and identifies requirements such as data dictionaries, workflow mapping, and decision-support logic (WHO, 2024c).

Interoperability should therefore be a fundamental component of the proposed hybrid BI architecture.

Difficulty Integrating Descriptive, Predictive, and Prescriptive Analytics

Another challenge is the separation of analytical capabilities within healthcare information environments. Descriptive analytics focuses on what has happened or what is currently happening, predictive analytics estimates what is likely to happen, while prescriptive analytics seeks to identify or recommend possible actions based on available information.

The integration of these analytical levels can increase the value of BI for decision-making. For example:

Descriptive: Current hospital bed occupancy is 92%.

Predictive: Based on current admissions and discharge patterns, occupancy is expected to reach 98% within six hours.

Prescriptive: The system recommends reviewing available capacity and considering appropriate resource redistribution.

This progression transforms BI from a reporting mechanism into a more comprehensive decision-support environment.

However, recent research indicates that integrating advanced analytical systems into healthcare practice remains challenging. Issues concerning workflow integration, validation, user acceptance, explainability, data quality, and real-world performance must be considered (Peek et al., 2025; Sáez et al., 2024).

The proposed hybrid model therefore seeks to integrate descriptive, predictive, and decision-support capabilities while maintaining appropriate human oversight.

Limited Support for Rapid Decision-Making by Healthcare Managers and Professionals

The combined effects of fragmented information systems, delayed data access, poor data quality, limited interoperability, and separated analytical tools can prevent healthcare decision-makers from receiving the right information at the right time.



This highlights an important distinction between data availability and decision-support capability. A healthcare organization may possess large amounts of data but still lack the technological capability to convert those data into immediate and actionable intelligence.

Recent research demonstrates the potential of AI-enabled decision-support systems to assist with diagnosis, risk prediction, treatment recommendations, and other healthcare decisions (Gomez-Cabello et al., 2024). Nevertheless, successful implementation requires attention to real-world clinical workflows, validation, usability, governance, and human oversight (Peek et al., 2025).

Therefore, the central problem addressed by this study is the lack of an integrated model capable of combining real-time healthcare data, Business Intelligence, predictive analytics, and decision-support mechanisms in a unified environment that can provide timely and actionable information to healthcare managers and professionals.

Synthesis of the Research Problem

The literature demonstrates that healthcare organizations are generating increasingly large and heterogeneous volumes of data, but the availability of data alone does not guarantee timely or effective decision-making. Fragmented information systems, poor data quality, limited interoperability, delayed access to information, and inadequate integration of descriptive, predictive, and prescriptive analytics can constrain the ability of healthcare organizations to respond rapidly to changing clinical and operational conditions.

Although existing research demonstrates the potential of real-time data, predictive analytics, BI, and AI-based decision-support systems, these capabilities are often considered separately or implemented within specific healthcare applications. There remains a need for an integrated approach that combines heterogeneous healthcare data sources, real-time processing, BI, predictive analytics, visualization, and decision-support mechanisms within a unified framework.

Consequently, this study proposes the Development of a Hybrid Model for Real-Time Business Intelligence Decision-Making in Healthcare. The proposed model seeks to address the identified gap by providing an integrated architecture through which healthcare data can be transformed into timely, predictive, and actionable intelligence.

Aim of the Study

To develop a hybrid model that integrates real-time business intelligence and advanced analytics to improve decision-making in the healthcare sector.

The study could pursue the following objectives:

To examine existing business intelligence approaches used for decision-making in healthcare.

To identify the major challenges affecting real-time healthcare decision-making.

To identify relevant healthcare data sources and analytical techniques for real-time BI.

To design a hybrid model for integrating real-time data, BI, and predictive analytics.

To develop and implement a prototype of the proposed model.

To evaluate the model's effectiveness in improving the speed, accuracy, and quality of healthcare decision-making.

Significance of the Study

Healthcare Managers: The study is significant to healthcare managers because they are responsible for making operational and managerial decisions concerning healthcare resources, patient flow, staffing, service utilization, and organizational performance. Conventional reporting systems may require managers to wait for periodic reports before obtaining information about important performance indicators.

Clinicians and Healthcare Professionals: The study is also significant to clinicians, including doctors, nurses, pharmacists, laboratory professionals, and other healthcare practitioners. Clinical decision-making often depends on the availability of accurate and current patient information.

Hospital Administrators: Hospital administrators are responsible for coordinating clinical services with financial, operational, human-resource, and infrastructure requirements. The proposed model can provide administrators with an integrated view of hospital performance rather than requiring information to be obtained separately from different systems.

Patients: Patients are indirect but important beneficiaries of the proposed model. Although the system is primarily designed to support healthcare decision-makers, improved decision-making can contribute to better patient experiences and healthcare service delivery.

Health Policymakers: The study may also be valuable to health policymakers because effective health policy depends on reliable information about healthcare demand, service utilization, resource availability, disease patterns, and health-system performance.

Healthcare Information-System Developers: The study can provide useful technical and architectural guidance to developers of healthcare information systems. The proposed model emphasizes the integration of: Heterogeneous healthcare data sources, Data-quality management, Interoperability, Real-time data processing, Business Intelligence, Predictive analytics, Decision-support mechanisms, Interactive visualization and Security and privacy.

Scope of the Study

Healthcare Setting/Hospitals Covered

The study will focus on hospital-based healthcare environments, particularly healthcare institutions where multiple information systems generate data that can support operational, administrative, and clinical decision-making.



Depending on the actual research location, the study can be restricted to selected hospitals within the specified geographical area. This approach will allow the researcher to obtain realistic data and requirements while keeping the development and evaluation of the model manageable.

Business Intelligence Technologies Considered

The study will consider BI technologies required to develop the proposed hybrid architecture. These may include: Data integration and ETL/ELT technologies, Relational and analytical databases, Data warehouses or appropriate analytical repositories, Real-time/stream-processing technologies, Business Intelligence dashboards, Data visualization tools, Predictive analytics and machine-learning techniques, Decision-support mechanisms, Application programming interfaces (APIs) and Cloud or hybrid computing infrastructure where appropriate.

The study will not necessarily evaluate every available BI technology. Instead, technologies will be selected according to their suitability for achieving the objectives of the proposed model.

II. LITERATURE REVIEW

Concept of Business Intelligence

Business Intelligence (BI) refers to the technologies, processes, architectures, and analytical methods used to collect, integrate, analyze, and present data in a form that supports organizational decision-making. Rather than simply representing a collection of reporting tools, BI provides an organizational capability through which raw data can be transformed into meaningful information and actionable knowledge. In healthcare, this capability is particularly important because healthcare organizations generate data continuously from clinical encounters, laboratory investigations, pharmacy transactions, financial systems, patient-monitoring devices, and administrative activities.

Earlier healthcare literature established that BI can improve organizational decision-making, although the empirical evidence was relatively limited. Loewen and Roudsari's literature review found evidence that BI improves healthcare decision-making but also noted that implementation success depends strongly on organizational culture and readiness. More recent research indicates that the role of BI is expanding from conventional reporting towards adaptive and intelligent systems. Lopes, Faria and Santos' 2024 systematic review of adaptive BI in healthcare found increasing use of predictive and autonomous capabilities, although fully autonomous decision-making remains inappropriate in many healthcare contexts.

From this perspective, healthcare BI can be conceptualized as an integrated decision-support capability that converts heterogeneous healthcare data into timely information for clinical, administrative, operational, and strategic decisions.

Components of Business Intelligence

A healthcare BI environment normally consists of several interconnected components. These include:

Data sources: EHRs, hospital information systems, laboratory systems, pharmacy systems, financial databases, medical devices, and other digital sources.

Data integration and ETL processes: extraction, transformation, and loading of data from heterogeneous systems.

Data warehouses and data marts: structured repositories that consolidate data for analysis.

Analytical engines: statistical analysis, data mining, machine learning, predictive and prescriptive analytics.

