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Power BI-Based Clinical Decision Support System for Evidence-Based Nurse Decision-Making

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Abstract
The integration of data analytics into healthcare has led to significant improvements in clinical decision-making, particularly for nursing professionals who require timely, evidence-based insights to enhance patient care. This study presents the development and implementation of a Power BI-based Clinical Decision Support System (CDSS) designed to support evidence-based nurse decision-making across diverse clinical settings. Leveraging Power BI's interactive visualization capabilities and real-time data processing, the system enables nurses to access patient records, diagnostic results, and treatment history through dynamic dashboards, fostering a data-driven approach to care delivery. The Power BI-based CDSS aggregates data from electronic health records (EHRs), laboratory systems, and nursing documentation, transforming them into actionable insights using customized key performance indicators (KPIs), risk stratification models, and clinical pathways. This approach ensures that nursing interventions align with current clinical guidelines, promoting consistency and quality in patient outcomes. Furthermore, the system provides predictive analytics that identify early warning signs of patient deterioration, enabling proactive intervention and reducing avoidable complications. A mixed-methods evaluation involving pilot deployment in surgical and medical wards demonstrated increased nurse confidence in clinical decisions, improved interprofessional communication, and reduced response times to patient needs. User feedback highlighted the intuitive design, adaptability, and ease of use as critical success factors. Challenges identified include the need for training in data interpretation and the importance of maintaining data quality and interoperability across systems. This research underscores the potential of Power BI-based tools to transform traditional nursing workflows into intelligent, evidence-informed decision models. By integrating clinical evidence with user-friendly analytics, the CDSS enhances critical thinking, supports real-time decision-making, and aligns nursing practice with organizational quality improvement goals. Future research should explore large-scale implementation, integration with artificial intelligence algorithms, and longitudinal impact on patient outcomes and cost-effectiveness.

Keywords: Power BI, Clinical Decision Support System (CDSS), Evidence-Based Practice, Nursing Informatics, Real-Time Analytics, Electronic Health Records (EHR), Data Visualization, Patient Outcomes, Predictive Analytics, Nursing Decision-Making

1. Introduction

Clinical decision-making in nursing is a complex and critical process that directly influences patient safety, treatment outcomes, and the overall quality of healthcare delivery. Nurses, as frontline caregivers, are often required to make rapid and accurate decisions in dynamic clinical environments. These decisions depend not only on clinical expertise and judgment but also on access to timely, relevant, and reliable information (Adelusi, Ojika & Uzoka, 2022, Osamika, *et al*., 2022). The growing complexity of healthcare demands that nursing professionals integrate evidence-based practices into their routine decision-making to ensure optimal patient outcomes. Evidence-based practice (EBP) emphasizes the use of the best available research, clinical expertise, and patient preferences to guide clinical decisions, thereby reducing variability in care and enhancing effectiveness.

In response to the need for more systematic and data-informed approaches, Clinical Decision Support Systems (CDSS) have

emerged as vital tools in modern healthcare. CDSS are computer-based systems designed to support healthcare professionals by providing intelligently filtered, context-specific information at the point of care. These systems can improve clinical workflow, reduce errors, and foster adherence to standardized guidelines. For nursing professionals, CDSS can bridge the gap between clinical knowledge and practice by offering real-time insights, alerts, and decision pathways aligned with best practices (Okoli, Akomolafe & Merotiwon, 2024, Olaboye, *et al*., 2024).

Power BI, a powerful business intelligence and data visualization tool developed by Microsoft, presents an innovative opportunity to enhance the effectiveness of CDSS within nursing informatics. Its ability to integrate disparate data sources, provide real-time analytics, and generate interactive dashboards makes it particularly suited for the fast-paced and information-rich environment of clinical nursing. By leveraging Power BI, healthcare organizations can create customized decision support tools that are intuitive, scalable, and aligned with evidence-based protocols (Olatunji, *et al*., 2024, Omaghomi, *et al*., 2024, Soyege, *et al*., 2024). This approach not only empowers nurses with actionable insights but also promotes consistency, transparency, and accountability in patient care. The integration of Power BI into clinical decision-making frameworks represents a transformative step in the pursuit of data-driven, patient-centered nursing practices.

2.1 Literature Review

The evolution of decision support tools in healthcare reflects the continuous effort to enhance clinical efficiency, accuracy, and patient outcomes. Historically, healthcare providers have relied on paper-based records, clinical guidelines, and professional intuition to guide decision-making. While these traditional methods were functional, they were susceptible to delays, inconsistencies, and human error (Akpan, Awe & Idowu, 2019). As the volume and complexity of clinical data increased, so did the need for more advanced, systematized approaches to manage and interpret this information. The emergence of Clinical Decision Support Systems (CDSS) represented a major shift in healthcare informatics, enabling the delivery of relevant clinical knowledge and patient-specific information at the point of care (Adelusi, Ojika & Uzoka, 2022). Early CDSS models were rule-based systems embedded within electronic health record (EHR) platforms, designed primarily to generate alerts, reminders, and guideline-based recommendations. Over time, these tools have evolved to incorporate machine learning, predictive analytics, and personalized medicine features, offering more nuanced and dynamic support to clinicians.

In parallel with the development of CDSS, the field of business intelligence (BI) has matured, offering powerful tools for data integration, analysis, and visualization. BI platforms such as Microsoft Power BI have found increasing relevance in healthcare settings due to their capacity to process large datasets, present real-time insights, and generate interactive dashboards. In nursing and clinical environments, BI tools have been used to monitor key performance indicators, track patient outcomes, and support quality improvement initiatives. For example, hospitals have implemented BI systems to analyze trends in patient readmissions, infection rates, medication errors, and staffing efficiency (Adeshina, 2021, Osabuohien, Omotara & Watti, 2021). These insights inform administrative decisions and clinical strategies, contributing to more effective resource allocation and better overall care.

Despite these advances, the application of BI tools specifically tailored for nurse-led decision-making remains limited. Traditional CDSS often prioritize physician-centric workflows, with less emphasis on the unique roles and responsibilities of nurses. Nurses are expected to make crucial clinical decisions related to patient assessment, medication administration, care planning, and emergency response often in time-sensitive scenarios (Odezuligbo, Alade & Chukwurah, 2024, Olaboye, *et al*., 2024). However, many CDSS platforms do not adequately support nursing workflows, and may lack features that align with nursing taxonomies, nursing-specific data entry fields, or tools for prioritizing nursing interventions. Additionally, the absence of intuitive interfaces and real-time visualizations in many legacy systems reduces their usability and adoption by nursing staff. Consequently, there is a critical gap between the potential of decision support technologies and their practical utility in nursing practice (Ajayi & Akanji, 2023, Kolawole, *et al*., 2023).

Power BI, with its flexible design and robust data modeling capabilities, offers a promising avenue for bridging this gap. By enabling the development of customized dashboards and visual analytics tailored to the needs of nursing professionals, Power BI enhances the visibility of patient data and supports evidence-based decision-making (Awe, 2017). For instance, a Power BI-based CDSS can integrate data from multiple hospital systems such as EHRs, lab information systems, and patient monitoring devices to create comprehensive patient profiles. These profiles can include real-time vital signs, lab results, medication history, risk scores, and nursing notes, all displayed in an interactive format that supports quick interpretation and response (Adelusi, Ojika & Uzoka, 2022, Osamika, *et al*., 2022). This level of data consolidation and visualization is particularly valuable in high-acuity settings such as emergency departments, intensive care units, and surgical recovery wards, where rapid decision-making is essential.

Moreover, real-time data and visualization are fundamental to improving clinical care. Nurses must often make decisions with incomplete or outdated information due to delays in documentation or lack of system interoperability. With real-time dashboards, Power BI empowers nurses to detect early warning signs of patient deterioration, such as abnormal vital signs or lab trends, facilitating timely intervention and escalation. This proactive approach can significantly reduce the incidence of adverse events such as sepsis, cardiac arrest, or medication errors. Visualization tools also enhance communication and collaboration among interprofessional teams by presenting data in a clear, standardized format that supports shared understanding and decision-making (Adeshina, Owolabi & Olasupo, 2023).

