Data-Driven Clinical Decision Support Systems Theory and Research

D

Cherie Noteboom
Dakota State University, USA

David Zeng
Dakota State University, USA

Kruttika Sutrave
Dakota State University, USA

Andrew Behrens
Dakota State University, USA

Rajesh Godasu
Dakota State University, USA

Akhilesh Chauhan
Dakota State University, USA

INTRODUCTION

Digitization, which has had a significant influence on the healthcare industry, is motivated by the prospect of optimizing performance, reducing costs, and improving the quality of patient care and healthcare (Lee et al., 2017). This digital process has transformed how patients and physicians engage with medical services. Although healthcare has been slow to accept technology, it is now embracing digital transformation. The use of information technology (IT) in the healthcare industry has transformed interactions between physicians and patients, giving way to the implementation and usage of clinical decision support systems (CDSS).

CDSS are examples of the transformative healthcare evolution because they analyze data and assist physicians in making timely patient-related decisions (Agency for Healthcare Research and Quality, 2013)[1]. Healthcare professionals also utilize these systems to enhance treatment by increasing patient safety, eliminating needless testing, and reducing costs. For example, medical errors can decrease through enhanced healthcare, safety, and efficiency. Clinicians use these systems in the preparation of diagnoses and subsequent evaluations and outcomes (Osheroff et al., 2012). Although CDSS have the potential to improve healthcare delivery, it has been a challenge to fully realize their potential (Linder et al., 2006).

Clinical decision making uses descriptive, predictive, and prescriptive analytics. Descriptive analytics analyzes and presents past data regarding patients and treatment (Gensinger, Jr., 2014). This type of analytic utilizes visualization, alerts, and reports to describe patient activities (Gensinger, Jr., 2014). Predictive analytics uses historical data to make predictions by performing an analysis with rule-based or artificial intelligence (AI) techniques like machine learning and deep learning (Bartley, 2017; Gensinger, Jr., 2014). Medical professionals can identify trends and patterns in treatment plans or uncover chronic

DOI: 10.4018/978-1-7998-9220-5.ch081

diseases in patients based on age, location, and ethnicity. Prescriptive analytics recommends actions that can produce the best outcome. This allows healthcare professionals to develop optimal clinical pathways for patient care (Bartley, 2017; Gensinger, Jr., 2014)

A recent Stanford study on the future of AI's impact on society suggests that AI-enabled systems will change the future by replacing tasks rather than eliminating jobs (Grosz & Stone, 2018). In fact, AI technologies and data analytics are transforming the way organizations operate. Tech giants like Google, Microsoft, and Amazon are investing heavily in data collection (Newman, 2020). Organizations are focusing on feeding large datasets into data analytic models to produce predictive and prescriptive information to obtain meaningful projections. This application in the healthcare field facilitates in the reduction of operating costs, improves treatment outcomes, increases access to patients and clinician resources, and optimizes healthcare provider satisfaction (Bartley, 2017). Using predictive and prescriptive analytics in healthcare can improve forecasting, real-time insights, and automated decision making (Bartley, 2017). In turn, physicians and clinicians will experience enhancements in their daily tasks.

Time and external constraints affect clinician and physician decision-making processes (Lynn, 2019; Schwartz & Cato, 2020; Tonekaboni, Joshi, McCradden, & Goldenberg, 2019). Innovative products and accessibility to evidence-based information gives physicians opportunities to identify the most effective options for patients (Moja et al., 2019). The healthcare industry uses diverse methods to collect data about patients (e.g., physical traits, medical history), professional disciplines (e.g., doctors, nurses, administrators, insurers), and treatment options, healthcare delivery processes, and interests of stakeholder groups (Fichman & Kemerer, 1997; Noteboom & Qureshi, 2014). This may prove challenging for the design and implementation of systems. Therefore, contextualizing healthcare systems is key to understanding the integration of information systems (IS) into healthcare organizations (Noteboom & Qureshi, 2014).

A theory is a statement of relations among concepts within a set of boundary assumptions and constraints (Bacharach, 1989; Bhattacherjee, 2012). Theories provide guidance on the analysis, explanation, and prediction of phenomena, as well as design and action guidelines (Bhattacherjee, 2012; Gregor, 2006; Lim, Saldanha, Malladi, & Melville, 2013). IS theories enable users to identify factors that inñuence intention toward a particular behavior; therefore, they are important to consider in relation to technology adoption and acceptance (Ajzen, 1985; Fishbein & Ajzen, 1975).

Reach, Efficacy, Adoption, Implementation, and Maintenance (RE-AIM) and the Consolidated Framework for Implementation Research (CFIR) are two practitioner-developed frameworks based on theory (Damschroder et al., 2009; Glasgow, Vogt, & Boles, 1999). These systems have the potential to positively impact quality of care and reduce costs. Still, there is a key challenge related to CDSS adoption, implementation, resistance, and acceptance from physicians and clinicians who use the systems to offer high-quality patient care. The users of the system often work with better visualizations, new recommendations, and more accurate predicted information. Although new system features could support the workflow of physicians and clinicians, it can be difficult to incorporate these features into the fabric of healthcare. This challenge opens the door for an investigation into the following research questions:

1. To what extent is data-driven decision making applied in CDSS?
2. What prevalent theories are used in data driven CDSS research?
3. What major system attributes contribute to the theoretical frameworks?

From a theoretical perspective, this study investigates the theories used to inform design and provides a glimpse into the current state of CDSS theory-informed design. The information enables researchers to study CDSS adoption, implementation, acceptance, and resistance more effectively by reframing the

Related Content

Financial Analytics With Big Data
Leon Wang (2023). *Encyclopedia of Data Science and Machine Learning (pp. 1891-1903).*
www.irma-international.org/chapter/financial-analytics-with-big-data/317594

Forecasting Price of Amazon Spot Instances Using Machine Learning
Manas Malikand Nirbhay Bagmar (2021). *International Journal of Artificial Intelligence and Machine Learning (pp. 71-82).*
www.irma-international.org/article/forecasting-price-of-amazon-spot-instances-using-machine-learning/277435

Corona: The Development Invader
Mansha Sharmaand Ajay Kumar Sharma (2021). *Machine Learning and Data Analytics for Predicting, Managing, and Monitoring Disease (pp. 204-211).*
www.irma-international.org/chapter/corona/286253

Identifying Disease and Diagnosis in Females Using Machine Learning
Sabyasachi Pramanikand Samir Kumar Bandyopadhyay (2023). *Encyclopedia of Data Science and Machine Learning (pp. 3120-3143).*
www.irma-international.org/chapter/identifying-disease-and-diagnosis-in-females-using-machine-learning/317743

Comparative Analysis and Detection of Brain Tumor Using Fusion Technique of T1 and T2 Weighted MR Images
Padmanjali A. Hagargi (2021). *International Journal of Artificial Intelligence and Machine Learning (pp. 54-61).*
www.irma-international.org/article/comparative-analysis-and-detection-of-brain-tumor-using-fusion-technique-of-t1-and-t2-weighted-mr-images/266496