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# Trends and Futuristic Applications of Big Data and Electronic Health Record Data in Empowering Constructive Clinical Decision Support Systems

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**ABSTRACT**

*Modern healthcare benefits significantly from big data, electronic healthcare record data technologies, and artificial intelligence, which provide robust tools for the collection and analysis of vast and diverse datasets originating from various sources, such as clinical care, administration, and research. This advancement enables the creation of information technology infrastructures that facilitate the realization of the "Learning Healthcare System Cycle," wherein healthcare practice and research seamlessly intertwine in a synergistic manner. This review focuses on illustrating how the integration of extensive data collections, empowered by big data, can enhance clinical decision-making and advance biomedical research. Most importantly, electronic health records offer several benefits, including heightened accessibility to patient information, enhanced interdisciplinary communication, improved continuity of care, legible documentation, minimized duplication, and increased efficiency. The incorporation of computerized physician order entry within electronic medical records contributes to patient safety by mitigating medication errors and offering clinical guidance through prompts and alerts during electronic order entry. Furthermore, when evidence-based clinical decision support is integrated with electronic health records, it serves as a valuable tool for guiding healthcare providers and clinicians in aligning their clinical practices with meaningful use standards and compliance with quality metrics. This review also outlines the contemporary application of clinical decision support systems in the field of medicine. Its types, their existing practical applications with documented effectiveness, prevalent challenges, and potential adverse consequences. The review concludes by offering evidence-based guidelines aimed at mitigating risks associated with support systems design, implementation, evaluation, and ongoing maintenance.*

**KEYWORDS:** *Big data, Computerized Clinical Decision Systems, Electronic Health Record Data, Artificial Intelligence, Medicine.*

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## INTRODUCTION

In accordance with a widely accepted definition, Big Data refers to data characterized by its vast scale, diversity, and complexity, necessitating the development of new architecture, techniques, algorithms, and analytics for its effective management and extraction of valuable insights and concealed knowledge. This definition acknowledges the multifaceted nature of such data and the technological challenges it presents. The integration of diverse information sources, spanning primary and secondary care to administrative data, represents a substantial opportunity that Big Data offers to the healthcare sector (Budrionis & Bellika, 2016; Harper, 2014; Murdoch & Detsky, 2013; Etheredge, 2014). This integration has the potential to provide a fresh perspective on patient care processes and individual patient behaviors, considering the intricate aspects of clinical and chronic care. The interest in collecting extensive and diverse healthcare data sources finds a unique application in the development of novel data-driven Decision Support Systems. Several authors delineate two primary areas where researchers should focus their efforts to yield valuable outcomes in this domain: (i) the secondary utilization of data to generate new evidence and glean important insights for improved clinical decision-making or the restructuring of healthcare organizational components, and (ii) the identification of novel correlations among asynchronous events to enable clinicians to promptly recognize potential complications, adjust treatments in a timely manner, or assist in the analysis of similar manifestations in clinical diagnoses. To pledge better-informed decision-making and consequent successful clinical outcomes, healthcare systems empowered by Big Data should effectively incorporate advanced computational tools, such as innovative similarity measures for patient stratification and predictive analytics for risk assessment and the selection of therapeutic interventions. The emergence of new data sources is paving the way for the creation of an innovative healthcare model that can fully harness the potential of data-driven decision-making. This development signifies that Big Data will not only play a crucial role in research but also in clinical and organizational decision-making. We will explore this perspective within the framework of the "Learning Healthcare System Cycle" (Halamka, 2014; Krumholz, 2014; Zillner et al., 2014; Kaltoft et al., 2014; Köhn et al., 2014). In this context, we emphasize the significance of utilizing "Learning Healthcare System Cycle" solutions in the creation of next-generation clinical and organizational decision systems through the following steps:

(i) We propose a possible formalization for the implementation of Learning Healthcare Systems, offering a conceptual solution based on state-of-the-art data production technologies.

(ii) As evidence of the validity of these formalized concepts in various clinical scenarios, we present two systems integrated into the Learning Healthcare Cycle as proof of concept.