In addition to clinical applications, Power BI can support nurse managers and educators in monitoring team performance, identifying training needs, and evaluating adherence to clinical protocols. For example, dashboards can be created to track documentation compliance, missed care events, or patient satisfaction scores by unit, shift, or individual nurse. These insights not only inform performance improvement initiatives but also promote accountability and professional development within nursing teams (Merotiwon, Akintimehin & Akomolafe, 2022). Fig 1

shows Precise-Caring for the benefits of CDSS presented by Chen, *et al*., 2023.

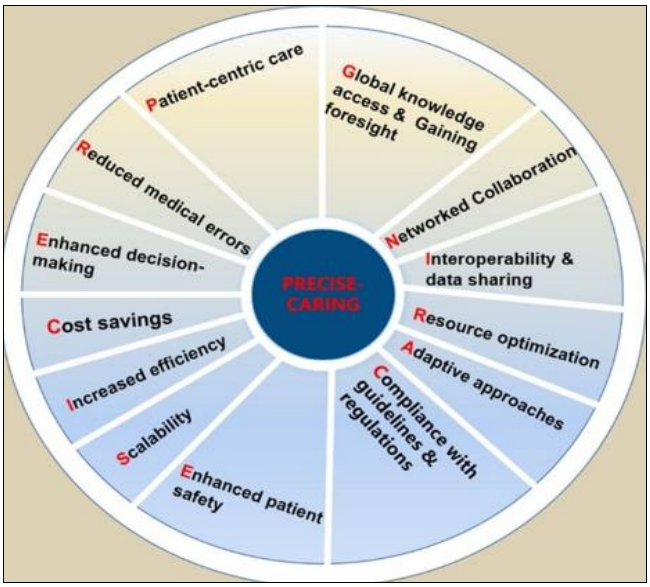

Fig 1: Precise-Caring for the benefits of CDSS. CDSS, clinical decision support system (Chen, *et al*., 2023)

Despite its potential, the adoption of Power BI-based CDSS in nursing practice is not without challenges. One major limitation is the variability in digital literacy and data interpretation skills among nurses. While some may be comfortable navigating interactive dashboards and interpreting trend lines, others may find such tools intimidating or difficult to use. To address this, it is essential to integrate user-centered design principles into the development of Power BI dashboards, ensuring simplicity, clarity, and relevance. Training and capacity-building programs should also be implemented to support nurses in understanding how to use these tools effectively in their daily practice (Olatunji, *et al*., 2024, Omaghomi, *et al*., 2024, Soyege, *et al*., 2024).

Furthermore, data quality and standardization remain significant barriers. Inconsistent documentation practices, fragmented data sources, and lack of standardized nursing terminologies can hinder the accuracy and utility of visualized data. Interoperability between EHR systems and BI platforms is critical to ensure seamless data flow and minimize manual data entry, which can be time-consuming and error-prone. Institutions must invest in data governance frameworks that support data accuracy, completeness, and consistency to maximize the benefits of BI tools in clinical decision-making (Ojeikere, Akintimehin & Akomolafe, 2021).

Privacy and security are also essential considerations. As Power BI connects to sensitive patient information, strict adherence to data protection regulations such as HIPAA is required. Role-based access control, data encryption, and audit logging should be incorporated into the system design to safeguard patient confidentiality and ensure compliance with legal standards.

In conclusion, the integration of Power BI into clinical decision support systems represents a significant opportunity to enhance evidence-based nurse decision-making through real-time data visualization and analytics. The evolution of CDSS has laid the foundation for more intelligent, responsive, and user-friendly tools, but existing systems often fall short of addressing the specific needs of nurses. Power BI's flexibility and power can help fill this gap by providing customized dashboards that support critical thinking, improve situational awareness, and facilitate timely interventions (Ajogwu, *et al*.. 2023, Maduka, *et al*., 2023). As healthcare systems continue to embrace digital transformation, it is imperative to ensure that nurses who play a central role in patient care are equipped with the tools and skills necessary to leverage data effectively. With thoughtful implementation, training, and support, Power BI-based CDSS can become a cornerstone of modern, evidence-informed nursing practice.

2.2 Methodology

The methodology for developing the Power BI-Based Clinical Decision Support System (CDSS) for evidence-based nurse decision-making follows a multi-layered, iterative approach, leveraging cloud computing platforms, robust data management practices, and advanced analytics techniques as outlined in recent works by Adelusi, Ojika, Uzoka, and colleagues (2022–2024) and Adeshina (2023).

The first phase involves data acquisition and integration, where heterogeneous data sources, including Electronic Health Records (EHRs), laboratory information systems, nursing notes, and real-time patient monitoring devices, are identified and ingested into a centralized data repository. Drawing from Adelusi *et al*. (2022), the data warehouse is architected using scalable, cloud-native platforms such as AWS Redshift, Google Cloud Platform (GCP) BigQuery, or Microsoft Azure Synapse Analytics to ensure elasticity, cost-efficiency, and high availability. Data ingestion pipelines are designed with data lineage and auditing mechanisms (Adelusi *et al*., 2022) to maintain traceability, data provenance, and compliance with healthcare data governance regulations such as HIPAA.

Next, a data transformation and modeling layer is developed employing advanced data engineering tools such as dbt (data build tool), which supports modular, maintainable SQL transformations as detailed in Adelusi *et al*. (2022). This layer ensures the cleaning, normalization, and harmonization of clinical data, establishing standardized vocabularies and coding systems (e.g., SNOMED CT, LOINC) to enable interoperability. To guarantee data security and privacy, quantum-resistant cryptographic protocols (Adelusi *et al*., 2023) and cloud infrastructure protections are implemented, safeguarding sensitive patient information against emerging cybersecurity threats.

In parallel, a business intelligence (BI) and visualization layer is developed using Power BI, capitalizing on its interactive dashboards and real-time data processing capabilities (Adeshina, 2021). The dashboard design incorporates user-centric principles, facilitating intuitive navigation for nurses, with drill-down features allowing detailed exploration of patient histories, vital signs trends, medication tracking, and risk stratification metrics. Power BI's integration with cloud data marts, as described by Adelusi *et al*. (2024), supports dynamic data refresh and multi-tenant accessibility for distributed nursing teams across healthcare facilities.

To embed clinical decision support capabilities, predictive analytics models are integrated into the system. Drawing on ensemble learning and AI-driven approaches from Adelusi *et al*. (2023), machine learning models are trained on historical clinical datasets to predict patient deterioration,

risk of complications, or adverse drug reactions. These models leverage deep learning architectures for time-series data from wearable sensors and EHRs (Adelusi *et al*., 2023). The predictions are incorporated as visual alerts and decision pathways within the Power BI dashboards, enabling nurses to make timely, evidence-based interventions.

The system development process follows agile methodologies, incorporating continuous feedback loops with end-users (nurses, clinicians) to iteratively refine the CDSS interface and functionalities. Usability testing sessions ensure that the tool meets clinical workflow needs, minimizes cognitive load, and enhances decision confidence.

A rigorous evaluation and validation phase is conducted, involving both technical and clinical assessments. Data accuracy and latency metrics are monitored to confirm real-time responsiveness. The predictive models are validated through cross-validation and prospective pilot testing in clinical environments, comparing system recommendations against clinician judgments and patient outcomes. Stakeholder engagement workshops assess user satisfaction and adoption barriers.

Throughout the project lifecycle, adherence to ethical standards and regulatory requirements is ensured through comprehensive data governance frameworks (Adelusi *et al*., 2023), including audit trails, consent management, and role-based access controls.