Reporting and visualisation tools: reports, dashboards, scorecards, charts, and key performance indicators.

Decision-support mechanisms: alerts, recommendations, predictions, and rules that assist users in making decisions.

Recent evidence supports the importance of these components. A 2025 scoping review of healthcare data warehousing found that general-purpose warehouses are primarily used to integrate disparate EHR and clinical data, commonly using star-schema architectures and OLAP capabilities, while specialised warehouses increasingly incorporate AI and data-mining techniques.

Thus, modern healthcare BI should not be viewed as a single software application. It is better understood as an ecosystem consisting of data infrastructure, analytics, visualisation, and decision-support mechanisms.

Business Intelligence Architecture

Traditional BI architecture can be represented as a layered structure:

Data Sources → Data Integration/ETL → Data Warehouse/Data Lake → Analytics → Dashboards/Reports → Decision-Making

At the source layer, data originate from operational healthcare systems. The integration layer cleans, transforms, standardizes, and combines these data. The storage layer provides a central repository for historical and analytical data. The analytical layer applies statistical and computational techniques, while the presentation layer delivers information through dashboards, reports, alerts, and decision-support interfaces.

Healthcare data warehousing literature indicates that integration remains one of the major purposes of clinical data warehouses. A large scoping review identified data integration, ETL optimization, data quality, semantic representation, and governance as continuing areas requiring attention.

For a real-time BI system, however, a purely traditional architecture may be inadequate. Conventional batch-oriented ETL processes can introduce delays between data generation and decision-making. Consequently, modern architectures increasingly combine batch processing with streaming/event-driven processing, allowing frequently changing data to be analyzed with minimal delay.



Data Warehouses and Data Marts

A **data warehouse** is a centralised repository that stores integrated and structured data for reporting and analytical purposes. A **data mart** is a more focused repository designed for a particular department, function, or subject area, such as finance, pharmacy, laboratory services, or human resources.

Data warehouses are particularly relevant to healthcare because information is frequently distributed across multiple information systems. The 2025 scoping review by Lyu et al. found that healthcare data warehouses support integration of disparate sources and provide comprehensive information for disease management, patient care, and resource management. However, the review also identified limitations involving flexibility, analytical capability, scalability, and data governance.

A data warehouse is therefore useful for analysing historical patterns, benchmarking hospital performance, monitoring trends, and supporting strategic planning. However, a real-time healthcare BI architecture may require additional technologies such as streaming platforms, operational data stores, event-processing engines, or data lakes to supplement the warehouse.

Dashboards and Reporting Systems

Dashboards translate complex datasets into visual information that healthcare professionals and managers can interpret quickly. They commonly display key performance indicators such as patient volume, waiting time, bed occupancy, mortality, infection rates, laboratory turnaround time, medication utilisation, revenue, and resource utilisation.

Healthcare dashboards can support evidence-driven decisions, but their effectiveness depends on more than attractive visual design. Hysong et al. argue that healthcare dashboards should be designed around the decision-making requirements of users rather than simply around information presentation.

Consequently, an effective healthcare BI dashboard should provide relevant, accurate, understandable, timely, and actionable information. For real-time BI, the dashboard must additionally refresh data rapidly and, where appropriate, provide alerts when predefined thresholds or abnormal patterns are detected.

BI Applications in Healthcare

BI applications in healthcare span several domains: clinical performance monitoring; patient risk identification; disease surveillance; resource and bed management; staff scheduling; financial management; supply-chain management; quality and safety monitoring; population health management; and strategic planning.

A recent scoping review of BI systems for population health management found 29 initiatives, of which 11 were considered sufficiently mature for detailed analysis. The review found substantial fragmentation in decision contexts and BI capabilities and reported that the impact on population health remained limited for many systems. This finding is important because it demonstrates that having BI technology does not automatically produce better healthcare outcomes. BI must be aligned with decision contexts, organizational processes, user requirement and healthcare objectives.

Healthcare Decision-Making

Healthcare decision-making is a multidimensional process involving clinicians, administrators, managers, policymakers, patients, and other stakeholders. It involves clinical, operational, administrative, and strategic choices, often under conditions of uncertainty and time pressure.

A systematic review of 140 studies on multi-criteria decision-making in healthcare demonstrated that healthcare decisions frequently involve multiple stakeholders, conflicting objectives, and medical, technological, social, ethical, and economic considerations.

Clinical Decision-Making

Clinical decision-making concerns decisions directly related to diagnosis, treatment, monitoring, and patient care. Examples include identifying high-risk patients, selecting treatment options, interpreting laboratory results, determining whether intervention is required, and predicting clinical deterioration.

BI supports clinical decisions by consolidating information from multiple sources. Predictive analytics and machine learning can extend this capability by identifying patterns that may not be immediately apparent to clinicians.

For example, Bazile et al. developed a data-driven decision-support model for treatment-pathway benchmarking in breast cancer and found that the data-driven approach produced greater cost savings than an experience-driven approach.

This demonstrates how BI and analytics can move decision-making from relying primarily on professional experience towards evidence generated from large-scale healthcare data.

Administrative Decision-Making

Administrative decisions concern the management of healthcare services and resources. Examples include staff allocation, procurement, billing, patient scheduling, resource utilization, and financial management.

BI can combine administrative and clinical information to identify inefficiencies and support performance monitoring. Data-driven hospital-resource research published in 2025 identified data-driven culture, data warehouses, and human-capital management as important themes associated with advanced analytics and organizational performance.



Strategic Decision-Making

Strategic decisions involve long-term organizational direction. Healthcare managers may use BI to determine whether to expand services, acquire equipment, introduce new clinical programs, allocate capital, or modify organizational policies. Strategic BI differs from operational BI because it generally focuses on trends, comparisons, forecasts, and organizational performance rather than immediate events. However, real-time information can increasingly contribute to strategic decision-making by providing continuously updated evidence about service utilization and organizational performance.

Operational Decision-Making

Operational decisions are short-term and frequently repeated. Examples include bed allocation, patient flow, appointment scheduling, staff deployment, emergency department management, and laboratory workload management.

Real-time BI has particular relevance here because operational decisions can become outdated quickly. A hospital manager deciding where to allocate beds, for example, benefits more from current occupancy information than from data that are several days old.

Evidence-Based Decision-Making

Evidence-based decision-making involves using reliable evidence alongside professional expertise, contextual knowledge, and stakeholder considerations. BI contributes to this process by improving access to organizational and clinical evidence. However, data should not automatically be treated as equivalent to truth. Healthcare data can contain missing values, inconsistent coding, measurement errors, biases, and delays. A 2023 systematic review of decision-making in healthcare under imperfect information highlighted the challenges created by incomplete and flawed information.

Real-Time Business Intelligence

Meaning and Characteristics

Real-Time Business Intelligence (RTBI) refers to the ability to collect, process, analyse, and present data sufficiently quickly to support decisions based on current or near-current conditions.

Traditional BI is predominantly retrospective. It answers questions such as:

Real-Time Data Processing

Healthcare generates continuously changing data from patient-monitoring devices, laboratory systems, EHRs, emergency departments, medical devices, and connected sensors.

A systematic review of healthcare data platforms found that streaming technologies, big data, IoT, and machine learning are creating opportunities for reducing the time between information generation and actionable insight. Nevertheless, the review concluded that the ability of healthcare institutions to process large volumes of sensor and event data and notify stakeholders rapidly was still relatively immature.

Real-time processing therefore requires architectures capable of handling high-volume and high-velocity data. Technologies may include message queues, stream-processing engines, event brokers, in-memory processing, cloud infrastructure, and edge computing.

Real-Time Dashboards

Real-time dashboards continuously update selected indicators as new information becomes available. In a hospital environment, such dashboards could display: emergency department waiting times; current bed occupancy; available intensive-care beds; patient vital signs; laboratory turnaround time; pharmacy stock; operating-theatre utilization; ambulance arrivals; and infection-control indicators.

The value of such dashboards lies in reducing the time between data generation, interpretation, and intervention.