## BIG DATA AND THE EVOLUTION OF THE LEARNING HEALTHCARE SYSTEM CYCLE

Recent advancements in the utilization of Big Data for healthcare, as reshaped by the medical informatics community, have introduced novel and indispensable directions. Specifically, the well-established concept of the "data, information, and knowledge" continuum has undergone a transformation into what is now known as the Learning Healthcare System Cycle (LHSC). In this revised approach, healthcare practice and research are intricately intertwined, forming a unified and synergistic process (Lupşe et al., 2014; Zhang et al., 2016; Suresh, 2018; Moghimi et al., 2013; Chen & Yang, 2014). The primary innovation of this approach lies in its emphasis on the notion that clinical practice and research are mutually reinforcing elements in the generation of both data and knowledge. Informatics plays a pivotal role in equipping us with the necessary tools to convert data into information and information into knowledge. It aids in uncovering underlying patterns, thereby facilitating a deeper understanding of data relationships. Moreover, informatics is instrumental in translating acquired knowledge into actionable support for patient care and, ultimately, in guiding individual behavior. Our perspective is that the integration of Big Data into medical informatics will prove equally vital across various stages of the LHSC, encompassing both research and data-driven decision-making. LHSC is, indeed, founded on the synergy of these two complementary endeavors: the first centered on harnessing medical data for research purposes (Care Informs Research and the second focused on developing innovative systems that harness Big Data to inform and enhance clinical decision-making (Research Informs Care) (Figure 1) (Wang et al., 2015).

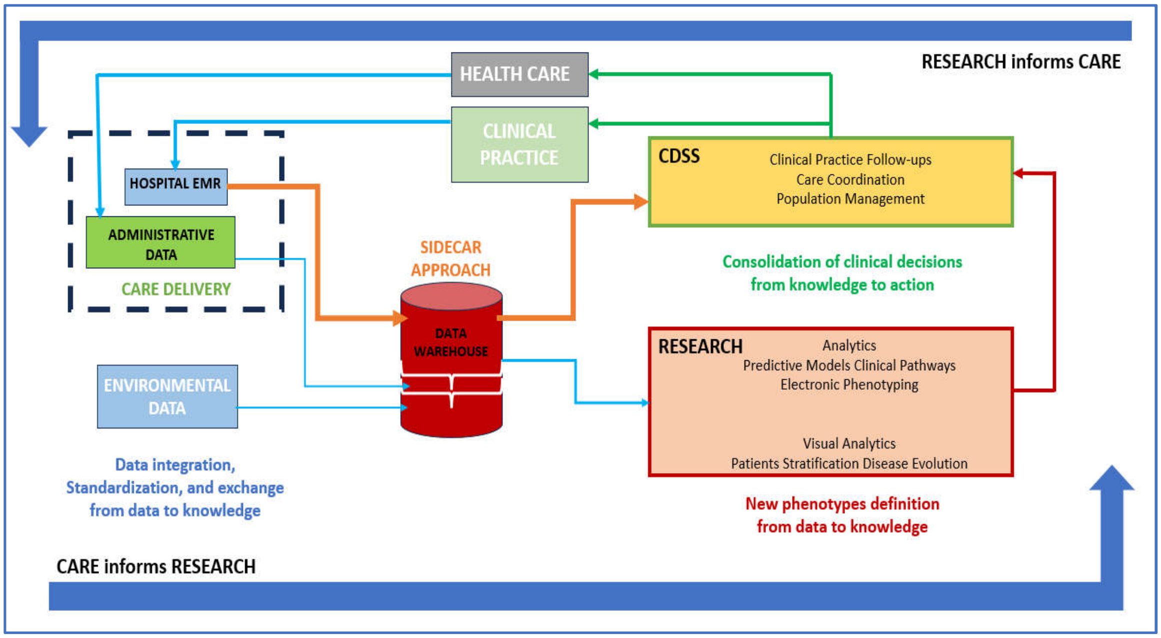


**Figure 1: Conceptual framework indicating integration of learning healthcare cycle relying on big data-enabled architecture.**

## CARE INFORMS RESEARCH- RESEARCH

In the realm of clinical practice, data primarily originates from electronic health records (EHR), which have become widely adopted, providing a unique repository of clinical information for research purposes. EHRs offer the opportunity to extract and interpret clinical data, automating support for clinical research and enhancing the quality of care. Specifically, EHR-based phenotyping leverages the data collected during healthcare delivery to identify individuals or groups with conditions or events pertinent to clinical studies (Skiba, 2011).

Several noteworthy facets in the current literature are worth highlighting:
i) Acknowledging the temporal aspect of the data, this approach encompasses not only clinical information from EHRs but also process information from administrative databases. Recent methodologies, for instance, enable the extraction of care trajectories, shedding light on the frequent patterns of disease progression and care utilization.
(ii) The computation of patients' similarity is achieved through advanced "multimodal" data fusion techniques, incorporating deep learning and tensor factorization methods.
(iii) Natural language processing pipelines are fully embraced as facilitators in the analytical process, allowing the integration of data and knowledge concealed within textual reports (Deeny & Steventon, 2015).