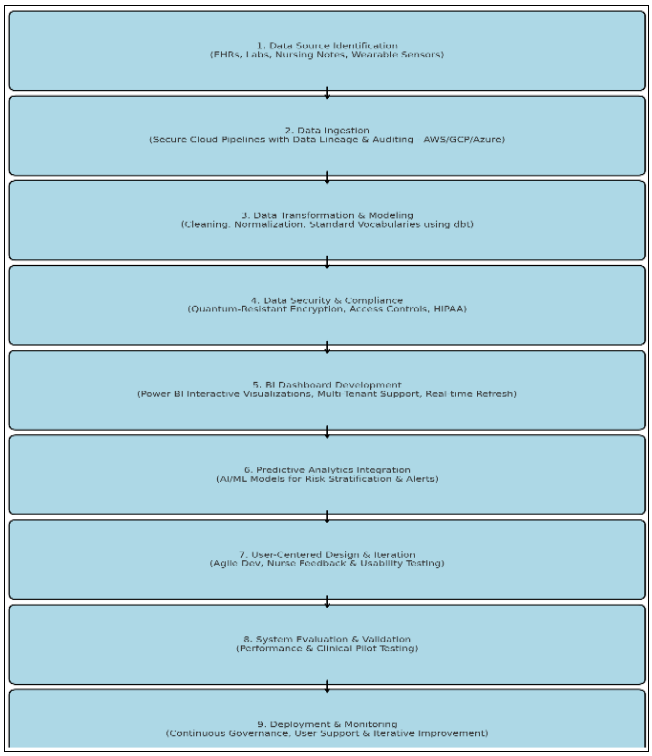

Fig 2: Flowchart of the study methodology

This methodology harnesses the strengths of cloud-native infrastructure, advanced data management, and AI-driven predictive analytics within a user-friendly Power BI platform to deliver a scalable, secure, and effective CDSS tailored for nursing professionals. The approach ensures that clinical decision-making is informed by reliable, real-time data visualizations and evidence-based risk assessments, ultimately contributing to enhanced patient care and safety.

2.3 Conceptual Framework

The conceptual framework for a Power BI-based Clinical Decision Support System (CDSS) for evidence-based nurse decision-making is rooted in a confluence of theoretical foundations, informatics integration, and user-centric design thinking. It reflects a systemic effort to modernize nursing practice by aligning data analytics with evidence-based clinical reasoning and workflow optimization. The framework is anchored in the principles of evidence-based nursing, which emphasize the use of current best evidence, clinical expertise, and patient preferences to guide nursing decisions and interventions (Awe, Akpan & Adekoya, 2017). This philosophy promotes a systematic approach to care delivery, reducing variability and improving patient outcomes through informed, data-driven practices.

Evidence-based nursing draws heavily on theoretical models such as the Iowa Model of Evidence-Based Practice and the ACE Star Model of Knowledge Transformation. These models advocate for the identification of clinical problems, appraisal of relevant research, and implementation of evidence into practice. They emphasize continual assessment and refinement of clinical interventions based on measurable outcomes. In this context, the Power BI-based CDSS functions as a catalyst that operationalizes these models by presenting real-time data and relevant evidence in a format that supports nursing decision-making at the point of care (Adelusi, Ojika & Uzoka, 2022). By translating abstract theoretical principles into actionable insights, the system reinforces the iterative nature of evidence-based practice and ensures that nurses are consistently guided by the latest standards and best practices.

A critical element of the conceptual framework is the seamless integration of informatics into existing clinical workflows. For any digital tool to be effective in a healthcare environment, especially in nursing, it must align with the rhythms and realities of clinical routines. Nurses operate in time-sensitive, high-stakes settings where information must be accessed, interpreted, and acted upon with minimal delay. The Power BI-based CDSS is designed to fit naturally within these workflows by pulling data from multiple clinical systems such as electronic health records (EHRs), laboratory systems, and patient monitoring devices and synthesizing them into intuitive dashboards (Adelusi, Ojika & Uzoka, 2023, Osunlaja, *et al*., 2023). These dashboards are strategically embedded into nurse stations, mobile devices, or personal workstations, ensuring that insights are readily available without disrupting the flow of care.

This integration hinges on the use of application programming interfaces (APIs) and data connectors that enable interoperability between Power BI and clinical data systems. The conceptual framework ensures that data flows seamlessly from its source to the dashboard, updating in near real time. This capability empowers nurses to make decisions based on the most current information available such as patient vitals, laboratory trends, medication adherence, and risk scores thereby minimizing errors caused by outdated or incomplete data. Moreover, the dashboards support clinical prioritization by highlighting patients who are deteriorating or showing signs of deviation from expected recovery trajectories (Adeshina, 2023, Osabuohien, *et al*., 2023). In this way, the framework supports early detection, timely interventions, and escalation of care, all within the parameters of existing nursing duties

and responsibilities. Evidence-Based Medicine Framework for Clinical Decision Making presented by Makam & Nguyen, 2017 is shown in Fig 3.

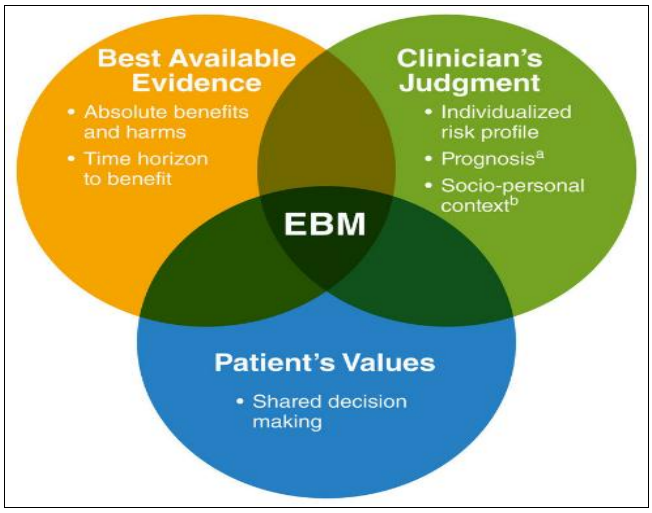

Fig 3: Evidence-Based Medicine Framework for Clinical Decision Making (Makam & Nguyen, 2017)

Equally important in the framework is the adoption of user-centric design principles, which place the end-user nurses at the core of system development. Traditional decision support tools have often suffered from poor adoption due to overly technical interfaces, irrelevant alerts, or rigid structures that fail to accommodate the variability of nursing practice. The Power BI-based CDSS seeks to overcome these limitations by applying design thinking and human factors engineering in its construction. The system is developed with active input from nurses to ensure that it meets their informational needs, fits their cognitive workflows, and supports their clinical judgment (Bolarinwa, Akomolafe & Sagay-Omonogor, 2023, Kolawole, *et al*., 2023).

Visualization is a key aspect of this user-centric approach. Rather than presenting raw data in tabular form, the Power BI dashboards employ color-coded charts, trend lines, gauges, and heatmaps that enable rapid comprehension and pattern recognition. For instance, a nurse might see a red indicator if a patient's temperature is rising beyond a threshold, or a declining trend line if a patient's oxygen saturation is dropping over time. These visual cues are intuitive and require minimal interpretation, reducing cognitive load and supporting quicker response times. Furthermore, the dashboards are customizable, allowing nurses to filter, sort, and drill down into data that is most relevant to their clinical role or patient assignment (Adelusi, Ojika & Uzoka, 2024, Okoli, *et al*., 2024, Soyege, *et al*., 2024).

Another element of the user-centric design is responsiveness across devices. Given the mobility of nursing roles, the framework accommodates both stationary and mobile access, supporting tablets, smartphones, and shared workstations. This ensures that nurses can access critical information whether they are at the bedside, in transit, or in multidisciplinary meetings. The ability to interact with data dynamically such as zooming in on a trend, adding annotations, or generating a report enhances the utility of the system and promotes greater engagement with data as a clinical asset (Awe, 2021, Halliday, 2021). Review of CDSS Implementations and Their Impact presented by Mashor, 2024 is shown in Fig 4.