Benefits and Limitations

The major benefits of RTBI include faster decision-making, earlier detection of adverse events, improved resource utilisation, continuous monitoring, improved patient safety, and potentially improved operational efficiency.

Nevertheless, RTBI introduces significant challenges. These include: data quality; network reliability; system scalability; privacy and security; interoperability; alert fatigue; computational requirements; integration with legacy systems; and the need for appropriate clinical validation.

IoMT research particularly highlights security and privacy as major concerns because increased connectivity also increases

Healthcare Data Sources

Healthcare BI depends heavily on the availability, quality, diversity, and interoperability of its data sources.

Electronic Health Records

Electronic Health Records (EHRs) provide one of the most important sources of healthcare data. They contain information such as patient demographics, diagnoses, clinical notes, medications, laboratory results, procedures, allergies, and clinical histories.



EHRs provide substantial analytical opportunities but also present challenges related to data quality, heterogeneity, unstructured information, missing values, and semantic interoperability.

The increasing use of HL7 FHIR is particularly relevant. A 2024 scoping review identified interoperability, clinical decision-support integration, and data export as major reasons for using FHIR in digital healthcare ecosystems.

Hospital Management Information Systems

Hospital Management Information Systems generate administrative and operational information concerning registration, appointments, admissions, discharge, billing, human resources, bed management, procurement, and hospital resources.

These systems are important for administrative and operational BI because they provide information about how healthcare services are being delivered and utilized.

Laboratory Information Systems

Laboratory Information Systems generate data from diagnostic investigations, including test requests, results, reference ranges, timestamps, and specimen information.

Integrating laboratory data with EHRs and BI systems can support clinical decision-making and real-time detection of abnormal results. However, laboratory systems may use different coding systems and data structures, making interoperability important.

Pharmacy Systems

Pharmacy information systems provide information about prescriptions, dispensing, medication inventory, drug utilization, and medication costs.

Integration with clinical and administrative data can enable analysis of medication adherence, prescribing patterns, stock levels, adverse events, and pharmaceutical expenditure.

Medical Devices and IoT Sensors

Medical devices and IoT sensors generate high-frequency physiological and operational data. Examples include: heart-rate monitors; pulse oximeters; blood-pressure monitors; glucose monitors; wearable devices; infusion pumps; and smart hospital equipment.

The IoMT literature demonstrates the growing use of these technologies for remote monitoring, diagnosis, disease prediction, and smart-hospital applications.

Patient Monitoring Systems

Patient-monitoring systems are especially important for real-time BI because they generate continuous physiological observations. Integrating such data with EHR and analytical systems can facilitate early warning and predictive monitoring. Edge computing has emerged as a relevant architectural approach because processing can be moved closer to the data-generating device. A 2024 review of Edge AI for IoMT found that edge computing can provide additional processing and storage resources closer to resource-constrained medical devices.

Financial and Administrative Databases

Financial and administrative databases provide information about revenue, expenditure, insurance claims, procurement, staffing, payroll, and other organisational activities.

These data are essential for strategic and managerial BI because healthcare decisions must consider not only clinical outcomes but also financial sustainability and resource constraints.

Analytics for Healthcare Decision-Making

Healthcare analytics can be broadly classified into descriptive, diagnostic, predictive, and prescriptive analytics.

Descriptive Analytics

Descriptive analytics examines historical and current data to determine what happened or what is happening.

Examples include: monthly patient admissions; average hospital stay; mortality rates; bed occupancy; revenue; laboratory workload; and medication utilization.

This is the traditional foundation of BI and is commonly implemented through reports, dashboards, and performance indicators.

Diagnostic Analytics

Diagnostic analytics investigates why something happened. For example, if patient waiting time increases, diagnostic analytics may examine staffing levels, patient volume, appointment scheduling, laboratory delays, or equipment availability.

Diagnostic analytics therefore moves BI beyond simple reporting towards understanding causal or contributing factors.



Predictive Analytics

Predictive analytics uses historical and current data to estimate future outcomes. Healthcare applications include: predicting hospital readmission; predicting patient deterioration; forecasting patient demand; predicting disease risk; forecasting medicine requirements; and predicting hospital resource utilization.

The 2024 adaptive BI review found that higher levels of system autonomy were particularly associated with predictive components, suggesting that predictive analytics represents an important transition point between conventional BI and intelligent decision-support systems.

Prescriptive Analytics

Prescriptive analytics attempts to answer what should be done after considering possible future scenarios and constraints.

Examples include recommending: treatment options; staff allocation; bed allocation; resource distribution; appointment scheduling; or intervention strategies.

However, the literature suggests that prescriptive analytics remains less mature than descriptive and predictive analytics. A 2024 systematic review of prescriptive analytics in healthcare identified 30 relevant studies and found a significant gap between proposed methodologies and their formalization and implementation in real-world healthcare settings.

Machine Learning

Machine learning enables systems to identify patterns in data and generate predictions without relying exclusively on explicitly programmed rules.

Supervised learning can be used for classification and prediction, while unsupervised learning can identify clusters and previously unknown patterns. Deep learning can process complex high-dimensional data, while reinforcement learning can support sequential decision problems.

Recent healthcare analytics literature demonstrates the expanding use of machine learning, although issues such as interpretability, bias, validation, and deployment remain significant. A 2025 thematic review of 2,281 Scopus-indexed publications identified intelligent predictive healthcare, adaptive AI, personalized care, and AI-driven decision support among the dominant themes, while highlighting interoperability, algorithmic opacity, evaluation standardization, and demographic bias as persistent challenges.

Data Mining

Data mining involves extracting meaningful patterns from large datasets. Healthcare applications include identifying disease patterns, discovering patient groups, analyzing utilization patterns, and identifying factors associated with clinical outcomes.

A systematic review of healthcare data mining found extensive application in clinical and administrative decision-making but identified limited use of prescriptive analytics and insufficient integration of domain-expert knowledge.

Artificial Intelligence

Artificial Intelligence extends healthcare analytics through machine learning, deep learning, natural language processing, knowledge representation, and intelligent decision-support systems.

However, AI should complement rather than automatically replace healthcare professionals. Recent research on hybrid AI systems emphasizes the importance of human governance, traceable reasoning, and real-world validation rather than prediction alone.

Hybrid Models in Healthcare Analytics

The limitations of individual analytical approaches have encouraged researchers to investigate **hybrid models**, in which complementary technologies are integrated into a single decision-support environment.

BI and Machine Learning

Traditional BI is strong at reporting, visualization, and organizational performance monitoring, while machine learning is strong at pattern recognition and prediction.

Real-Time Analytics and Predictive Analytics

Real-time analytics determines what is happening now, whereas predictive analytics estimates what is likely to happen next. Combining them can enable a healthcare organization to detect an emerging event and immediately estimate its likely consequences. For example, a system could detect increasing emergency admissions and predict future bed demand.

This combination is particularly relevant to real-time healthcare BI because streaming platforms are increasingly being explored for rapid analysis of healthcare events, although large-scale real-time processing remains an area of technological and organizational difficulty.

Data Warehouse and Data Lake

Data warehouses are generally structured and optimized for analytical querying, whereas data lakes can accommodate larger volumes and greater varieties of structured and unstructured information.



A hybrid warehouse-lake architecture can therefore support: structured clinical reporting; historical BI; unstructured clinical information; machine learning; IoT data; streaming data; and advanced analytics.

This is especially relevant where healthcare organizations need to combine conventional enterprise reporting with modern AI and real-time analytics.

Rule-Based Systems and Machine Learning

Rule-based systems encode expert knowledge through predefined rules, while machine learning discovers patterns from data.

A hybrid model can use rules where clinical knowledge is well established and machine learning where patterns are complex or difficult to specify manually. This can improve explainability because clinicians can understand explicit rules while benefiting from predictive models.

Cloud Computing and Edge Computing

Cloud computing provides scalable storage and computational resources, while edge computing processes data closer to where it are generated.