## RESEARCH INFORMS CARE—DATA-DRIVEN DECISION MAKING

Clinical decision support systems (CDSS) have traditionally been defined as software intended to enhance clinical decision-making by customizing computerized clinical guidelines and protocols according to individual patient characteristics. While it is acknowledged that the development and implementation of CDSSs can greatly benefit contexts requiring intricate decision-making, such as chronic disease management, their adoption in routine clinical practice remains limited. This limitation may be attributed to factors such as suboptimal user interfaces, inadequate integration with Electronic Health Records (EHRs), and limited analytical capabilities that hinder data-driven reasoning.

We contend that to provide effective decision support, CDSSs must meet essential criteria, including:

(i) Comprehensive content encompassing knowledge, references, and data evidence.

(ii) The ability to process vast datasets with rapid response times.

(iii) User-friendly implementations that is visually appealing and capable of capturing users' attention without causing delays in clinical actions (Budrionis & Bellika, 2016b).

These essential features translate into the core components of CDSS: data and knowledge repositories, inference engines, and user interfaces. It's worth noting that IT infrastructures originally designed to support research can also serve as valuable tools for aiding clinical decision-making. An intriguing paradigm is represented by the "sidecar" approach, where the same data warehouse serves dual purposes: analyzing patient cohorts at a population level and facilitating "case-based" reasoning when confronted with complex clinical cases by extracting information about similar patients and potential treatment options (Batran et al., 2022).

## THE UTILIZATION OF BIG DATA IN CLINICAL DECISION SUPPORT: EXISTING SOLUTIONS AND SYSTEMS

Numerous conceptual design elements and software components are currently available to facilitate the development of systems for implementing the Learning Healthcare System Cycle (LHSC). Prominent initiatives and networks supporting Big Data research include the National Institutes of Health's (NIH) Big Data to Knowledge (BD2K) projects, the Electronic Medical Records and Genomics (eMERGE) network, and the Patient-Centered Outcomes Research Network (PCORNet) (Richesson et al., 2013).

BD2K represents a substantial funding initiative addressing various aspects of enhancing Big Data in biomedical research, from data accessibility and reusability to the development of novel methodologies and tools for Big Data analysis. The eMERGE network is dedicated to creating and sharing high-throughput clinical phenotyping algorithms to support precision medicine. It includes valuable tools like PheKB, a collaborative knowledgebase for phenotype discovery and validation. In the context of clinical decision support, the eMERGE network has proposed the use of "infobuttons" as a decision support tool, providing context-specific links within electronic health records to pertinent genomic medicine content. PCORNet aims to enhance the capacity for conducting comparative clinical effectiveness research by utilizing patient-centered common data models, which leverage standard terminologies and coding systems (including ICD, SNOMED, CPT, HCPCS, and LOINC) to ensure interoperability and responsiveness to evolving data standards. Applications of these networks to chronic diseases include creating a common data model for patients with metabolic diseases using PCORNet and secondary data analysis for personalized medicine and phenotype definition in Type 2 Diabetes using eMERGE (Henry et al., 2016).

One of the most widely employed open-source tools for aggregating multidimensional data from various sources is the Informatics for Integrating Biology and the Bedside (i2b2) framework (https://www.i2b2.org). Funded by the U.S. National Institute of Health (NIH) Roadmap for Biomedical Computing (http://www.ncbcs.org), i2b2's mission is to provide clinical investigators with a service-based software infrastructure capable of integrating clinical records and research data, enabling easy querying. To streamline the querying process, data are mapped to concepts organized in an ontology-like structure within i2b2. These ontologies organize concepts related to each data stream in a hierarchical manner (Tejero & de la Torre, 2012). For instance, drug prescriptions can be represented using their

ATC drug codes in the Drug Ontology, while subsets of laboratory tests from Anatomy Pathology can be linked to the SNOMED (Systematized Nomenclature of Medicine) Ontology. Furthermore, i2b2 is linked to ontologies available from BioPortal (http://i2b2.bioontology.org/) to seamlessly integrate common medical ontologies into the system.