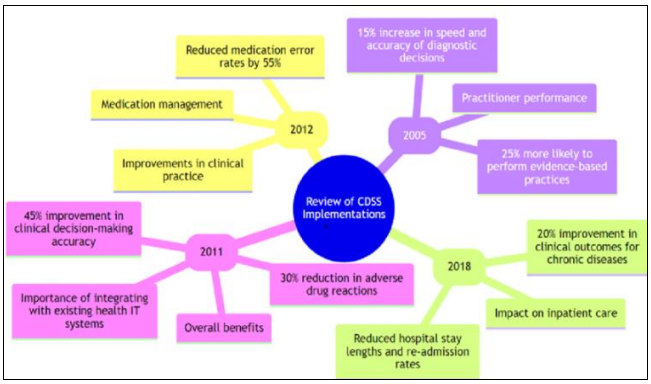

Fig 4: Review of CDSS Implementations and Their Impact (Mashor, 2024)

Training and capacity building are integral components of the framework to ensure successful adoption and sustained use. The implementation of a Power BI-based CDSS necessitates targeted training sessions focused on data interpretation, dashboard navigation, and understanding evidence-based indicators. Simulation exercises and hands-on workshops can be used to build familiarity and confidence among nurses, while continuous feedback loops allow for iterative improvements to the dashboard design based on user experience. In this way, the framework not only provides a technological tool but also cultivates a culture of data literacy and evidence-informed practice within nursing teams (Adelusi, *et al*., 2022).

The conceptual framework also accounts for organizational and policy alignment. For the CDSS to be truly effective, its outputs must be synchronized with institutional protocols, clinical guidelines, and regulatory requirements. This alignment ensures that the decisions prompted by the system are not only clinically appropriate but also compliant with broader standards of care and accreditation benchmarks. Dashboards can include embedded clinical guidelines or links to policy documents, helping nurses to quickly reference best practices while making patient care decisions (Bolarinwa, Akomolafe & Sagay-Omonogor, 2023, Kolawole, *et al*., 2023).

Finally, the framework promotes sustainability and scalability. Built on Power BI's cloud-based architecture, the CDSS can be continuously updated with new data sources, clinical indicators, and analytical models. This flexibility ensures that the system evolves with changes in clinical practice, emerging evidence, and institutional needs. Moreover, its scalability allows healthcare organizations to expand the tool beyond nursing to include multidisciplinary teams, fostering a more collaborative approach to patient care supported by shared data and insights (Olatunji, *et al*., 2024, Omaghomi, *et al*., 2024).

In sum, the conceptual framework for a Power BI-based Clinical Decision Support System in nursing is an innovative synthesis of evidence-based practice theory, informatics integration, and human-centered design. It aims to transform the way nurses access, interpret, and apply clinical data in their daily practice, ultimately leading to more informed, timely, and consistent decision-making. By aligning with the core values of nursing, addressing the practicalities of clinical workflows, and leveraging modern

data visualization technologies, this framework holds the potential to significantly enhance the quality, safety, and efficiency of patient care across healthcare settings.

2.4 System Design and Architecture

The system design and architecture of a Power BI-based Clinical Decision Support System (CDSS) for evidence-based nurse decision-making is structured to ensure seamless access to critical patient data, provide intelligent insights through visual analytics, and maintain high standards of data privacy, security, and compliance. The architecture brings together disparate clinical data sources, integrates and transforms the data for meaningful use, and presents it through intuitive dashboards that align with the cognitive workflows of nursing professionals. This system is not merely a tool for displaying information but an intelligent interface that supports timely and accurate clinical decisions, particularly in fast-paced healthcare environments where nurses must make real-time judgments.

At the foundation of this system are the various data sources that feed into the Power BI platform. The most critical among these are electronic health records (EHRs), laboratory information systems, and nursing documentation systems. EHRs serve as the primary repository for patient information, encompassing demographic details, clinical histories, medication records, allergy information, diagnoses, and care plans. EHR data is essential for providing nurses with a comprehensive understanding of a patient's condition and care trajectory (Adelusi, *et al*., 2023). Laboratory systems contribute diagnostic test results such as blood counts, metabolic panels, infection markers, and other critical values that support ongoing monitoring and clinical assessments. These lab results must be accurate and timely, as they often influence decisions regarding medication administration, isolation protocols, and escalation of care.

In addition to structured clinical data, the system incorporates nursing notes and narrative observations, which are vital for capturing the nuanced, subjective assessments that nurses perform. These notes often contain information not found in structured fields such as patient behaviors, pain responses, emotional state, or reactions to treatment. Natural language processing (NLP) tools or structured data entry templates may be used to convert these insights into usable data formats compatible with the analytics engine. Together, these sources ensure a holistic view of the patient's condition and care needs, which is critical for informed nursing decisions.

The design of the Power BI dashboards is central to the system's functionality. The dashboard must present complex data in an easily interpretable format, allowing nurses to identify trends, flag anomalies, and respond quickly to clinical changes. The architecture supports customizable dashboards based on the unit, nurse role, or patient population. For instance, a dashboard in a surgical recovery unit may prioritize vital signs, pain scores, and wound care notes, whereas an intensive care unit dashboard may highlight ventilator settings, fluid balance, and real-time lab results (Odilibe, *et al*., 2024, Olaboye, *et al*., 2024, Umukoro, *et al*., 2024). Key dashboard components include dynamic charts, color-coded indicators, filterable tables, and alert widgets.

Power BI's data visualization features allow for the use of gauges, trend lines, heatmaps, and bullet charts to present critical metrics. For example, a trend line showing a steady increase in a patient's heart rate over several hours may be flagged in orange or red, drawing the nurse's attention to potential deterioration. Gauges may be used to indicate whether a lab value falls within the expected range, and conditional formatting may highlight areas requiring intervention. The use of drill-down features enables deeper exploration into specific data points, such as viewing past medication administrations or tracing the timeline of a particular symptom (Ojeikere, Akintimehin & Akomolafe, 2021).

A critical part of the system architecture is the data integration and transformation pipeline, which connects disparate systems and converts raw data into structured, usable formats suitable for analytics. This pipeline begins with data extraction from source systems using standard connectors, APIs, or ETL (Extract, Transform, Load) tools. Power BI supports connections to common healthcare systems via ODBC, Azure Data Factory, or dedicated APIs, enabling real-time or scheduled data refreshes.

Once extracted, the data is transformed to ensure consistency, accuracy, and usability. This involves cleaning and normalizing data values, resolving discrepancies (such as different units of measurement), removing duplicates, and structuring the data according to predefined schemas. For example, blood glucose levels from different lab instruments may need to be standardized before being visualized. Data from narrative nursing notes may require parsing or encoding using NLP techniques to identify key themes or patterns. This transformation layer is essential to ensure that the dashboards present reliable and coherent information, as inconsistencies could lead to misinterpretations or clinical errors (Ojeikere, Akintimehin & Akomolafe, 2024, Osabuohien, 2024).

The transformed data is then loaded into a centralized data model within Power BI, where it is linked through relationships that reflect the clinical logic. For example, a patient's ID may be used to connect their EHR data with lab results, medication history, and nursing observations, ensuring a unified view. Power BI's DAX (Data Analysis Expressions) language is used to create calculated fields and measures that support clinical logic, such as early warning scores, trend calculations, or patient risk stratification indicators (Adeyemo, Mbata & Balogun, 2024, Oparah, *et al*., 2024).

Given the sensitivity of healthcare data, the system's design also places a strong emphasis on security, compliance, and privacy. The integration of patient information from multiple sources necessitates strict adherence to data protection regulations such as HIPAA in the United States or GDPR in European contexts. One of the first lines of defense is role-based access control (RBAC), which ensures that only authorized personnel can access specific data views. Nurses, physicians, and administrators may each have tailored access rights based on their responsibilities, ensuring that data is protected without impeding workflow efficiency.