This combination is particularly useful for IoMT because some decisions require immediate local processing while large-scale model training and historical analysis can occur in the cloud. Recent Edge AI research specifically identifies the role of edge computing in bringing processing and storage closer to medical IoT devices.

Existing Healthcare BI Models and Systems

Existing healthcare BI studies demonstrate substantial diversity in methodologies, technologies, application areas, and maturity.

Theoretical/Conceptual Framework

Several theoretical frameworks can be used to guide the development and evaluation of a healthcare BI system.

Technology Acceptance Model

The **Technology Acceptance Model (TAM)** explains users' acceptance of technology primarily through perceived usefulness and perceived ease of use.

TAM is relevant because even a technically sophisticated BI system will have limited value if clinicians, managers, and administrators do not use it.

A 2024 systematic review of TAM applications in health information systems analyzed 29 studies published between 2018 and 2023. The review emphasized the importance of user characteristics and training in the acceptance and utilization of healthcare information systems.

TAM can therefore be used to evaluate whether users perceive a proposed BI system as useful, easy to use, and acceptable.

III. RESEARCH METHODOLOGY

Research Design

This study will adopt a Design Science Research (DSR) methodology combined with a quantitative evaluation approach. The choice of DSR is appropriate because the study seeks not only to investigate an existing healthcare problem but also to design, develop, implement, and evaluate an artefact capable of addressing the identified problem. In Information Systems research, design science focuses on creating and evaluating innovative artefacts—including models, methods, architectures, and systems—to solve identified organisational or technological problems. Hevner et al. established design science as a major research paradigm for developing and evaluating such artefacts. \

The proposed study will therefore treat the integrated real-time healthcare Business Intelligence and decision-support system as the principal research artefact. The DSR process will provide a systematic mechanism for moving from identification of the healthcare decision-making problem through requirements analysis, system design, implementation, evaluation, and refinement.

The research process will consist of the following major phases:

1. Problem identification and motivation.
2. Requirement analysis.
3. Data-source and system analysis.
4. Conceptual and architectural design.
5. Prototype development.
6. Data integration and preprocessing.
7. Analytics and decision-support implementation.
8. System testing.
9. Quantitative evaluation.
10. Refinement of the artefact.



11. Final validation and documentation.

The methodology can therefore be represented as:

Problem Identification → Requirements → Architecture Design → Prototype Development → Data Integration → Analytics → Testing → Evaluation → Refinement → Final System

The iterative nature of DSR is important because findings obtained during testing and evaluation can be used to modify the system before the final version is produced.

Justification for Design Science Research

DSR is preferable to a purely descriptive research design because the intended outcome of the research is a technological artefact rather than only an explanation of an existing phenomenon. The study aims to demonstrate how different technologies—such as BI, real-time data processing, predictive analytics, machine learning, data warehousing/data lakes, and dashboards—can be integrated to support healthcare decision-making.

The DSR approach also permits evaluation of the artefact against practical criteria. These may include: accuracy of analytical results; data-processing speed; system response time; dashboard usability; prediction performance; reliability; scalability; user satisfaction; perceived usefulness; decision-support effectiveness; and overall system performance.

Study Population

The study population will comprise stakeholders who either generate, manage, analyze, or use healthcare information for decision-making. Depending on the selected healthcare organization and availability of participants, the population may include: healthcare administrators; doctors; nurses; health information managers; hospital managers; IT professionals; data analysts; health informaticians and other relevant healthcare decision-makers.

The inclusion of multiple categories of participants is important because healthcare BI serves different decision-making levels. Clinicians may require patient-level information, nurses may require patient-monitoring and workflow information, administrators may require operational and financial indicators, while IT and data professionals may focus on system integration, security, reliability, and data quality.

A multidisciplinary population will therefore provide a more comprehensive assessment of the proposed system than relying on a single professional group.

Unit of Analysis

The study may employ more than one unit of analysis depending on the research question.

The individual healthcare professional will constitute the unit of analysis for questionnaire-based evaluation of usability, perceived usefulness, user satisfaction, and decision-support effectiveness.

The healthcare data record or event will constitute a unit of analysis for evaluating data-processing and analytical performance.

The **system** will constitute the unit of analysis for technical evaluation, including response time, throughput, prediction accuracy, availability, and reliability.

Clearly defining these units of analysis will prevent ambiguity during data analysis.

Inclusion Criteria

Participants may be included if they: are employed within the selected healthcare organization; have direct involvement in healthcare information management or decision-making; have experience using healthcare information systems or digital technologies; are willing to participate; and provide informed consent.

Exclusion Criteria

Participants may be excluded if they: have no involvement with healthcare information or decision-making; are temporary visitors without relevant system experience; are unavailable during the data-collection period; or decline to provide informed consent and The criteria should be finalised after the research setting has been identified.

Data Collection

The study will use a **mixed-source data-collection strategy**, combining primary data from participants with secondary and system-generated healthcare data.

Questionnaires

Structured questionnaires will be administered to selected healthcare professionals to collect quantitative information concerning: current use of BI systems; challenges associated with existing healthcare information systems; perceived usefulness of real-time information; perceived ease of use; information-quality requirements; dashboard requirements; decision-support requirements; system acceptance; user satisfaction; and perceived effectiveness of the proposed system.

Likert-scale questions can be used, for example, ranging from

1 = Strongly Disagree to 5 = Strongly Agree.

The questionnaire should be pilot-tested before full administration to identify ambiguous questions and assess reliability. Internal consistency can subsequently be examined using **Cronbach's alpha**, where appropriate.



Interviews

Semi-structured interviews may be conducted with selected key informants, particularly hospital managers, clinicians, health information managers, IT professionals, and data analysts.

The interviews will help identify requirements that may not be captured adequately through questionnaires.

Potential interview topics include: current decision-making processes; weaknesses of existing BI systems; data availability; data-quality challenges; interoperability problems; preferred dashboard indicators; real-time information requirements; alert requirements; security and privacy concerns; and barriers to adoption.

The qualitative findings can subsequently inform the design of the proposed architecture.

Hospital Records

Where appropriate ethical and institutional approval is obtained, historical hospital records can be used for developing and testing the analytical components of the system.

Possible variables include: patient demographics; admission and discharge information; diagnoses; laboratory results; medication records; length of stay; readmission; patient flow; bed occupancy; mortality; waiting times; and resource utilization.

The precise variables should depend on the research objectives and availability of data.

Existing Healthcare Databases

Existing databases may be integrated to demonstrate the ability of the proposed BI architecture to combine heterogeneous data sources.

Potential databases include: EHR databases; hospital management systems; laboratory information systems; pharmacy databases; financial systems; human-resource systems; and patient-monitoring systems.

This component is particularly important because the literature identifies data integration and interoperability as continuing challenges in healthcare analytics.

System Logs

System logs will provide objective measures of system performance. These may include:

processing time; query response time; dashboard refresh time; number of processed records; failed transactions; system errors; user activity; alert generation; and system availability.

System logs can therefore complement questionnaire-based measures, reducing reliance on subjective assessments.

Real-Time Sensor Data

Where available, real-time patient-monitoring or IoT data may be incorporated into the prototype. These could include physiological observations such as: heart rate; blood oxygen saturation; blood pressure; temperature; and other relevant measurements.

If actual clinical sensor data cannot be obtained, appropriately authorized secondary datasets or simulated streaming data may be used to test the real-time processing architecture.

This distinction should be explicitly stated in the final methodology rather than implying access to clinical sensor data that may not be available.

Secondary Datasets

Secondary datasets may be used to supplement institutional data or evaluate machine-learning models where local datasets are insufficient.

The selected dataset should have characteristics relevant to the research problem and should be appropriately documented regarding its source, variables, sample size, data quality, and licensing/usage conditions.

Data Preprocessing

Data preprocessing will be a critical stage because healthcare data obtained from multiple sources are likely to differ in structure, format, completeness, quality, and terminology.

