# T2DM Clinical Decision Support System: Comprehensive Patient Care

Dong-Gil Ko
*University of Cincinnati*, donggil.ko@uc.edu

Judith W. Dexheimer
*Cincinnati Children's Hospital Medical Center*, judith.dexheimer@cchmc.org

Mark H Eckman
*University of Cincinnati*, eckmanmh@ucmail.uc.edu

Robert M. Cohen
*University of Cincinnati*, cohenrm@ucmail.uc.edu

Daniel Schauer
*University of Cincinnati*, schauedp@ucmail.uc.edu

*See next page for additional authors*

## Presenter Information

Dong-Gil Ko, Judith W. Dexheimer, Mark H Eckman, Robert M. Cohen, Daniel Schauer, and Brett Harnett

# T2DM Clinical Decision Support System: Comprehensive Patient Care

*Emergent Research Forum (ERF)*

**Dong-Gil Ko**
University of Cincinnati
kodg@ucmail.uc.edu
**Judith W. Dexheimer**
Cincinnati Children's Hospital Medical Center
judith.dexheimer@cchmc.org
**Mark H. Eckman**
University of Cincinnati
eckmanmh@ucmail.uc.edu
**Robert M. Cohen**
University of Cincinnati
cohenrm@ucmail.uc.edu
**Daniel P. Schauer**
University of Cincinnati
schauedp@ucmail.uc.edu
**Brett M. Harnett**
University of Cincinnati
harnetbm@ucmail.uc.edu

## Abstract

We report on the current state of type 2 diabetes clinical decision support systems (CDSS), identify gaps that contribute to the lack of CDSS success, and apply lessons learned from practice for developing and implementing a localized diabetes CDSS. A survey of the literature reveals mixed findings regarding the efficacy of the CDSS; they do not include patient-rich information – the patient experience data in the electronic health records. We believe that diabetes care can improve by guiding clinical decisions using published evidence, patient preferences, and clinical data augmented by the local patient experience and social determinants of health using natural language processing and machine learning techniques.

#### Keywords

clinical decision support systems, type 2 diabetes mellitus, electronic health records, social determinants of health, natural language processing, machine learning

## Introduction

Academic research on healthcare information technologies (HIT), including clinical decision support systems (CDSS), that seeks to extend Information Systems (IS) theory has grown over the past decade but has had a limited impact (Romanow et al., 2012). Developing a deep knowledge of the healthcare context by leveraging electronic health records (EHR) data could reduce the gap between HIT researchers and clinicians giving rise to new methods and applications (Bardhan et al., 2020). This study examines diabetes CDSS, identifies gaps that contribute to the lack of CDSS success, and applies lessons learned from practice for developing and implementing a localized diabetes CDSS.

## Background

Diabetes places a significant burden on the health care system and patients. Worldwide, diabetes affects 537 million people with 50% of T2DM patients failing to achieve adequate glycemic control (HbA1c < 7%) (IDF Diabetes Atlas, 2021). Diabetes affects 34 million people in the U.S., and contemporary medical management results in excess of $100 billion in healthcare costs (CDC, 2020). Moreover, the disease burden is large and accounts for an average of 42-174 missed workdays for each type 2 diabetes mellitus (T2DM) person (Persson et al., 2020). Poor diabetes management can lead to chronic morbidities and increase mortality, accounting for 1.5 million deaths in the U.S. alone in 2019 (Sutton et al., 2020). Current diabetes CDSS, underlying theoretical frameworks, and algorithms and informatics methods for diabetes management have significant limitations. Providing personalized, evidence-based diabetes management recommendations to patients can mitigate this growing disease burden (Sutton et al., 2020).

While there are standards of care guidelines for diabetes (DSoC), they remain underutilized in clinical care. These guidelines are frequently not integrated into the EHR (Contreras & Vehi, 2018). EHRs offer a wealth of treatment data, yet social determinants of health (SDoH) have not been effectively digitized or applied for use in clinical care and automated algorithms (Sutton et al., 2020). CDSS frequently do not provide personalized treatment recommendations leading to non-optimized patient recommendations (Sutton et al., 2020). Compounding the challenge is the failure to accommodate patient preferences or circumstances in treatment recommendations (Contreras & Vehi, 2018) as we have witnessed throughout the pandemic (Czeisler et al., 2021). What is needed is an effective "user-friendly" decision-making tool using artificial intelligence and big data approaches to integrate published evidence, patient preferences, and clinical data augmented by patient experience evidence including SDoH and lifestyle practices. A diabetes-specific CDSS that integrates guidelines with knowledge gained from local clinician experience and patient outcomes using novel informatics methods could serve as an individual and population care tool to improve health system planning, health outcomes, minimize complications, and reduce costs (Sutton et al., 2020).