Data encryption is implemented both at rest and in transit. For data stored within the Power BI service, encryption ensures that unauthorized parties cannot access patient information even in the event of a security breach. When data is transmitted from source systems to Power BI or between users and dashboards, secure protocols such as HTTPS and SSL/TLS are used to safeguard the transmission

path. In addition, audit logging features are incorporated to track access and changes to the data, enabling institutions to detect and investigate potential breaches or misuse (Ogugua, *et al*., 2024, Omaghomi, *et al*., 2024).

The system also includes compliance mechanisms to ensure that the data being visualized and acted upon meets clinical quality standards. This includes the use of validation rules to detect outlier values, checks for data completeness, and regular reconciliation of data with source systems. Furthermore, metadata and version control practices are employed to maintain transparency regarding the origin and transformation of data elements.

A final layer of the system architecture is its deployment and maintenance structure. The Power BI-based CDSS may be hosted on a secure on-premises server or in a cloud environment such as Microsoft Azure, depending on institutional policies and infrastructure. Cloud deployment offers scalability and ease of updates, allowing healthcare organizations to expand the system as new data sources are integrated or as clinical needs evolve. Regular system monitoring and performance audits are conducted to ensure availability, minimize downtime, and address user feedback (Olatunji, *et al*., 2024, Omaghomi, *et al*., 2024, Tomoh, *et al*., 2024).

In summary, the system design and architecture of a Power BI-based Clinical Decision Support System for nurse decision-making are meticulously constructed to support real-time, evidence-based practice in clinical settings. By aggregating data from EHRs, lab systems, and nursing documentation, transforming it into accurate and usable formats, and delivering it through highly visual and interactive dashboards, the system enhances situational awareness and decision accuracy. Through robust security and compliance measures, it ensures the ethical and legal handling of sensitive patient information. Ultimately, this architecture empowers nurses with the tools they need to deliver high-quality, informed care in increasingly complex healthcare environments.

2.5 Implementation Process

The implementation of a Power BI-based Clinical Decision Support System (CDSS) for evidence-based nurse decision-making is a multi-phase process that requires strategic planning, strong stakeholder collaboration, robust infrastructure, and continuous evaluation. The goal is to embed real-time, data-driven insights into the daily workflows of nursing professionals, thereby improving clinical accuracy, decision speed, and patient outcomes. Effective implementation is not just a technological upgrade but a transformation in the way nursing care is delivered and supported by informatics tools.

The first consideration in the implementation process is the selection of the healthcare setting and nursing units where the CDSS will be introduced. For the pilot phase, facilities with moderate to high patient acuity, well-established electronic health records (EHRs), and a strong nursing leadership structure are ideal. Units such as intensive care, surgical recovery, emergency, or medical-surgical wards are prime candidates due to the dynamic nature of patient care and the volume of clinical decisions made by nurses. These units also typically experience higher levels of data activity, making them suitable environments to evaluate the responsiveness and impact of a real-time CDSS (Nwokedi, *et al*., 2024, Sagay, *et al*., 2024). Once the site and units are selected, a baseline assessment is conducted to understand the existing decision-making workflows, identify gaps in information access, and assess the digital literacy of nursing staff.

The deployment of the Power BI-based CDSS proceeds through four key phases: planning, pilot testing, training, and full-scale roll-out. The planning phase focuses on developing an implementation roadmap, defining objectives, identifying key performance indicators (KPIs), and assembling an interdisciplinary implementation team. This team typically includes nurse leaders, clinical informatics specialists, IT personnel, Power BI developers, quality improvement managers, and hospital administrators (Adeshina & Ndukwe,2024, Olaboye, *et al*., 2024, Taiwo, *et al*., 2024). During this phase, data sources are mapped, data fields are standardized, and dashboards are designed based on clinical priorities and user feedback. An essential part of planning is risk assessment, where potential barriers such as staff resistance, workflow disruptions, or data integration challenges are identified and addressed through mitigation strategies.

The pilot testing phase involves the limited deployment of the CDSS within selected units. This allows for real-time assessment of functionality, usability, and integration into clinical workflows. The pilot is typically conducted over a period of several weeks and includes continuous monitoring and feedback collection. Nurses using the system are observed for how they interact with the dashboards, interpret visualizations, and apply insights to patient care. Their experiences are documented to refine the dashboard design, data refresh frequency, and user interface. Technical issues, such as delays in data updates or system lags, are also identified and addressed during this phase (Adelusi, *et al*., 2020). Importantly, the pilot phase serves as a proof-of-concept that demonstrates the system's impact on decision-making accuracy, response times, and overall satisfaction.

The training phase overlaps with the pilot and roll-out stages, ensuring that all users are adequately prepared to interact with the system. Training is delivered through a combination of hands-on workshops, online modules, simulation exercises, and one-on-one coaching. The focus is on building competencies in data interpretation, dashboard navigation, and integrating insights into nursing care plans (Afolabi, Ajayi & Olulaja, 2024, Odezuligbo, 2024, Tomoh, *et al*., 2024). Training materials are customized for different levels of digital fluency, and super-users or nurse champions are designated to provide ongoing peer support. Training also covers best practices for identifying clinical risks through the dashboard, responding to alerts, and documenting care decisions based on data findings. This capacity-building initiative fosters a culture of data-informed practice and ensures that the technology is embraced rather than resisted.

The final phase is the full-scale roll-out of the system across the selected healthcare facility or broader network. This phase involves expanding the CDSS to additional nursing units, refining configurations based on pilot findings, and establishing long-term maintenance protocols. Integration with other clinical systems is also finalized, including EHRs, laboratory systems, pharmacy systems, and patient monitoring devices. The system is deployed on both desktop and mobile platforms to ensure accessibility at the bedside or during rounds. Periodic evaluations are conducted post-deployment to measure key outcomes such as nurse

satisfaction, frequency of dashboard use, adherence to evidence-based guidelines, and reductions in clinical errors or delays (Adelusi, *et al*., 2023, Sagay-Omonogor, Bolarinwa & Akomolafe, 2023).

A critical success factor throughout the implementation process is stakeholder engagement and interprofessional collaboration. From the outset, the involvement of nursing staff, physicians, administrators, and IT personnel is vital to ensure that the CDSS aligns with the goals and realities of clinical practice. Nurses must feel that their input is valued in the design and customization of the dashboards. Interprofessional meetings, user feedback sessions, and cross-functional design workshops are essential strategies to ensure alignment and consensus. Physicians and allied health professionals are also engaged to understand how the CDSS might influence team-based care, interdepartmental communication, and clinical escalation protocols (Osabuohien, 2019).

In addition, clinical governance structures are established to oversee the ethical and safe use of the system. These include data governance committees, digital health taskforces, and quality assurance teams that monitor system performance, resolve issues, and ensure compliance with institutional policies. The implementation process is further supported by leadership endorsement, with nurse executives and chief information officers advocating for the system's value and aligning its goals with strategic healthcare priorities.

The technical requirements and infrastructure needed to support a Power BI-based CDSS are foundational to its success. A secure and scalable data environment is essential, with capabilities to host and process large volumes of clinical data from multiple sources. Power BI can be deployed via the Microsoft Azure cloud or on-premises servers, depending on institutional policies and data residency regulations. A robust data warehouse or data lake is required to serve as the intermediary between clinical systems and the Power BI service, ensuring that data is organized, cleaned, and transformed prior to visualization (Adelusi, *et al*., 2023, Osunlaja, *et al*., 2023).

High-speed internet connectivity, reliable network infrastructure, and secure authentication protocols are necessary to ensure system responsiveness and protect patient data. Integration middleware or API management tools are used to connect disparate systems, enabling real-time data exchange without manual intervention. System administrators and developers maintain control over data models, user access rights, and performance optimization to ensure the dashboards remain responsive and relevant.