The preprocessing pipeline will consist of:

Data Acquisition → Data Cleaning → Data Integration → Missing-Value Treatment → Transformation → Normalization → Data Quality Assessment → Anonymization → Analytical Dataset

Data Cleaning

Data cleaning will identify and correct or remove: duplicate records; invalid values; inconsistent formats; incorrect data types; impossible measurements; inconsistent coding; duplicate patient identifiers; and incomplete records where appropriate.

For example, dates may occur in different formats across source systems and therefore need to be standardized before integration.



Data Integration

Data integration will combine information from heterogeneous healthcare sources into a unified analytical environment. The integration process may involve: schema matching; common identifiers; data mapping; terminology standardization; ETL/ELT processes; API-based integration; and interoperability standards where available. The proposed system should be designed to avoid unnecessary duplication and maintain data provenance. Healthcare interoperability is particularly important because contemporary healthcare environments frequently contain multiple systems that were developed independently.

Missing-Value Handling

Missing data will be identified and assessed before analytical modelling. Depending on the nature and proportion of missingness, possible approaches include: deletion of records were justified; mean or median imputation; mode imputation for categorical variables; interpolation for appropriate time-series data; model-based imputation; or explicit treatment of missingness as an analytical variable. The chosen approach will depend on the variable, the mechanism of missingness, and the requirements of the analytical model.

Data Transformation

Data transformation will convert source data into formats appropriate for analysis. This may involve: categorical encoding; date/time standardisation; aggregation; feature engineering; temporal transformation; creation of calculated indicators; and conversion of unstructured information where appropriate. For real-time analytics, timestamps will be particularly important because events must be correctly ordered and processed according to their occurrence time.

Data Quality Assessment

Data quality will be assessed across dimensions such as: completeness; accuracy; consistency; validity; timeliness; uniqueness; and reliability. This is especially important for real-time BI because a system can process information rapidly but still produce poor decisions if the underlying data are inaccurate. The methodology should therefore distinguish between processing speed and information quality.

Data Security and Anonymization

Healthcare information is sensitive, and data processing must therefore incorporate privacy and security controls. Where patient-level data are used, personally identifiable information should be removed, masked, pseudonymised, or otherwise protected as appropriate. Access should be restricted according to authorized roles, and data should be protected during storage and transmission.

Proposed System Development Method

The DSR process can be operationalised through the following stages.

Stage 1: Problem Identification

The study will investigate limitations associated with existing healthcare decision-support and BI systems, particularly: delayed information; fragmented data sources; limited interoperability; historical rather than real-time reporting; inadequate predictive capability; and limited integration between BI and decision support.

Stage 2: Requirement Analysis

Information obtained through questionnaires, interviews, literature, and existing system analysis will be translated into functional and non-functional requirements.

Functional requirements may include: data acquisition; data integration; real-time processing; dashboard generation; prediction; alerts; reporting; and decision support.

Non-functional requirements may include: security; scalability; usability; reliability; interoperability; availability; and response time.

Stage 3: Architecture Design

The proposed architecture may comprise:

Stage 4: Prototype Development

A functional prototype will be developed based on the identified requirements and architecture.

Stage 5: Testing

The prototype will undergo several forms of testing: **unit testing** — testing individual components;

- i. **integration testing** — testing interactions among components;
- ii. **system testing** — testing the complete system;
- iii. **performance testing** — measuring speed and resource requirements;



- iv. **security testing** — evaluating access controls and vulnerabilities; and
- v. **user acceptance testing** — assessing whether the system satisfies user requirements.

Stage 6: Evaluation

The system will then be evaluated using quantitative measures.

Possible measures include:

Dimension	Possible measure
Predictive performance	Accuracy, precision, recall, F1-score, AUC
Processing performance	Response time, throughput, latency
Dashboard performance	Refresh time, availability
Data quality	Completeness, consistency, accuracy
Usability	SUS or Likert-based usability measures
User acceptance	Perceived usefulness/ease of use
Decision support	Decision accuracy, response time, user-rated usefulness
Reliability	Error rate, uptime
Scalability	Performance under increasing data volume

Quantitative Data Analysis

Questionnaire data will be analyzed using appropriate statistical techniques.

Descriptive Statistics

Descriptive statistics will include: frequencies; percentages; means; standard deviations and minimum and maximum values.

These statistics will describe participant characteristics and responses to system requirements and evaluation measures.

Reliability Analysis

The internal consistency of multi-item scales can be evaluated using Cronbach's alpha.

A commonly used interpretation is that values around 0.70 or above indicate acceptable internal consistency, although interpretation should consider the number of items and the context of the scale.

Inferential Statistics

Depending on the research questions and measurement characteristics, inferential techniques may include: independent-samples t-test; paired-samples t-test; ANOVA; correlation analysis; regression analysis; and non-parametric alternatives where assumptions are not satisfied.

For example, if the study measures decision-making performance before and after exposure to the proposed BI system, a paired-samples test could be used where the assumptions are satisfied.

Machine-Learning Evaluation

Where predictive models are developed, the dataset may be divided into: training set; validation set; and testing set.

Cross-validation may also be applied where appropriate.

For classification problems, evaluation can include:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$F1 = 2 \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F1 = 2 \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$



Ethical Considerations

Ethics will be incorporated throughout the research process because the study may involve healthcare professionals and potentially sensitive patient data.

The research will address: informed consent; confidentiality; anonymity/pseudonymisation; secure data storage; restricted access; responsible data use; institutional authorisation; ethical approval; and responsible use of AI and predictive analytics.

IV. MODEL REQUIREMENTS

The proposed hybrid model is based on eight fundamental requirements: real-time data acquisition, data integration, data storage, real-time processing, analytics, decision support, visualisation, and security/privacy.

Real-Time Data Acquisition

The first requirement is the ability to acquire healthcare information continuously or at sufficiently frequent intervals to support timely decision-making.

The system should be capable of receiving data from: Electronic Health Records (EHRs); hospital management databases; laboratory information systems; pharmacy systems; medical devices; IoT sensors; patient-monitoring systems; financial systems; and administrative databases.

Data Integration

Healthcare information is frequently distributed across systems developed using different technologies, data structures, terminologies, and standards. The proposed model therefore requires an integration layer capable of combining heterogeneous sources.

The integration layer should provide: ETL/ELT; API-based integration; data mapping; data standardization; interoperability mechanisms; semantic integration; identity matching; metadata management; and data provenance.

Interoperability is particularly important because recent healthcare research continues to identify it as a major challenge in developing integrated digital-health ecosystems. FHIR-based approaches are increasingly being used to facilitate the exchange and reuse of healthcare information across systems.

The proposed architecture should therefore avoid assuming that all source systems use the same database structure. Instead, it should provide an abstraction layer through which heterogeneous information can be converted into a consistent analytical representation.

Data Storage

The model requires scalable storage capable of supporting both historical and high-velocity healthcare information.

A hybrid data warehouse/data lake architecture is proposed.

The data warehouse can support: structured reporting; historical analysis; KPI monitoring; management dashboards; and OLAP analysis.

The data lake can accommodate: raw data; semi-structured information; unstructured information; streaming data; IoT data; and machine-learning datasets.

This approach is consistent with recent healthcare data-warehouse research, which identifies data warehouses as important mechanisms for integrating heterogeneous clinical information but also recognises limitations concerning flexibility, scalability, and advanced analytics.

The proposed model therefore does not replace the traditional warehouse; rather, it extends the warehouse with complementary storage and processing capabilities.

Real-Time Processing

The real-time processing layer constitutes one of the principal distinguishing features of the proposed model.

This layer should perform: stream ingestion; real-time validation; event detection; filtering; aggregation; anomaly detection; event correlation; and alert generation.

For example, if a patient's physiological measurements change rapidly, the system should not wait for a nightly data-loading process before analysing the information. Instead, the incoming event can be validated, analysed, compared against rules or predictive models, and presented to an authorised user with minimal delay.