## Efficacy of Diabetes CDSS

A variety of theoretical frameworks has guided diabetes management using CDSS including information network, social cognition, planned behavior, outcome expectancies, and design. Their focus on a narrow set of constructs concerning individual (e.g., self-efficacy) and environmental (e.g., virtual support) factors has failed to improve diabetes health outcomes; they have not addressed the challenging task for clinicians to keep up with the most recent guidelines and evidence and they have not incorporated patient healthcare experiences (Paddison et al., 2015). Lacking knowledge about best evidence and patient experience, clinicians may be recommending less-than-optimal treatments. The current state of CDSS does not provide mechanisms to support clinicians to combat this dilemma.

We conducted a systematic review and meta-analysis using PubMed and Google Scholar. We limited our search to articles in English published in peer-reviewed journals between the years 2007 and 2020. Our search included the keywords clinical decision support/CDSS, type 2 diabetes, and randomized controlled trials yielding 124 results. We reviewed 124 abstracts and limited our search to studies examining the efficacy of CDSS interventions for T2DM in adults with a focus on clinical outcomes; we excluded studies that examined CDSS feasibility, adoption, use, screening, adherence, or other process evaluations. We included only those studies that explicated the use of best evidence, electronic health records (EHR), and patient preferences. Seventeen studies met our inclusion criteria. We define the efficacy of CDSS as the extent to which its use impacts diabetes clinical indicators or outcomes. Our descriptive statistics reflect the frequency of occurrences in which CDSS interventions improved ("Yes") or did not improve ("No") clinical outcomes showing research that was conducted inside and outside the U.S. – See **Table 1**.

| | **Hemoglobin A1c** | | | **Blood Pressure** | | | **Cholesterol** | | | **Body Mass Index** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Yes* | *No* | *Total* | *Yes* | *No* | *Total* | *Yes* | *No* | *Total* | *Yes* | *No* | *Total* |
| US | 4 | 3 | 7 | 3 | 2 | 5 | 1 | 3 | 4 | 1 | 1 | 2 |
| Outside US | 6 | 4 | 10 | 2 | 2 | 4 | 1 | 2 | 3 | 0 | 0 | 0 |
| **Total** | **10** | **7** | **17** | **5** | **4** | **9** | **2** | **5** | **7** | **1** | **1** | **2** |

**Table 1. Efficacy of CDSS Interventions in Improving Diabetes Outcomes**

The 17 publications of diabetes-specific CDSS comprised 24,218 T2DM patients from ten countries. They investigated the efficacy of CDSS by evaluating clinical outcomes hemoglobin A1c (HbA1c), blood pressure (BP), cholesterol (namely, low-density lipoprotein or LDL), and/or body mass index (BMI). All 17 studies evaluated HbA1c with eight exclusively focused on HbA1c, one on two outcomes (HbA1c and BP), seven on three outcomes (HbA1c and BP with LDL (six) or BMI (one)), and one on four outcomes (HbA1c, BP, LDL, and BMI). Overall, CDSS interventions in eight studies improved diabetes outcomes (47.1%), four experienced mixed results (23.5%), and five did not improve outcomes (29.4%). Researchers across the globe examined diabetes care using HbA1c, BP, Cholesterol, and BMI clinical outcome measures with the U.S. taking more interest in evaluating a variety of outcomes. A closer inspection of HbA1c – the universal diabetes outcomes measure in this review – reveals that CDSS interventions generally improved diabetes care, as evidenced by ten studies (58.8%). In comparison, five of nine studies (55.6%) noted improvements in BP, two of seven (28.6%) improved cholesterol levels, and one of two (50%) lowered BMI readings.

This survey of the literature summarizes the role of CDSS interventions in improving diabetes outcomes. Ten studies (58.8%) of CDSS interventions showed improved outcomes, while seven did not. These studies describe CDSS as algorithm-driven tools for providing treatment recommendations and improving decision-making using the best evidence, EHR patient health data, and patient preferences.