Data security and compliance are non-negotiable components of the technical infrastructure. Encryption, user authentication, access controls, and audit logs are implemented to protect sensitive health information. Compliance with regulations such as the Health Insurance Portability and Accountability Act (HIPAA) is ensured through routine audits, staff training, and incident response protocols. Moreover, backups and disaster recovery systems are in place to guarantee business continuity and data integrity in the event of technical failures (Adeyemo, Mbata & Balogun, 2024, Oboh, *et al*., 2024).

In conclusion, the implementation process of a Power BI-based Clinical Decision Support System for evidence-based nurse decision-making is a multidimensional endeavor that blends technology, training, workflow design, and human engagement. By thoughtfully selecting pilot sites, structuring the deployment in phases, fostering interprofessional collaboration, and investing in a secure and responsive technical infrastructure, healthcare institutions can achieve meaningful transformation in clinical practice. The result is a system that empowers nurses with real-time, actionable insights, improves patient care outcomes, and contributes to a culture of evidence-informed decision-making across the organization.

2.6 Functional Features of the CDSS

The functional features of the Power BI-based Clinical Decision Support System (CDSS) for evidence-based nurse decision-making are designed to enhance the timeliness, accuracy, and effectiveness of clinical decisions in dynamic healthcare environments. These features align closely with the daily responsibilities of nurses, integrating intelligent technologies with practical clinical tools that support both routine care and high-acuity scenarios. At the core of the system's functionality is its capacity for real-time monitoring and alerts, a capability that transforms passive data repositories into active clinical intelligence tools (Adelusi, *et al*., 2023). Real-time monitoring ensures that vital signs, lab results, and other patient parameters are continuously updated and displayed in an accessible format, enabling nurses to respond promptly to clinical changes. Alerts are configured based on predefined thresholds for parameters such as blood pressure, heart rate, respiratory rate, and oxygen saturation. When any parameter deviates from safe ranges, the system generates visual or auditory notifications on the dashboard, prompting immediate clinical attention. These alerts help nurses prioritize care, initiate timely interventions, and escalate cases to physicians or rapid response teams before conditions worsen.

Another vital component of the CDSS is the inclusion of risk stratification models and key performance indicators (KPIs), which aid in identifying patients at risk of adverse outcomes and evaluating the quality of nursing interventions. Risk stratification models categorize patients into different levels of clinical risk based on a combination of data points such as age, diagnosis, comorbidities, lab results, and vital trends. For example, the system may use an early warning score (EWS) model to flag patients at risk of clinical deterioration (Olatunji, *et al*., 2024, Omaghomi, *et al*., 2024, Taiwo, *et al*., 2024). These models are embedded into the dashboards and automatically update as new data becomes available, providing nurses with an up-to-date view of which patients require closer monitoring or intervention. KPIs are also incorporated to track critical aspects of nursing care, such as time to intervention, medication adherence, patient pain management, and frequency of nursing assessments. These indicators not only guide immediate clinical decisions but also support quality assurance and performance improvement efforts at the unit or institutional level.

Interactive dashboards are a hallmark feature of Power BI and play a central role in the usability of the CDSS. These dashboards consolidate multiple data sources into a single, coherent view, allowing nurses to access a comprehensive picture of each patient's status at a glance. Treatment history is one of the key components visualized on the dashboard, providing a timeline of interventions, procedures, and medication administrations. This enables nurses to quickly understand what care has been delivered, what is pending, and how the patient has responded to various interventions

(Ogugua, *et al*., 2024, Olulaja, Afolabi & Ajayi, 2024). Vital sign trends are visualized using line graphs and gauges that show changes over time, helping nurses detect subtle deteriorations or improvements in a patient's condition. This visualization supports both retrospective review and prospective planning, enhancing clinical judgment and confidence.

Medication tracking is another essential feature embedded within the dashboard, helping nurses ensure accurate medication administration and adherence to protocols. The system displays current medication orders, administration times, dosages, and any recorded side effects or interactions. Color-coded indicators may be used to highlight missed doses, potential drug interactions, or medications requiring immediate administration. This feature not only supports safe medication practices but also improves coordination between nursing staff and pharmacy services. In addition, nurses can use filters to view data by shift, patient, or clinical unit, which enhances workflow organization and ensures that care delivery is synchronized across teams (Adelusi, *et al*., 2023).

Predictive analytics and clinical decision pathways are advanced features of the CDSS that extend its capabilities from reactive support to proactive guidance. Predictive analytics involves the use of algorithms and historical data to forecast potential patient outcomes, such as the likelihood of readmission, development of sepsis, or progression to critical illness. These predictions are presented in visual formats that quantify risk levels and suggest potential interventions. For example, a predictive model might analyze a combination of laboratory values, nursing assessments, and previous hospitalizations to determine a patient's risk of developing complications (Adeyemo, Mbata & Balogun, 2021, Osamika, *et al*., 2021). Nurses can use this information to initiate preventive measures, consult with specialists, or implement targeted monitoring protocols.

Clinical decision pathways are embedded within the dashboard to provide structured guidance on managing specific conditions or scenarios. These pathways are based on clinical guidelines, institutional protocols, and evidence-based best practices, offering step-by-step recommendations tailored to the patient's current status. For instance, a decision pathway for managing postoperative pain may recommend a sequence of analgesic administration, pain scoring intervals, and escalation steps depending on patient response. Similarly, a pathway for suspected infection may guide nurses through obtaining cultures, initiating antibiotics, and monitoring vital signs at specific intervals. These pathways serve as cognitive aids, reducing variability in care and ensuring that decisions are grounded in validated practices (Adelusi, *et al*., 2023).

The integration of all these features into a single platform significantly enhances the decision-making environment for nurses. The real-time alerts draw immediate attention to critical changes, risk stratification provides a snapshot of patient vulnerabilities, interactive dashboards support ongoing monitoring and care coordination, and predictive analytics offer foresight into potential complications. Together, they create a synergistic decision support environment where nurses are empowered with actionable insights, reducing reliance on memory, intuition, or fragmented information sources.

Furthermore, these functional features support interprofessional collaboration by promoting transparency and shared understanding of patient status. When all members of the care team have access to the same data visualizations, it fosters better communication during handovers, interdisciplinary rounds, and care planning meetings. For example, nurses can use the dashboard during shift reports to highlight changes in patient risk scores, summarize treatment history, and flag upcoming interventions. This level of clarity and consistency enhances team-based care and ensures that critical information is not lost in verbal handoffs or paper records (Afolabi, Ajayi & Olulaja, 2024, Nwokedi, *et al*., 2024).

From a broader perspective, the system's functionalities also enable nurse managers and quality improvement teams to monitor trends at the unit level. Aggregated dashboard views can reveal patterns in patient outcomes, staff responsiveness, and protocol adherence, supporting data-driven decisions for training, staffing, or process improvement. For instance, a manager might observe that pain management scores are consistently low on night shifts and implement targeted training or resource allocation to address the gap.

Importantly, the customization and scalability of the Power BI platform ensure that these features can be adapted to various care settings, patient populations, and institutional goals. Whether deployed in a rural clinic or a metropolitan hospital, the functional components of the CDSS remain consistent in their goal: to support evidence-based, patient-centered nursing care through intelligent data use.

In conclusion, the functional features of the Power BI-based Clinical Decision Support System represent a comprehensive suite of tools designed to enhance the quality and timeliness of nurse-led decision-making. Through real-time monitoring and alerts, risk stratification models, interactive dashboards, and predictive analytics, the system transforms raw data into meaningful insights that guide clinical practice. These features not only improve patient outcomes but also foster a culture of data-driven care, interprofessional collaboration, and continuous quality improvement. As healthcare systems continue to evolve in complexity, such intelligent support systems will become indispensable in ensuring safe, efficient, and evidence-based nursing care.