The real-time layer consequently establishes the connection between data generation and immediate analytical response.

Analytics

The analytical layer should integrate four levels of analytics:

Descriptive → Diagnostic → Predictive → Prescriptive

Descriptive analytics explains what has happened or what is happening. Diagnostic analytics investigates why it happened.

Predictive analytics estimates what is likely to happen, while prescriptive analytics evaluates possible actions.

This progression allows the proposed system to move beyond conventional BI reporting.

For example:



Descriptive: Emergency admissions have increased by 15%.

Diagnostic: The increase is concentrated in specific periods and patient categories.

Predictive: Admissions are likely to increase further over the next 24 hours.

Prescriptive: Additional staff and beds should be allocated to the emergency unit.

The literature indicates that predictive analytics is becoming increasingly important in healthcare BI, whereas prescriptive analytics remains comparatively less mature and insufficiently validated in real-world settings.

Decision Support

The decision-support engine represents the transition from Precision $\times$ Recall. It should integrate several mechanisms: rule-based recommendations; predictive models; risk scoring; threshold-based alerts; anomaly detection; what-if analysis; resource-allocation recommendations; and scenario analysis.

A hybrid decision-support mechanism is preferable because healthcare decisions cannot always be represented effectively through one analytical technique.

For well-established clinical or administrative conditions, explicit rules can provide transparent recommendations. For complex patterns, machine-learning models can generate risk scores or predictions. These outputs can then be combined before being presented to the decision-maker.

The proposed system should therefore use AI as an augmentation mechanism, rather than positioning the system as an autonomous replacement for clinicians or managers.

Visualization

The visualization layer should transform analytical results into information that can be rapidly interpreted by users.

The proposed dashboards should include: KPIs; interactive charts; trend analysis; real-time indicators; risk scores; alerts; predictive forecasts; comparative analysis; and drill-down functionality.

Proposed Model Architecture

The proposed architecture consists of **seven interconnected layers**.

Layer 1: Healthcare Data Sources

The first layer represents the point at which healthcare information is generated.

Layer 2: Data Integration Layer

The second layer is responsible for transforming heterogeneous source data into an integrated information environment.

Layer 3: Real-Time Processing Layer

The third layer distinguishes the proposed model from conventional healthcare BI architectures.

It consists of:

Streaming $\rightarrow$ Validation $\rightarrow$ Event Detection $\rightarrow$ Analytics $\rightarrow$ Alert/Action

Stream Processing

Layer 4: BI and Analytics Engine

The fourth layer integrates conventional BI with advanced analytics.

The four principal analytical levels are: Descriptive Analytics, Diagnostic Analytics, Predictive Analytics and Recommends potential interventions.

Layer 5: Decision Support Engine

The fifth layer converts analytical outputs into decision-support information.

The engine will contain several complementary mechanisms.

Layer 6: Visualisation and Dashboard Layer

The sixth layer presents analytical results to users.

The proposed interface should provide role-based dashboards, meaning that users receive information relevant to their responsibilities.

Layer 7: Decision-Maker Interface

The final layer connects the analytical system to the individuals responsible for decisions.

The principal users are:

Security, Privacy and Governance Layer

Although security can be implemented across every architectural layer, it should be treated as a cross-cutting requirement rather than merely another processing component.

The proposed model should incorporate: authentication; role-based access control; encryption; audit trails; data anonymisation/pseudonymisation; secure APIs; data governance; consent management where applicable; model governance; and monitoring of system access.

This is particularly important because integrating EHRs, IoT devices, analytics, and real-time processing increases the number of potential points through which sensitive information can be accessed.

WHO guidance on AI for health emphasizes privacy, human oversight, transparency, accountability, and appropriate governance when AI is used in healthcare.

The model should consequently adopt a privacy-by-design and security-by-design philosophy.



Expected Advantages of the Proposed Model

The proposed hybrid model is expected to provide several benefits.

- 1. Timelier Decision-Making:** Real-time processing reduces the delay between data generation and decision-making.
- 2. Improved Data Integration:** The integration layer provides a mechanism for combining information from previously isolated healthcare systems.
- 3. Better Situational Awareness:** Real-time dashboards allow decision-makers to understand current clinical and organizational conditions.
- 4. Early Risk Detection:** Predictive models can identify potentially adverse events before they occur.
- 5. Actionable Intelligence:** Prescriptive analytics and decision-support mechanisms transform predictions into possible interventions.
- 6. Improved Resource Management:** Predictive demand analysis can support allocation of beds, staff, medicines, equipment, and other resources.
- 7. Support for Multiple Decision Levels:** The model supports clinical, operational, administrative, and strategic decisions.
- 8. Human-Centred AI:** The architecture provides AI-generated evidence and recommendations while retaining human oversight.
- 9. Scalability:** The combination of cloud/data-lake capabilities with real-time and potentially edge processing allows the architecture to accommodate increasing data volumes.
- 10. Continuous Improvement:** Feedback from decisions and outcomes can be incorporated into subsequent analytical processes and model refinement.

Proposed Model Evaluation

Evaluation dimension	Example indicators
Real-time performance	Latency, throughput, processing time
Data integration	Number of successfully integrated sources, interoperability success
Data quality	Completeness, accuracy, consistency, timeliness
Predictive performance	Accuracy, precision, recall, F1, AUC
Prescriptive performance	Recommendation quality, resource-utilisation improvement
Dashboard performance	Refresh rate, response time, availability
Usability	SUS score, user satisfaction
Acceptance	Perceived usefulness, perceived ease of use
Decision support	Decision accuracy, decision time, perceived usefulness
Security	Access violations, auditability, encryption coverage

V. MODEL DEVELOPMENT

The development phase translates the proposed hybrid healthcare Business Intelligence (BI) architecture into a functional technological artefact. The development process integrates data management, real-time processing, advanced analytics, machine learning, decision rules, and visualization into a unified decision-support environment.

The model is designed around the principle that healthcare decision-makers require access to accurate, timely, integrated, predictive, and actionable information. Consequently, the development process does not treat database management, analytics, and visualization as independent activities. Instead, they are implemented as interconnected components of a single analytical pipeline.

The development process can be represented as: Data Sources → Data Integration → Storage → Real-Time Processing → Analytics → Decision Rules → Dashboard → Decision

The model will be developed iteratively, allowing the outputs of testing and evaluation to inform subsequent refinement.

Technology Selection

Technology selection will be guided by the functional and non-functional requirements identified in Sections 5.1 and 5.2. The selected technologies should support interoperability, scalability, real-time processing, analytical performance, security, usability, and integration with existing healthcare information systems.

Technology selection should therefore not be based simply on popularity or availability. Each technology should be evaluated against the requirements of the proposed healthcare BI architecture.

Database Technologies:

The system requires a database environment capable of storing structured healthcare information and supporting analytical queries.

A relational database can be used for structured information such as: patient demographics; admissions; diagnoses; laboratory results; pharmacy transactions; financial information; and hospital operations.

A data warehouse can subsequently provide an analytical representation of integrated historical information.



Big-Data Technologies

Healthcare data have characteristics associated with the major dimensions of Big Data:

Volume — large quantities of patient and operational information;

Velocity — continuously generated monitoring and IoT data;

Variety — structured, semi-structured, and unstructured information;

Veracity — varying data quality; and

Value — potential contribution to clinical and organizational decisions.

Machine-Learning Frameworks

Machine-learning frameworks will be used to develop predictive components of the model.

Depending on the selected prediction problem, algorithms may include: logistic regression;

Decision trees; random forests; gradient boosting; support vector machines; artificial neural networks; and deep-learning models.

BI and Dashboard Tools

The visualization component can be implemented using a suitable BI platform or a custom web-based dashboard.

The selected tool should support: real-time data refresh; interactive charts; KPI cards; filtering;

Drill-down; role-based views; alerts; trend analysis; and predictive visualization.

The choice should be based on functionality, integration capability, licensing, security, scalability, and deployment requirements rather than brand preference.