Though the DSoC guidelines are updated regularly, they remain underutilized – the CDSS improved outcomes in half of the studies (**Table 1**, "US" row). Despite advances in technologies, health informatics, and high CDSS use rates, challenges remain. A new direction to improve diabetes care is to develop CDSS that capture knowledge-based evidence (e.g., guidelines) and local practice-based evidence/experience (e.g., EHR). Challenges in using artificial intelligence to produce recommendations are acknowledged; however, integration of untapped patient's SDoH and experience can reap benefits similar to how large technology organizations discovered customer purchasing patterns to recommend programs with reported 70%-80% success. Future work aimed at implementing CDSS using the best medical, socio-economical, and socio-behavioral "local" evidence could lead to predictive models that enhance health outcomes.

## Social Determinants of Health

The Agency for Healthcare Research and Quality (AHRQ) and the National Institute of Health's (NIH) joint study reveals five attributes impacting individual health (Kaplan et al., 2015). Medical sciences explain 40% of health, with genetics and health/clinical care contributing 30% and 10%, respectively; SDoH explain 60% of health, with socio-economical and socio-behavioral contributing 20% and 40%, respectively. SDoH are the conditions in the environments where people are born, live, learn, work, play, worship, and age that affect a wide range of health, functioning, and quality-of-life outcomes and risks. The growing importance of SDoH is highlighted in NIH's 2022 estimated allocation of funds to Basic and Behavior and Social Sciences categories in the amount of $11.07B – the fourth highest category. Moreover, NIH created a new category in 2020 – Social Determinants of Health – with a 2022 estimated budget of $3.5B highlighting the need to research, discover, and understand non-medical factors impacting individual health.

Future CDSS should consider incorporating SDoH if health outcomes are to improve. An individual makes an average of 2.67 provider office visits per year (CDC, 2018), and those diagnosed with T2DM are recommended to visit every three months. In the most optimistic scenario, a T2DM patient will experience 18-minute face time with a provider during a 90-day period which leaves the patient to self-manage the vast majority of health care (Neprash et al., 2021). CDSS today have not prioritized the inclusion of SDoH in recommending treatments which may partially explain the mixed findings.

## Development and Implementation Process

We successfully implemented the Atrial Fibrillation Decision Support Tool (AFDST) (Eckman et al., 2015) as a point-of-care tool that "pulls" data from the EHR and then "pushes" patient-specific recommendations. Following a similar approach, the development and implementation of diabetes CDSS (dCDSS) involve a four-step process – (1) develop natural language processing and machine learning (NLP/ML) models and generate personalized evidence-based recommendations, (2) integrate dCDSS and the EHR system, (3) design effective dashboards, and (4) identify performance metrics.

*Step 1:* A retrospective analysis of the EHR using medical and SDoH data can allow the development of NLP/ML algorithms that optimizes personalized evidence-based recommendations. Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology is useful to identify valid, potentially useful, and understandable information based on patterns (Chapman et al., 2000). Diabetes-specific clinical and SDoH data from the EHR system can be stored and maintained in a local data mart and refreshed every predetermined period. The EHR data will serve as the gold standard to train and evaluate the model. This information will continuously enhance the algorithms for generating patient-specific recommendations.

*Step 2:* Adopt an industry-standard framework (e.g., scrum) to develop the dCDSS. When integrating the dCDSS with the EHR system, leverage the HL7 SMART on FHIR capability – a health-compliant technological "highway" that integrates the database, the application, and the EHR system. FHIR resources can be identified in the EHR system and resources can be called at runtime to populate the patient's profile in accordance with the DSoC guidelines. The FHIR standard automates the process of ingesting parameters, storing them appropriately, and accessing needed data in real-time.

*Step 3*: Dashboards are application tools that use data visualization techniques to support decision-makers (e.g., clinicians, nurses) in viewing and exploring processes and outcomes of healthcare. dCDSS that offer immediate access to provider-specific feedback information including evidence-based guidelines, patient-specific outcomes, medical history, and adherence have been shown to improve patients' target glycemic control (Fischer et al., 2011). As a step towards realizing precision medicine, dashboards that incorporate SDoH could enable the clinicians to improve patient engagement, facilitate shared decision-making and improve treatment decisions and patient outcomes.