Since its development, the i2b2 framework has spawned parallel projects. The "Substitutable Medical Applications and Reusable Technologies" (SMART) interoperability project was designed to create a platform that allows medical applications to be developed once and run across different healthcare IT systems (Faxvaag et al., 2011; Hripcsak& Albers, 2013; Colpas, 2013). SMART has recently been updated to take advantage of clinical data models and the application programming interface outlined in a new, openly licensed Health Level Seven (HL7) draft standard known as Fast Healthcare Interoperability Resources (FHIR).A recently introduced platform, known as SMART on FHIR, has been leveraged to develop an interface that serves patient data sourced from i2b2 repositories. With i2b2/SMART, it becomes possible to effectively implement the sidecar approach, allowing the continued use of existing clinical systems (EHR) without modification, while relying on a secondary database (the i2b2 instance) for decision-making support. When Big Data is specifically harnessed for Clinical Decision Support (CDS), visual analytics plays a pivotal role in hypothesis generation and facilitates real-time clinical decisions (Bonney, 2013). Visual analytics becomes a potent tool when coupled with longitudinal models for the analysis of extended time series. It enhances pattern visualization, directing attention toward monitoring clinical actions and identifying health-risk scenarios by detecting and displaying patient behaviors (Jensen et al., 2012).Numerous Clinical Decision Support Systems (CDSSs) exemplify the synergy of visual analytics methods, combining evidence-based and data-driven approaches to enhance clinical performance. These systems, for instance, retrieve information about drug interactions, integrate analytics and electronic guidelines, or collect Electronic Health Record (EHR) data for input into models capable of risk stratification. Furthermore, there are ongoing efforts to incorporate visual analytics into the field of epidemiology, aimed at comprehending the interactions among time-dependent variables (Vilar et al., 2012).

**ELECTRONIC HEALTH RECORD**

The electronic health record (EHR) itself can be categorized as "big data," encompassing the manipulation and application of data stored within EHRs. Incentives stemming from the Health Information Technology (HITECH) Act of 2009 in the United States have contributed to an adoption rate of approximately 80 percent of certified EHRs in acute care hospitals (Yoon et al., 2012). EHR adoption rates have also witnessed an increase on a global scale (Harpaz et al., 2012). Projections suggest that in the United States alone, there will soon be documentation of one billion patient visits annually within EHR systems (figure 2) (Pathak et al., 2011).

Alongside the patient data housed in EHRs, there exists a substantial volume of additional data pertaining to medical conditions, underlying genetics, medications, and treatment approaches. However, human cognitive capabilities to learn, comprehend, and process this vast data are finite. Consequently, there is a pressing need for computer-based methods to organize, interpret, and discern patterns from these data (Roque et al., 2011).

While the adoption of EHRs for healthcare is promising, it is imperative that the data continue to serve secondary purposes in quality improvement and research, which can contribute to enhancing patient care and potentially curtailing healthcare costs (Lyalina et al., 2013). Over the years, EHR data have been harnessed with the intention of improving care, increasing patient engagement, facilitating quality improvement, establishing shared models and standardization across institutions, generating new knowledge, conducting research in real-world settings rather than controlled trials, enabling public health surveillance and intervention, and supporting personalized care and decision-making. The ultimate objective is to establish an ever-evolving healthcare infrastructure characterized by real-time knowledge production and create an ecosystem that is predictive, preventive, personalized, and participatory (Pantazos et al., 2011).