APIs

Application Programming Interfaces (APIs) will provide controlled communication between the BI system and external healthcare applications.

APIs may be used to: retrieve patient information; receive laboratory results; exchange pharmacy information; transmit monitoring data; expose prediction services; provide dashboard data; and

Integrate with existing hospital systems.

VI. SYSTEM IMPLEMENTATION

Following development and validation of the individual components, the proposed model will be implemented as an integrated system.

The implementation phase will connect the data sources, integration mechanisms, storage environment, streaming layer, analytics engine, decision-support engine, and dashboards.

The resulting system will implement the complete pipeline:

Data → Information → Analytics → Intelligence → Recommendation → Decision

System Architecture

The technical architecture of the developed system will consist of several interconnected layers.

Source Layer

The source layer contains the healthcare systems and devices generating data.

The architecture should support both structured and streaming data.

Integration Layer

The integration layer provides the interface between source systems and the analytical environment.

Where appropriate, healthcare interoperability standards such as FHIR can be incorporated.

Storage Layer

The storage architecture should support both historical and real-time analytics.

The warehouse supports structured BI and historical analysis, while the data lake can accommodate high-volume, heterogeneous, and machine-learning-oriented data.

Real-Time Processing Layer

The streaming component receives continuously generated information.

This layer is responsible for reducing data latency and enabling timely responses.

BI and Analytics Layer

The analytical layer combines conventional BI with advanced analytics.

This creates a progression from describing the situation to recommending an appropriate response.



Decision-Support Layer

The decision-support engine receives analytical outputs and applies appropriate rules and models. The resulting recommendations are then transmitted to the visualization layer.

Presentation Layer

The presentation layer provides role-specific dashboards. This ensures that users see information appropriate to their responsibilities.

Cross-Cutting Security and Governance

Security should not be represented as an isolated final stage. It should operate across the entire architecture. The following mechanisms should therefore be embedded throughout the system: authentication; role-based access control; encryption; audit logging; anonymisation/pseudonymisation; secure API communication; data governance; model governance; backup and recovery; and monitoring. This is particularly important because the architecture integrates sensitive patient information with real-time devices and AI-based analytics. WHO guidance continues to emphasize privacy, transparency, accountability, human oversight, and appropriate governance in healthcare AI.

End-to-End System Workflow

The complete implementation can be described through the following workflow:

Step 1: Data Generation

Healthcare data are generated by EHRs, hospital systems, laboratory systems, pharmacy systems, financial systems, and IoT devices.

Step 2: Data Acquisition

The system receives data through APIs, ETL/ELT processes, database connections, and streaming interfaces.

Step 3: Data Validation

Incoming information is checked for completeness, validity, consistency, duplication, and other quality issues.

Step 4: Data Storage

Validated information is stored in the appropriate warehouse, lake, or operational storage environment.

Step 5: Real-Time Processing

Streaming information is processed continuously and significant events are detected.

Step 6: Analytics

The BI and analytics engine performs descriptive, diagnostic, predictive, and prescriptive analysis.

Step 7: Decision Support

Predictions and analytical results are evaluated against decision rules and operational requirements.

Step 8: Visualization

Relevant information, alerts, predictions, and recommendations are displayed through role-specific dashboards.

Step 9: Human Decision

The healthcare professional or manager evaluates the information and makes the appropriate decision.

Step 10: Feedback

The resulting decision and outcome can subsequently become additional information for monitoring, evaluation, and model refinement.

VII. MODEL EVALUATION

The evaluation of the proposed hybrid healthcare Business Intelligence (BI) model is necessary to determine whether the integration of real-time data processing, BI, predictive analytics, prescriptive analytics, and decision support produces measurable improvements over conventional BI approaches. Evaluation should therefore extend beyond technical functionality to include analytical performance, system performance, usability, decision-making effectiveness, and practical value to healthcare organizations.

This multidimensional approach is particularly important for healthcare decision-support systems because a model can demonstrate strong predictive performance in an offline experiment without necessarily improving decisions in practice. The DECIDE-AI framework emphasises that healthcare AI systems should be evaluated not only for technical performance but also for clinical utility, safety, human factors, usability, integration into workflows, and the interaction between the system and its users.

EVALUATION CRITERIA

The evaluation will focus on nine principal criteria: decision-making speed, decision accuracy, prediction accuracy, data-processing latency, usability, scalability, reliability, resource utilisation, and user satisfaction.



Decision-Making Speed: Decision-making speed refers to the time required for a healthcare decision-maker to move from receiving relevant information to making an informed decision.

Decision Accuracy: measures whether users make the correct or appropriate decision based on the information provided.

Prediction Accuracy: evaluates the performance of the machine-learning component.

Data-Processing Latency: Latency measures the time between the generation or arrival of data and the availability of the corresponding analytical result.

System Usability: Usability evaluates whether intended users can effectively interact with the system.

Scalability: Assesses whether system performance remains acceptable as: data volume increases; the number of concurrent users increases; the number of data sources increases; and the frequency of incoming events increases.

Reliability: Measures the system's ability to operate consistently without failures.

User Satisfaction: measures users' perceptions of the system.

Questionnaire items may assess: perceived usefulness; perceived ease of use; confidence in system outputs; trust; satisfaction with dashboards; satisfaction with alerts; intention to use the system; and perceived impact on decision-making. The Technology Acceptance Model (TAM) discussed earlier in the article can provide a theoretical basis for assessing perceived usefulness and perceived ease of use.

Performance Metrics

The performance evaluation should use different metrics for the different components of the hybrid system.

Predictive Analytics Metrics

Where the prediction task is a classification problem, the following measures can be used.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad 1$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad 2$$

Accuracy represents the proportion of predictions that are correct.

However, accuracy alone may be misleading when healthcare outcomes are highly imbalanced.

Precision measures the proportion of predicted positive cases that are actually positive.

$$\begin{aligned} &\text{Recall/Sensitivity} \\ \text{Recall} &= \frac{TP}{TP+FN} \end{aligned} \quad 3$$

Recall measures the proportion of actual positive cases correctly identified by the model.

For healthcare applications involving potentially serious adverse events, recall can be particularly important because failure to identify a high-risk patient may have greater consequences than generating an additional false alert.

$$\begin{aligned} &\text{F1-Score} \\ \text{F1} &= 2 \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \end{aligned} \quad 4$$

The F1-score provides a combined measure of precision and recall.

ROC-AUC

The Area Under the Receiver Operating Characteristic Curve (ROC-AUC) measures the model's ability to discriminate between classes across different classification thresholds.

Where the outcome is substantially imbalanced, precision-recall analysis should also be considered.

Calibration: Calibration should be assessed where the model produces probabilities or risk scores. A model that predicts a 70% risk should, approximately, correspond to a 70% observed event rate among comparable cases.

This is important because a clinically useful risk score should not only rank patients correctly but should also provide reasonably reliable probabilities.

Regression and Forecasting Metrics

For continuous predictions such as hospital demand, bed occupancy, waiting time, or patient length of stay, the following measures can be used.



Mean Absolute Error

$$= \frac{1}{n} \sum_{i=1}^n [y_i - y_i^A]$$

MAE measures the average absolute difference between observed and predicted values.

Root Mean Square Error

RMSE gives greater weight to larger errors.

Mean Absolute Percentage Error

$$= \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y_i^A)^2}$$

MAPE may be useful for some demand-forecasting tasks, although it should be avoided or interpreted carefully when actual values can be zero or very close to zero.

Real-Time Processing Metrics

The real-time component requires a separate technical evaluation.

Response time is the time required for the system to respond to a user request or event.

$$\text{Response Time} = T_{\text{Response}} - T_{\text{Request}}$$

Processing Latency

Processing latency measures the delay between data arrival and completion of processing.

$$\text{Latency} = T_{\text{Process}} - T_{\text{Received}}$$

Throughput

Throughput measures the quantity of data/events processed within a given period.

$$\text{Throughput} = \frac{\text{Numbers of Events Processed}}{\text{Time}}$$

For example:

15,000 events/minute

could be used as a system-throughput indicator.