*Step 4*: Though dCDSS have been shown to augment healthcare providers with decisions and patient care, they can disrupt workflow if not designed properly. dCDSS also relies on EHR data, and the operational impact of poor data quality and content can be problematic. Initial costs to set up and integrate a new dCDSS are substantial, and the ongoing costs are even greater. The lack of standardized metrics suggests much work needs to be done to advance our understanding of the financial impact and the ROI of CDSS (Jacob et al., 2017) prompting a greater need to identify metrics.

## Impact

Our goal is to impact the health and quality of life of T2DM patients by leveraging technologies and empowering clinicians with evidence-based, interpretable guidelines for diabetes management that use the most up-to-date guidelines augmented by the clinician and patient experiences and outcomes. Following the development and implementation process described above, we use patient data and develop NLP/ML algorithms. Implementing and testing a variety of ML models require a sufficient number of cases and controls. The 92,358 unique T2DM adults seen in our integrated healthcare system between 2012 and 2021 enable us to examine many independent variables for predicting and validate the ML models. We have patient demographics, encounter (including medical notes), lab tests, medication, patient portal (including message content), and many other data. Clinical features will be extracted from the collected structured data elements with categorization and binarization. Clinical findings will be extracted from unstructured notes with an NLP system developed in our earlier study (Ni et al., 2019) and added to the feature set. This rich data categorized as Real-World Evidence (RWE) (Schneeweiss & Patorno, 2021) enables us to develop optimal algorithms and models for our local population for use in our dCDSS. Our endocrinology experts can prospectively evaluate whether the dCDSS-generated recommendations are reasonable.

## Conclusion

Diabetes is the most expensive chronic disease with one-third of its annual $327 billion costs attributed to poor compliance and another nearly one-third from reduced productivity (American Diabetes Association, 2018). A survey of the literature suggests that CDSS sometimes do not improve outcomes. Our research adds to the cumulative knowledge by identifying gaps that contribute to the lack of CDSS success – namely, the lack of patient-rich information – and suggests a more comprehensive approach to health care by integrating patients' SDoH and RWE (IDF Diabetes Atlas, 2021). This study illustrates the need to leverage EHR data to develop methods and applications to integrate the SDoH and RWE. It also highlights the importance of learning from industry practice – health-IT shared understanding, a familiar concept in IS project management and competitive advantage.

## Acknowledgment

The project described was supported by the National Center for Advancing Translational Sciences of the National Institutes of Health, under Award Number 5UL1TR001425-03. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.

## REFERENCES

American Diabetes Association. (2018). Economic Costs of Diabetes in the U.S. in 2017. *Diabetes Care*, *41*(5), 917–928.

Bardhan, I., Chen, H., & Karahanna, E. (2020). Connecting systems, data, and people: A multidisciplinary research roadmap for chronic disease management. *MIS Quarterly*, *44*(1), 185–200.

CDC. (2018). *National Ambulatory Medical Care Survey: 2018 National Summary*. 40.

CDC. (2020). *National Diabetes Statistics Report 2020. Estimates of diabetes and its burden in the United States*. (p. 32).

Chapman, P., Clinton, J., Kerber, R., Khabaza, T., Reinartz, T., Shearer, C., & Wirth, R. (2000). *CRISP-DM 1.0*. SPSS. https://www.the-modeling-agency.com/crisp-dm.pdf

Contreras, I., & Vehi, J. (2018). Artificial Intelligence for Diabetes Management and Decision Support: Literature Review. *Journal of Medical Internet Research*, *20*(5), e10775.

Czeisler, M. É., Barrett, C. E., Siegel, K. R., Weaver, M. D., Czeisler, C. A., Rajaratnam, S. M., Howard, M. E., & Bullard, K. (2021). Health Care Access and Use Among Adults with Diabetes During the COVID-19 Pandemic—United States, February–March 2021. *MMWR. Morbidity and Mortality Weekly Report*, *70*(46), 1597–1602.

Eckman, M. H., Wise, R. E., Naylor, K., Arduser, L., Lip, G. Y. H., Kissela, B., Flaherty, M., Kleindorfer, D., Khan, F., Schauer, D. P., Kues, J., & Costea, A. (2015). Developing an Atrial Fibrillation Guideline Support Tool (AFGuST) for shared decision making. *Current Medical Research and Opinion*, *31*(4), 603–614.