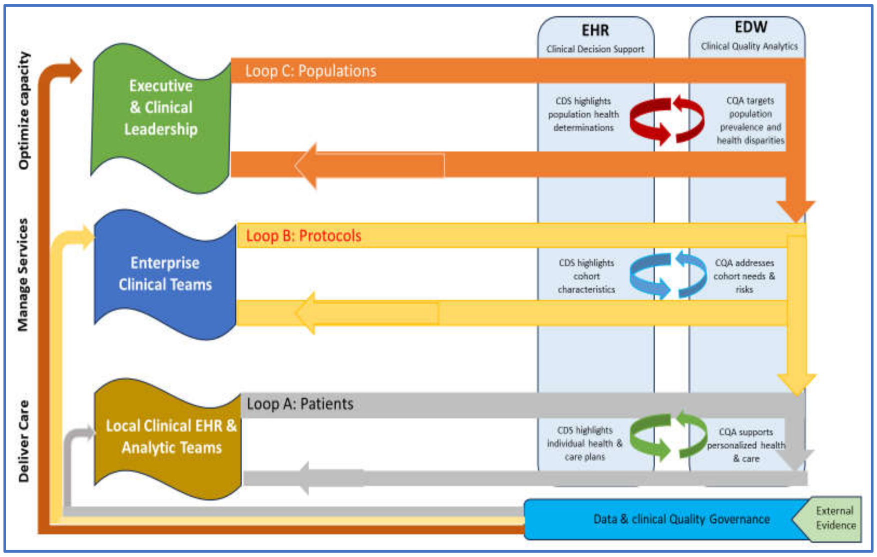


**Figure 2: Main three closed loops and their integration for clinical decision support**

The utilization of the EHR system to address healthcare questions diverges from the traditional research approach of collecting data after posing a question. Although EHRs and the concept of secondary data use have existed for many years, the process is currently not streamlined, and numerous challenges persist. Principal challenges encompass limitations in processing capacity, interoperability, and the absence of standardized practices, concerns regarding the accuracy and completeness of records, cost considerations, apprehensions about security and privacy, and difficulties in extracting the required information (Xu et al., 2011; Minard et al., 2011; Uzuner et al., 2012).

Lately, the healthcare industry has been met with unexpected developments, prompting a reconsideration of the future of electronic health records (EHRs). The emergence of COVID-19 in recent years underscored the immense value of digital solutions in addressing the myriad challenges confronting healthcare institutions. As a result, what novel trends can we anticipate in the realm of EHR and EMR software? EHRs have become an integral part of the healthcare landscape, largely supplanting traditional paper-based record-keeping in contemporary medical facilities. Given this, it is imperative to remain vigilant about forthcoming developments to ensure that your clinic or hospital remains at the forefront. The advent of COVID-19 significantly accelerated the adoption of telehealth, driven by the demand for alternatives to in-person visits, especially for non-emergency healthcare needs, during lockdowns and restrictions. However, the adoption of transformative technology trends need not hinge on global pandemics alone (Warner et al., 2013).

A report by Grand View Research reveals that the global EHR market, valued at $28.1 billion in 2022, is projected to reach $38.5 billion by 2030, with a Compound Annual Growth Rate (CAGR) of 4%. The pandemic compelled both healthcare providers and patients to explore innovative solutions, making virtual care a permanent fixture. EMRs and EHRs have evolved significantly since their inception in the 1960s, yet they have ample room for further growth and enhancement. So, what does the future hold for electronic health records? The industry is now pivoting towards a value-based care model, spurred by government incentives in the United States, which encourage a transition from volume-based models. Thus, having an EHR system prepared for value-based care is crucial. As long as human beings continue to require medical care (at least until the prospect of uploading our consciousness into robots becomes a reality – a topic for another time), electronic health records will play an essential role (Rothman et al., 2012).

## CHALLENGES OF EHR

Electronic Medical Records (EMRs) face a significant challenge in terms of their ability to seamlessly integrate with other systems. When a patient enters a healthcare facility, such as a hospital, there is a need for access to records from outpatient practices and any previous hospitals the patient has visited to obtain a comprehensive understanding of their health. Traditionally, EMRs lack interoperability, making it essential for organizations seeking this functionality to prioritize Electronic Health Record (EHR) systems over EMR systems. In the upcoming year, developers, vendors of EHRs, and IT specialists will continue their efforts to ensure that EHR systems are updated to comply with interoperability policies (Murphy et al., 2013). EHRs, in general, offer more extensive capabilities and may even include internal record-keeping features, rendering the need for an EMR redundant. The Centers for Medicare & Medicaid Services made final adjustments to its payment systems for acute care hospitals in 2023, effective August 1st, 2022. The new policies for the 2023 Medicare Promoting Interoperability Program aim to reward eligible hospitals and critical access hospitals (CAHs) for the meaningful use of EHRs (Mills, 2019).

EMRs do not possess the same level of integration with various systems as EHRs do. Interoperability, functionality absent in EMRs, is essential for integration with tools like patient portals to facilitate information exchange with patients. As the demand for interoperability continues to rise, the line between EMRs and EHRs is becoming increasingly blurred. Many people now use these terms interchangeably, even though historically, interoperability was a significant distinguishing factor between the two. Consequently, while vendors may label a product as an EMR, they are progressively evolving to resemble what was originally EHRs. Although interoperability challenges also exist in cloud infrastructures, they are widely adopted in the healthcare industry today (Abraham et al., 2020).

Cloud-based EHR solutions that offer a pay-as-you-go model assist providers in managing their operations within budget constraints. This affordability allows those with limited financial resources to opt for EHRs instead of purchasing EMRs, especially when interoperability is a critical requirement. Furthermore, the cloud environment allows providers to partially delegate security responsibilities. Most cloud EHR vendors provide round-the-clock support and professional security programs to ensure the continuous protection of sensitive health information (PHI). The implementation of blockchain technology can enhance semantic interoperability. Blockchain eliminates the need for costly EHR integrations, requiring only a private key to access a patient's records. With valid credentials, medical professionals may access health records from any location and at any time without the need for integrations (Nuckols et al., 2014).