Alert Latency

Because alerts are a major feature of the proposed architecture, alert latency should be measured separately:

$$\text{Alert Latency} = T_{\text{alert}} - T_{\text{critical event}}$$

VIII. RESULTS AND DISCUSSION

Results

Real-Time Data Processing Results

The real-time component should demonstrate whether the architecture can transform continuously generated healthcare information into analytical outputs within an acceptable time.

The results should report the performance of the pipeline:

Data Event → Ingestion → Validation → Processing → Analytics → Alert/Dashboard

Dashboard Results

The dashboard results should demonstrate how the system transforms analytical outputs into actionable information.

The results can include screenshots or figures showing: real-time KPIs; bed occupancy; patient-risk indicators; emergency workload; pharmacy inventory; predictive trends; alerts; resource utilization; and recommended actions.

A representative dashboard could show: The dashboard results should demonstrate the central proposition of the research: the system does not merely display data; it combines current information, predictions, alerts, and recommendations to support decisions.



Discussion

Discussion of System Performance

If the proposed model demonstrates lower processing latency and faster dashboard/alert response than traditional BI, this would support the argument that integrating streaming technologies with conventional BI can reduce the temporal gap between healthcare data generation and decision-making.

This finding would be consistent with recent research describing the increasing importance of streaming data, IoT, Big Data, and machine learning in real-time healthcare analytics. However, recent literature also indicates that real-time healthcare platforms continue to face challenges involving scalability, interoperability, data quality, and system complexity. The contribution of the present study would therefore not simply be the implementation of streaming technology, but the demonstration of how streaming, BI, predictive analytics, and decision support can operate as one integrated architecture.

Discussion of Decision-Making Results

If participants make decisions significantly faster and/or more accurately using the proposed system, this would provide direct evidence that the model addresses the principal problem identified in the literature review.

The likely explanation is that the system reduces the cognitive and informational burden associated with manually locating, integrating, and interpreting information from multiple systems.

Instead of requiring a manager or clinician to:

Search → extract → combine → analyze → interpret → decide, the proposed architecture performs much of the information-processing process automatically:

Integrate → process → analyze → predict → recommend → present.

The decision-maker remains responsible for the final decision, but receives more timely and structured evidence.

This human-in-the-loop approach is particularly important in healthcare. Current guidance and research on healthcare AI emphasize the importance of human oversight, transparency, accountability, and evaluation within real-world workflows rather than assuming that algorithmic outputs should automatically determine clinical actions.

Discussion in Relation to the Research Objectives

The same principle should be applied to the research objectives.

For example:

Research Objective	Evidence from Results
Identify limitations of conventional healthcare BI	Baseline evaluation/literature findings
Develop a hybrid real-time BI model	Proposed architecture and implemented prototype
Integrate predictive analytics	Predictive model results
Develop decision-support capabilities	Rules, recommendations, alerts
Implement real-time dashboards	Dashboard/system results
Evaluate the model	Comparative and user evaluation
Determine effect on decision-making	Decision-speed and accuracy results

This provides a clear traceability chain from the research objectives to the empirical evidence.

Discussion of Practical Healthcare Requirements

The findings should finally be interpreted against actual healthcare requirements.

Healthcare environments require information that is: Timely; accurate; available; secure; interoperable; understandable; actionable; and relevant to specific decisions.

Implications for Healthcare Organizations

The proposed model has implications for healthcare organizations seeking to transition from conventional reporting systems towards intelligent, data-driven operations.

The model can support organizations in moving from:

Retrospective reporting → real-time monitoring → predictive planning → proactive intervention.

Instead of waiting for monthly or weekly reports to identify performance problems, managers can monitor operational indicators continuously and receive alerts when conditions require attention.

Potential organizational benefits include: improved resource allocation; better capacity management; earlier identification of operational problems; improved patient-flow management; improved monitoring of service performance; and more evidence-based management.

However, implementation requires organizational readiness, appropriate infrastructure, data governance, staff training, and sustained management support.



Implications for Clinical Practice

For clinicians, the model can support earlier identification of potentially high-risk patients and facilitate prioritization. However, the findings should not be interpreted as evidence that AI should replace clinical judgement. Instead, the model should be positioned as: Clinical intelligence augmentation rather than clinical autonomy. Predictions, alerts, and recommendations should be interpreted alongside clinical context. This is consistent with contemporary healthcare-AI principles emphasising human oversight, safety, transparency, and accountability.

Implications for Healthcare Policy

At policy level, the proposed model highlights the importance of developing an enabling digital-health ecosystem. Policy considerations include: Interoperability standards; healthcare data governance; privacy protection; cybersecurity; AI governance; data-quality standards; responsible AI; Infrastructure investment; workforce development; and mechanisms for evaluating AI-enabled healthcare systems. A real-time healthcare BI ecosystem cannot operate effectively if individual hospitals use completely isolated information environments. Consequently, interoperability and data governance should be treated as strategic healthcare infrastructure, not merely technical IT concerns.

Implications for Digital Transformation

The broader implication is that digital transformation should not be understood simply as replacing paper records with electronic systems. The proposed model contributes to the final stages by connecting integrated healthcare data with analytics and decision support. Recent research similarly indicates that healthcare BI is moving towards more adaptive and intelligent systems, including predictive and prescriptive capabilities.

IX. CONCLUSION

Healthcare organisations generate large volumes of data through electronic health records, hospital information systems, laboratory and pharmacy systems, medical devices, financial databases, and other digital platforms. However, the availability of healthcare data does not necessarily translate into timely and effective decision-making. The literature reviewed in this study indicates that conventional Business Intelligence (BI) systems remain largely oriented towards historical reporting and descriptive analytics. Consequently, healthcare decision-makers may experience delays in accessing relevant information, fragmented data sources, limited predictive capabilities, and insufficient integration between analytical outputs and actionable decisions.

This study therefore proposed a hybrid real-time Business Intelligence model for healthcare decision-making. The model integrates heterogeneous healthcare data sources through an interoperability and data-integration layer, processes streaming and historical data, and combines BI with descriptive, diagnostic, predictive, and prescriptive analytics. A decision-support engine further transforms analytical outputs into alerts, risk scores, recommendations, and what-if information, while interactive dashboards provide healthcare professionals and managers with timely and understandable intelligence.

The principal contribution of the proposed model is its integration of capabilities that are frequently treated separately in existing healthcare information systems. Rather than restricting BI to retrospective reporting, the proposed architecture connects real-time data acquisition, streaming analytics, machine learning, decision rules, predictive forecasting, and visualisation within a unified decision-support environment. This creates a pathway from raw healthcare data to information, analytical knowledge, prediction, recommendation, and ultimately human decision-making.

The effectiveness of the model should be established through empirical evaluation using measures including data-processing latency, system response time, prediction accuracy, decision-making speed, decision accuracy, usability, scalability, reliability, resource utilisation, and user satisfaction. Importantly, technical performance alone should not be considered sufficient evidence of effectiveness. The model should demonstrate that analytical intelligence can be translated into meaningful improvements in healthcare decision processes.

The proposed model also adopts a human-in-the-loop approach. Its predictions, alerts, and recommendations are intended to augment rather than replace healthcare professionals. This distinction is important because healthcare decisions involve clinical, organisational, ethical, and contextual considerations that cannot always be captured by computational models. Contemporary guidance for healthcare AI likewise emphasises evaluation of usability, safety, workflow integration, and clinical utility in addition to algorithmic performance.

Overall, the study contributes a conceptual and technical framework for moving healthcare BI from a retrospective reporting paradigm towards real-time decision intelligence. If validated through empirical evaluation, the model has the



potential to improve the timeliness, quality, and responsiveness of healthcare decision-making while providing a scalable foundation for the integration of advanced analytics and artificial intelligence into healthcare information systems.

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