Fischer, H. H., Eisert, S. L., Durfee, M. J., Moore, S. L., Steele, A. W., McCullen, K., Anderson, K., Penny, L., & Mackenzie, T. D. (2011). The impact of tailored diabetes registry report cards on measures of disease control: A nested randomized trial. *BMC Medical Informatics and Decision Making*, *11*(1), 12.

IDF Diabetes Atlas. (2021). *IDF Diabetes Atlas 10th Edition*. https://diabetesatlas.org/

Jacob, V., Thota, A., Chattopadhyay, S., Njie, G., Proia, K., Hopkins, D., Ross, M., Pronk, N., & Clymer, J. (2017). Cost and economic benefit of clinical decision support systems for cardiovascular disease prevention: A community guide systematic review. *Journal of the American Medical Informatics Association*, *24*(3), 669–676.

Kaplan, R. M., Spittel, M., & David, D. (Eds.). (2015). *Population health: Behavioral and social science insights*. Agency for Healthcare Research and Quality.

Lazem, S., Webster, M., Holmes, W., & Wolf, M. (2015). Games and Diabetes: A Review Investigating Theoretical Frameworks, Evaluation Methodologies, and Opportunities for Design Grounded in Learning Theories. *Journal of Diabetes Science and Technology*, *10*(2), 447–452.

Lee, L. T., Bowen, P. G., Mosley, M. K., & Turner, C. C. (2017). Theory of Planned Behavior: Social Support and Diabetes Self-Management. *The Journal for Nurse Practitioners*, *13*(4), 265–270.

Neprash, H. T., Everhart, A., McAlpine, D., Smith, L. B., Sheridan, B., & Cross, D. A. (2021). Measuring Primary Care Exam Length Using Electronic Health Record Data. *Medical Care*, *59*(1), 62–66.

Ni, Y., Bermudez, M., Kennebeck, S., Liddy-Hicks, S., & Dexheimer, J. (2019). A Real-Time Automated Patient Screening System for Clinical Trials Eligibility in an Emergency Department: Design and Evaluation. *JMIR Medical Informatics*, *7*(3), e14185.

O'Connor, P. J., & Sperl-Hillen, J. M. (2019). Current Status and Future Directions for Electronic Point-of-Care Clinical Decision Support to Improve Diabetes Management in Primary Care. *Diabetes Technology & Therapeutics*, *21*(S2), S2-26.

Paddison, C. A. M., Saunders, C. L., Abel, G. A., Payne, R. A., Adler, A. I., Graffy, J. P., & Roland, M. O. (2015). How Do People With Diabetes Describe Their Experiences in Primary Care? Evidence From 85,760 Patients With Self-reported Diabetes From the English General Practice Patient Survey. *Diabetes Care*, *38*(3), 469–475.

Persson, S., Johansen, P., Andersson, E., Lindgren, P., Thielke, D., Thorsted, B. L., Jendle, J., & Steen Carlsson, K. (2020). Days absent from work as a result of complications associated with type 2 diabetes: Evidence from 20 years of linked national registry data in Sweden. *Diabetes, Obesity & Metabolism*, *22*(9), 1586–1597.

Riazi, H., Langarizadeh, M., Larijani, B., & Shahmoradi, L. (2016). Conceptual Framework for Developing a Diabetes Information Network. *Acta Informatica Medica*, *24*(3), 186–192.

Romanow, D., Cho, S., & Straub, D. (2012). Riding the Wave: Past Trends and Future Directions for Health IT Research. *Management Information Systems Quarterly*, *36*(3), iii–x.

Schneeweiss, S., & Patorno, E. (2021). Conducting Real-world Evidence Studies on the Clinical Outcomes of Diabetes Treatments. *Endocrine Reviews*, *42*(5), 658–690.

Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: Benefits, risks, and strategies for success. *Npj Digital Medicine*, *3*(1), 1–10.

Vorderstrasse, A., Shaw, R. J., Blascovich, J., & Johnson, C. M. (2014). A theoretical framework for a virtual diabetes self-management community intervention. *Western Journal of Nursing Research*, *36*(9), 1222–1237.