## EHR FUTURE TRENDS ON CLINICAL DECISION SYSTEMS

This can be explained by various attributes (figure 3) such as

**Cloud Computing:**
The healthcare sector has grappled with significant staff shortages since the onset of the COVID-19 pandemic. According to Mercer's report on the U.S. healthcare labor market, California and New York are projected to experience a workforce deficit of approximately 500,000 professionals by 2026. In response to this challenge, medical institutions are increasingly turning to cloud computing as a solution. This shift allows healthcare organizations to outsource both administrative and clinical services, encompassing tasks such as medical billing, reporting, and lab integration, among others. The global medical billing outsourcing market is anticipated to exhibit robust growth,

with a Compound Annual Growth Rate (CAGR) of 9.6%. This growth trajectory is expected to culminate in a market size of approximately $23 million by 2028 (Singh et al., 2009).

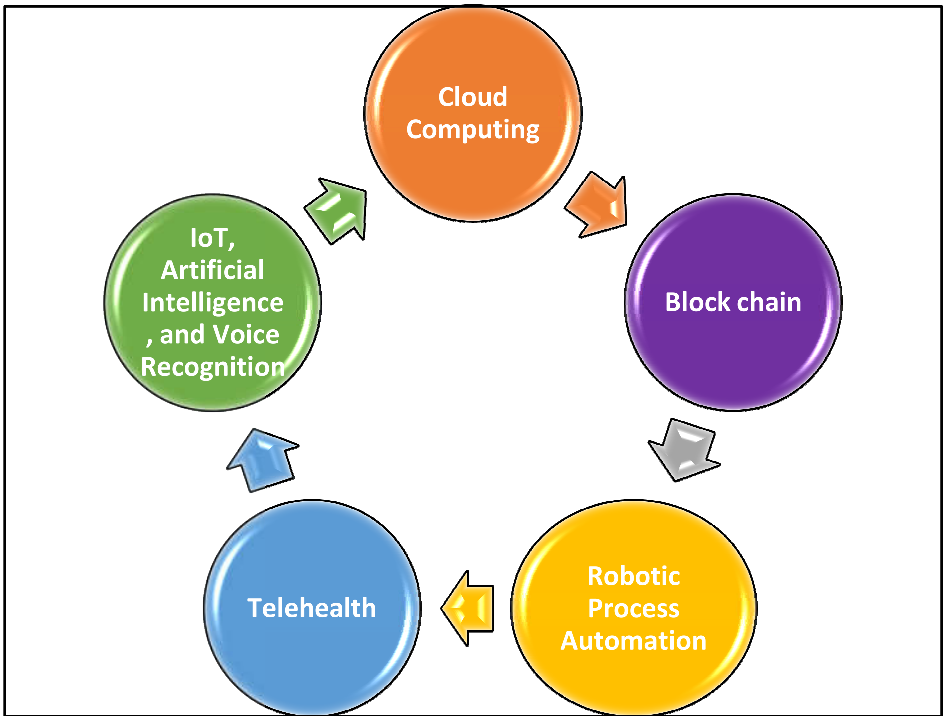


**Figure 3: Current and future trends of EHR on clinical decision systems**

**Standardization:**

EHR regulations are established and maintained by the Office of the National Coordinator for Health Information Technology. Failure to adopt EHR systems that adhere to these standards can result in penalties and disqualification from meaningful-use programs. The ONC strongly advocates for the implementation of standardized Application Programming Interfaces (APIs) within the healthcare sector. This move aims to simplify and enhance the safe use of smartphone applications for accessing structured electronic health information. Integrating APIs with EHR technology significantly improves communication between IT systems and apps responsible for creating and storing medical data (DeSalvo et al., 2015). The development and standardization of APIs facilitate rapid access and seamless information exchange among multiple stakeholders, which is the primary driving force behind their increasing adoption. Under these guidelines, electronic access to a patient's entire electronic health information (EHI), regardless of its structure, is mandated to be provided free of charge (Haynes & Wilczynski, 2010).