2.7 Evaluation and Results

The evaluation of the Power BI-based Clinical Decision Support System (CDSS) for evidence-based nurse decision-making was structured using a mixed-methods approach that combined both quantitative and qualitative data to assess the system's impact comprehensively. This approach enabled the evaluators to capture measurable improvements in clinical performance as well as understand user experiences, perceptions, and behavioral changes among nursing staff. The study was conducted over a six-month period in a medium-sized urban hospital, involving two medical-surgical units and one intensive care unit, with a total of 78 nurses participating.

Quantitatively, the evaluation focused on several core metrics to determine the effectiveness of the CDSS. These included the accuracy of clinical assessments, system usability, nurse satisfaction, and confidence in decision-making. Accuracy was measured by comparing the number of correct clinical interventions and early detection of patient deterioration before and after the CDSS implementation. Usability was assessed using the System

Usability Scale (SUS), while nurse satisfaction and decision-making confidence were measured through structured questionnaires and Likert-scale items designed to gauge perceived usefulness, ease of use, and overall impact on clinical practice (Adelusi, *et al*., 2023, Sagay-Omonogor, Bolarinwa & Akomolafe, 2023).

Pre- and post-implementation comparisons revealed significant improvements across all key metrics. One of the most notable outcomes was a 32% increase in the timely identification of early warning signs of patient deterioration. Prior to implementation, nurses reported frequent challenges in recognizing subtle changes in patient status due to fragmented data and time constraints. After the integration of the Power BI-based CDSS, these challenges were mitigated by the availability of real-time, visual trend analyses and automatic alerts for abnormal vital signs. Nurses were able to quickly detect downward trends in oxygen saturation, blood pressure, or temperature, and respond proactively, reducing the incidence of late-stage interventions (Osabuohien, 2017).

In terms of accuracy, chart audits revealed a marked improvement in clinical documentation and decision alignment with evidence-based protocols. The rate of protocol-adherent interventions increased from 68% pre-implementation to 89% post-implementation. For example, in cases of suspected sepsis, nurses initiated sepsis protocols including timely administration of fluids and antibiotics more consistently when guided by real-time dashboard prompts. This improvement was attributed to the embedded clinical pathways and predictive risk scores visible on the CDSS dashboard, which supported prompt and standardized responses.

System usability also scored highly, with the average SUS score increasing from 61 to 84 over the course of the implementation period. Nurses reported that the system's intuitive design, color-coded alerts, and interactive dashboards facilitated ease of navigation and interpretation. Many users appreciated the ability to customize their dashboards based on patient assignments or clinical focus, which helped streamline their workflow and prioritize care tasks. The drag-and-drop interface and real-time updates were particularly praised, allowing nurses to monitor multiple patients simultaneously without needing to toggle between multiple systems or physical records (Adeyemo, Mbata & Balogun, 2023).

The qualitative findings further reinforced the system's effectiveness. Semi-structured interviews and focus groups revealed a strong sense of empowerment among nurses regarding their clinical decisions. Prior to implementation, many nurses expressed hesitancy in escalating care due to uncertainty about clinical trends or fear of overreacting. After the system's deployment, nurses reported increased confidence in communicating with physicians and advocating for patients, supported by the objective data and visualizations provided by the CDSS (Ogunwale, *et al*., 2024, Olaboye, *et al*., 2024, Tomoh, *et al*., 2024). Statements such as "Now I can walk into the team meeting with clear trends and data to support what I'm seeing" were common, highlighting a shift in how nurses used data as a tool for advocacy and clinical justification.

Nurse satisfaction also improved notably, with 86% of respondents indicating that the CDSS made their job easier and improved their clinical decision-making. Satisfaction was especially high among early-career nurses and those new to the unit, who found that the visual cues and built-in clinical pathways helped them make decisions more confidently and quickly. Experienced nurses also reported that the system supported their intuition with data, helping them validate their clinical assessments and feel more secure in their interventions.

The evaluation also captured important lessons learned during the implementation process. One key finding was the need for continuous training and support, especially during the first month of deployment. While most nurses adapted quickly, some initially struggled with interpreting the dashboard elements or trusting automated alerts. This was addressed through follow-up training sessions, quick-reference guides, and the presence of nurse champions who provided real-time support on shifts. The importance of involving nurses in the design phase was also reinforced. Dashboards that were co-designed with end users saw higher engagement, more effective use, and fewer usability issues (Adelusi, *et al*., 2023, Osamika, *et al*., 2023).

Another lesson learned was the value of customization and flexibility. Different units had varying priorities; for example, the ICU focused more on real-time lab trends and ventilation data, while the medical-surgical unit emphasized pain scores and fall risk indicators. The ability to tailor dashboard content to suit these needs greatly enhanced adoption and user satisfaction. Additionally, administrators found value in using aggregate data from the CDSS to identify broader patterns, such as which shifts had higher rates of missed care or delays in protocol initiation, enabling targeted interventions.

Despite the overall success, some limitations were noted. Technical constraints, such as delayed data refresh due to EHR integration issues, were encountered in the early stages but were eventually resolved through back-end optimization. Another limitation was related to alert fatigue. While alerts were valuable in highlighting at-risk patients, over-alerting led to occasional desensitization among users. This issue was addressed by refining the alert thresholds and allowing nurses to personalize notification settings based on clinical judgment (Adelusi, Ojika & Uzoka, 2022, Sagay, *et al*., 2022).

In terms of patient outcomes, although the study period was limited, there were early indicators of positive trends. The average response time to clinical deterioration decreased by 25%, and there was a slight reduction in unplanned ICU transfers. Additionally, preliminary patient satisfaction surveys suggested improvements in communication and perceived responsiveness of nursing care, which were attributed to more proactive interventions and enhanced nurse-patient interactions enabled by real-time data access.

Overall, the evaluation demonstrated that the Power BI-based CDSS significantly enhanced evidence-based nursing practice by improving access to real-time information, supporting clinical judgment, and standardizing care interventions. The combination of data visualization, predictive analytics, and user-friendly interfaces created an environment where nurses could make faster, more accurate decisions aligned with best practices. Beyond immediate clinical benefits, the system fostered a culture of data-informed care, increased interprofessional communication, and strengthened nursing autonomy (Awe, *et al*., 2023, Kelvin-Agwu, *et al*., 2023, Maduka, *et al*., 2023).

These findings underscore the importance of investing in intelligent decision support systems tailored to the nursing

role. With continued refinement, wider deployment, and ongoing support, such systems hold the potential to transform nursing practice and improve patient outcomes at scale. As healthcare environments grow increasingly complex and data-rich, tools like the Power BI-based CDSS will become essential in bridging the gap between clinical data and actionable insight, empowering nurses to deliver safer, more efficient, and more effective care.

2.8 Discussion and Future Directions

The implementation of a Power BI-based Clinical Decision Support System (CDSS) has significant implications for transforming nurse-led decision-making and promoting a culture of evidence-based practice in clinical environments. One of the most profound impacts of the system is its ability to empower nurses with real-time, actionable insights that support clinical judgment and elevate the role of nursing within multidisciplinary care teams. By integrating data visualization, clinical pathways, and predictive analytics into daily workflows, nurses are better equipped to make informed decisions quickly and confidently. This represents a substantial shift from traditional models where data was either fragmented or delayed, leading to reactive rather than proactive care. The CDSS bridges this gap by offering immediate access to patient information in a structured, intuitive format, thereby enhancing the nurse's role as a frontline clinical decision-maker.

From the perspective of patient safety and quality of care, the system provides measurable benefits. Real-time alerts, risk stratification, and standardized clinical decision pathways contribute to earlier detection of complications, faster interventions, and better adherence to clinical guidelines. These elements are especially valuable in high-acuity settings such as intensive care units or emergency departments, where delays or errors in judgment can result in critical outcomes. Nurses using the CDSS are more likely to recognize subtle signs of deterioration and respond according to predefined protocols, reducing variability and enhancing consistency in care delivery (Afrihyia, *et al*., 2022, Isa, 2022). Additionally, the visualization of trends such as vital signs, medication adherence, and lab values supports continuous monitoring and fosters situational awareness, enabling clinicians to intervene before issues escalate. As a result, the quality of care improves not only through the accuracy of decisions but also through the timeliness and coordination of care processes.