**Robotic Process Automation:**

The global market for automated data capture in electronic medical records is experiencing significant growth due to improved workflows and enhanced accuracy. Robotic process automation (RPA) plays a vital role in ensuring the necessary precision by replacing manual data entry with robot-based automation. In the healthcare sector, RPA serves as a valuable tool for addressing EHR shortcomings without the need for a complete system overhaul. RPA primarily enables the use of digital labor to maintain existing effective processes while resolving underlying issues (Weingart et al., 2009). RPAs employ system algorithms and software programs to automate tasks typically performed efficiently and securely by human resources within an organization. These automation solutions enable healthcare facilities to expedite their digitization efforts and rectify imperfections rapidly. The global robotic process automation market was valued at $2.9 billion in 2022 and is projected to reach $6.2 billion by 2030. These integrations are poised to offer EHR users substantial time savings in the long term, allowing them to allocate their manual resources to more critical tasks (Van De Velde et al., 2018).

**Telehealth:**

The integration of EHR systems with telehealth platforms is instrumental in enabling medical organizations to deliver remote care and optimize clinical workflows. These seamless integrations empower healthcare providers to transfer patient information efficiently and securely between systems or interfaces (Baker, 2001). The combination of telehealth and EMR systems yields numerous advantages for both you and your staff, including:

- Automation of data entries.
- Consolidation of insurance information in a unified window.
- Streamlining of virtual care activities.
- Enhancement of patient-physician engagement.
- Facilitation of collaboration.

Moreover, any modifications made in the telehealth system automatically update patient records, ensuring that healthcare providers have immediate access to current and accurate patient information during virtual care. The global telehealth market is anticipated to exhibit substantial growth, with a projected Compound Annual Growth Rate (CAGR) of 26.6%. It is expected to reach $285.7 billion by 2027, driven by factors such as increasing demand for EHR/EMR health apps, a growing number of internet users, shifting demographics, and significant healthcare expenditure (Lytle et al., 2015).

**IoT, Artificial Intelligence, and Voice Recognition:**

IoT devices, particularly within the healthcare sector, are experiencing a surge in usage. The global market for the Internet of Things (IoT) in healthcare is projected to grow at a Compound Annual Growth Rate (CAGR) of 21.41%, reaching $960.2 billion by 2030. Many healthcare practices are also incorporating artificial intelligence to aid physicians in diagnosing and identifying patient health trends. Numerous companies are actively researching the integration of voice recognition using AI into Electronic Health Record (EHR) software. A noteworthy example is the collaboration between Northwell Health and All scripts, initiated in 2019 [51]. Dissatisfied with their existing software infrastructure, Northwell Health partnered with all scripts to develop a customized solution tailored to their specific requirements. Under this agreement, the AI-based platform is not exclusive to Northwell Health, allowing Allscripts to offer it to other healthcare organizations upon completion. Furthermore, the incorporation of Natural Language Processing (NLP) into EHR systems promises to enhance physician efficiency and patient care. AI systems capable of comprehending spoken language naturally and assisting physicians are at the forefront of technological advancement (Ernesäter et al., 2009). The integration of artificial intelligence technology into the healthcare sector streamlines electronic systems, enabling healthcare professionals to swiftly examine and analyze unstructured patient cases through automation tools. This, in turn, aids administrative staff in expeditiously preauthorizing insurance claims, minimizing errors and discrepancies in the process. Artificial intelligence offers a multitude of benefits to healthcare professionals, including the development of personalized treatment plans, prompt feedback on critical patient cases involving rare or complex health issues, and the analysis of patient databases for valuable insights (Greenes, 2014; Duggal et al., 2015).

**EHR and its integration with blockchain:**

Blockchain technology, primarily renowned for its association with cryptocurrency, has recently found application within the healthcare sector. The global market for blockchain technology in healthcare is anticipated to experience substantial growth, with a projected Compound Annual Growth Rate (CAGR) of 39.9%, ultimately reaching $5.8 billion by 2028

(Bezemer et al., 2019). Blockchain leverages cryptographic techniques to safeguard Electronic Health Record (EHR) data, limiting access solely to authorized individuals. For instance, blockchain can validate the outcomes of clinical trials and claims, monitor the distribution of medications, authenticate prescriptions, and mitigate instances of insurance fraud. Through the utilization of smart contracts, blockchain can automate actions based on predefined conditions, reducing the need for human intervention. Although the integration of blockchain technology into healthcare is still in its nascent stages, several EHR systems have already adopted it to enhance security, scalability, and confidentiality (Roosan et al., 2016).

## KEY OPINION

When technology becomes cumbersome or operates at a high frequency, clinicians can experience alert fatigue. A study conducted by Sidebottom and colleagues found that clinicians cited several reasons for not utilizing Clinical Decision Support (CDS) system tools. These reasons included a lack of trust in the data, perceived irrelevance, information overload, insufficient training, information located outside their workflow, absence of actionable items, and the intrusiveness of pop-up notifications (Shear et al., 2023). Notably, the study revealed that nurses expressed a desire to have the opportunity to proactively "do the right thing" before receiving a notification indicating that a task had not been completed. This underscores the critical importance of providing timely information to clinicians. The incorporation of alerts into the workflow of clinicians is essential and highlights the necessity of involving end-users in the design, training, and implementation phases of these systems (figure 4). Since not all nurses possess the educational and technical expertise required to evaluate the usability of an electronic health record, informatics nurse specialists can play a pivotal role in assessing clinical applications. These informaticists can collaborate with technical staff to design clinical information systems that bridge nursing science, computer science, and information science. By applying informatics principles, they can evaluate system feasibility and enhance usability (Macias et al., 2022; Afshar et al., 2023; Sittig et al., 2023; Campbell et al., 2023).

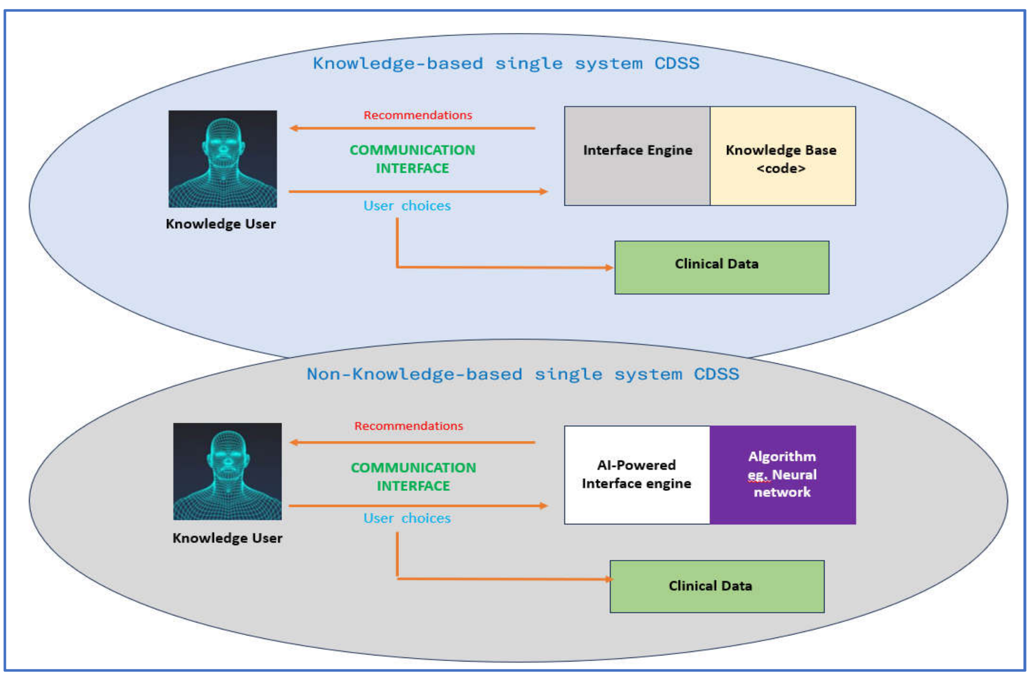


**Figure 4: Artifact of key interaction in knowledge-based and non-knowledge-based CDSS.**

## CONCLUSION

Clinical decision support systems hold significant value for clinicians, but they can also be harnessed by patients to access pertinent, evidence-based clinical information. This information from big data and EHR can aid patients in collaborating more effectively with their healthcare providers. The American Medical Informatics Association has underscored the significance of fostering a partnership between patients, providers, and information technology. Within this collaborative framework, a virtual structure for healthcare and information delivery offers a range of interactive tools designed to personalize care. As big data and EHR /patient portals continue to gain traction, coupled with the integration of biosensors and fitness applications, there is a rising demand for health and medical information, as well as guidance and decision support. This trend is expected to see continued growth in the future. The transformation of healthcare information technology, instigated by the HITECH Act of 2009, is just in its nascent stages. By harnessing intuitive clinical decision support systems, mobile technology, and medical devices capable of seamless integration with big data and EHR /patient records, there exists immense potential to enhance the quality and efficiency of patient care. These advancements in patient care can lead to better outcomes, supported by robust data, and subsequently, they have the potential to catalyze advancements in population health and disease prevention.

**Conflicts of interest:** None.

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