The system also improves workflow efficiency by streamlining information access and reducing cognitive burden. Instead of manually compiling data from multiple sources or relying on verbal handovers, nurses can access an integrated dashboard that aggregates relevant clinical data in a user-friendly interface. This efficiency translates to more time for direct patient care, better prioritization of nursing tasks, and enhanced communication during shift changes and interdisciplinary rounds (Awe & Akpan, 2017, Isa & Dem, 2014). Moreover, managers and quality assurance teams can use aggregated data to monitor unit-level performance, identify process gaps, and initiate targeted interventions for staff development or workflow redesign.

Despite these benefits, several challenges must be addressed to ensure successful adoption and sustainability of the system. One of the primary challenges is training and ongoing support. While Power BI's dashboards are designed to be user-friendly, effective use requires a certain level of data literacy and technological familiarity, which may vary among nursing staff. Training programs need to be robust and continuous, incorporating not only technical instructions but also clinical case-based simulations that demonstrate how the system informs real-world decisions. Nurse champions and super-users can be instrumental in fostering peer-to-peer learning and addressing usability concerns as they arise (Merotiwon, Akintimehin & Akomolafe, 2023).

Data literacy also intersects with the broader issue of cultural readiness for change. Some nurses may initially be skeptical of relying on technology for clinical judgment or may perceive the system as an added burden rather than a support tool. Overcoming these barriers requires leadership engagement, clear communication of benefits, and visible alignment with the organization's mission to enhance patient care through innovation. Change management strategies, including involvement of end-users in the design and implementation process, help build trust and ensure that the system meets real clinical needs (Merotiwon, Akintimehin & Akomolafe, 2021).

System integration presents another challenge, especially in facilities with multiple, disconnected digital platforms. For the CDSS to function optimally, it must draw real-time data from electronic health records, laboratory systems, medication administration records, and other clinical applications. This requires interoperability and robust backend infrastructure capable of handling data exchange securely and efficiently. Delays in data refresh, mismatches in data formats, or incomplete data streams can compromise the utility and reliability of the dashboards. Investment in health information technology infrastructure, data standardization, and vendor collaboration is essential to address these issues.

The implications of the Power BI-based CDSS for clinical practice and hospital policy are substantial. On a practical level, the system supports a shift toward more standardized, data-driven care that aligns with institutional quality improvement goals and regulatory expectations. It enables nurses to provide care that is not only compassionate and patient-centered but also grounded in real-time evidence (Ajayi & Akanji, 2021, Isa, Johnbull & Ovenseri, 2021). Hospital policies may need to evolve to formally incorporate CDSS outputs into clinical documentation, performance appraisal, and escalation protocols. Guidelines around the use of predictive analytics, data interpretation, and clinical decision pathways must also be developed to ensure ethical and safe application.

Looking toward the future, integrating artificial intelligence and machine learning algorithms into the CDSS presents opportunities for even more sophisticated decision support. AI models can analyze vast datasets to identify hidden patterns, predict complications, and personalize care recommendations based on patient history and contextual variables. For example, machine learning could help forecast which patients are at highest risk for sepsis or readmission and suggest tailored care pathways (Ajayi & Akanji, 2022, Isa, 2022). As these technologies mature, they could be embedded into Power BI dashboards, enhancing their predictive capabilities and making decision support more precise and personalized.

Scalability is another important direction for the future. While the initial implementation may focus on a few nursing units, the system can be expanded to other departments and specialties such as pediatrics, oncology, mental health, or

outpatient services. Each of these areas has unique data needs and decision points, and the flexibility of the Power BI platform allows for customization to fit these contexts. Expanding the system hospital-wide ensures consistency in care quality, fosters interdisciplinary data sharing, and supports enterprise-level performance monitoring (Merotiwon, Akintimehin & Akomolafe, 2023).

A long-term goal of the system is the tracking and analysis of patient outcomes over extended periods. By capturing data on care processes, interventions, and outcomes, the CDSS can contribute to longitudinal studies that assess the impact of nursing decisions on health trajectories. These insights can inform policy development, clinical guideline refinement, and strategic planning for workforce and resource allocation. For example, trends in fall prevention, pain control, or pressure injury rates can be linked to specific nursing interventions visualized in the dashboard, offering data-backed justification for staffing changes, training needs, or equipment procurement (Ajayi & Akanji, 2022, Merotiwon, Akintimehin & Akomolafe, 2022).

Continuous improvement and customization remain central to the system's sustainability and relevance. Regular feedback loops involving end-users ensure that the dashboard remains responsive to evolving clinical needs and technological advancements. Periodic system audits, user surveys, and performance metrics should be used to identify what works, what doesn't, and what can be enhanced. Iterative improvements may include adding new KPIs, adjusting alert thresholds, refining visual layouts, or integrating patient feedback features. Additionally, the system should remain adaptable to changes in regulatory requirements, healthcare standards, and emerging evidence (Merotiwon, Akintimehin & Akomolafe, 2023).

In summary, the Power BI-based Clinical Decision Support System represents a transformative advancement in supporting nurse-led decision-making and promoting evidence-based practice. It brings tangible benefits in patient safety, clinical efficiency, and care quality while also fostering a data-driven culture within healthcare organizations. Addressing challenges related to training, system integration, and data literacy is essential for sustained success, as is the strategic use of policy alignment and stakeholder engagement (Ajayi & Akanji, 2023, Kelvin-Agwu, *et al*., 2023, Maduka, *et al*., 2023). The future integration of AI, expansion to other specialties, and long-term outcome tracking promise to elevate the system from a clinical tool to a cornerstone of institutional excellence. Through continuous adaptation and commitment to user-centered design, the CDSS will remain an invaluable asset in the evolving landscape of modern healthcare.

2.9 Conclusion

The Power BI-based Clinical Decision Support System (CDSS) for evidence-based nurse decision-making represents a significant advancement in the integration of data analytics into clinical nursing practice. By consolidating data from multiple sources such as electronic health records, laboratory systems, and nursing documentation into real-time, interactive dashboards, the system empowers nurses to make faster, more accurate, and evidence-informed decisions at the point of care. It enhances situational awareness through real-time alerts, supports risk identification through predictive models, and promotes care consistency through embedded clinical pathways and standardized key performance indicators. These contributions lead to measurable improvements in patient safety, clinical efficiency, nursing confidence, and care quality, establishing the CDSS as a vital component in modern healthcare delivery.

Power BI's flexibility and visual analytics capabilities offer immense potential for transforming how nursing professionals access and use data. Unlike traditional decision-making processes that often rely on retrospective or fragmented information, Power BI enables a proactive, integrated, and intuitive approach to clinical reasoning. Nurses are no longer limited by time delays or system complexity; instead, they are equipped with intelligent tools that align with their workflow and clinical responsibilities. This digital support elevates the nursing role, facilitates interprofessional collaboration, and creates a foundation for scalable, system-wide improvements in care delivery. As healthcare systems continue to evolve, the ability of platforms like Power BI to adapt, expand, and integrate with advanced technologies such as artificial intelligence will only deepen their relevance and impact in the clinical space.

To fully realize the benefits of such systems, further research is needed to evaluate long-term outcomes, explore broader clinical applications, and refine integration with other health information technologies. Institutional support is equally crucial, particularly in the areas of training, infrastructure investment, data governance, and policy alignment. By committing to sustained innovation and evidence-based digital transformation, healthcare organizations can ensure that tools like the Power BI-based CDSS become indispensable assets in advancing patient care and empowering the nursing workforce in the digital age.

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