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Clinical decision support and electronic interventions to improve care quality in chronic liver diseases and cirrhosis

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Abstract

Significant quality gaps exist in the management of chronic liver diseases and cirrhosis. Clinical decision support systems—information-driven tools based in and launched from the electronic health record—are attractive and potentially scalable prospective interventions that could help standardize clinical care in hepatology. Yet, clinical decision support systems have had a mixed record in clinical medicine due to issues with interoperability and compatibility with clinical workflows. In this review, we discuss the conceptual origins of clinical decision support systems, existing applications in liver diseases, issues and challenges with implementation, and emerging strategies to improve their integration in hepatology care.

INTRODUCTION

Chronic liver diseases and their end-stage manifestation, cirrhosis, are associated with significant morbidity, mortality, and high health care utilization in the United States.[1–3] The gap and opportunity is most acute in patients with cirrhosis, who experience up to three times the rate of in-hospital mortality compared to patients with congestive heart failure.[1,4,5] Treatments for patients with chronic liver diseases and cirrhosis can be highly variable; significant quality gaps have been identified in both the inpatient and ambulatory settings.[6–8] Worse yet, these quality gaps are thought to contribute to persistent racial/ethnic, sex, and socioeconomic-based disparities seen in cirrhosis care outcomes.[9–11] Since

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2010, national practice societies have developed and disseminated practice guidelines and quality measures to improve cirrhosis care. These guidelines, however, were developed based on Delphi-expert consensus methods and supported by observational studies.[12–15] Multiple strategies have been suggested to improve care quality, including integrated care models, population health-based patient identification, mandatory gastroenterology co-management/consultation, educational outreach, discharge care bundles, and standardized templates.[16–18]

Electronic health record (EHR)-based clinical decision support (CDS) systems are potentially scalable interventions that could help standardize clinical care for patients with chronic liver diseases, cirrhosis, and cirrhosis complications.[19–21] CDS systems, in the context of this review, are defined as any on-screen tools that deliver interventions within clinical information systems routinely used by providers (eg, not an application separate from the EHR) at the time of providing care to targeted patients.[22] The scope of functions provided by CDS is vast and varied, including diagnostic support, clinical management, medication management, and workflow improvement.[23] In addition, CDS systems applied in various clinical fields, such as cardiology,[24] pediatrics,[25] and endocrinology have demonstrated cost savings or improved clinical outcomes.[26] Despite these advantages, the historical record on CDS systems is mixed—and the reasons for this are thought to be due to lack of interoperability, alert fatigue, and incompatibility with established clinical workflows.[23,27]

In this review, we discuss the conceptual origins of CDS, existing CDS applications in chronic liver disease and cirrhosis care thus far, pitfalls and challenges in implementation, and emerging strategies to improve their integration in hepatology care. Finally, we feature a conceptual framework for considerations in the design of CDS systems for hepatology care to maximize usability and adoption.

THE HISTORY OF CDS

The idea of utilizing computers to aid clinical decision-making in clinical medicine was first introduced in 1959 when Ledley and Lusted identified 3 mathematical concepts (symbolic logic, probability, and value theory) that could be used in clinical medicine.[28] True computer-based CDS systems were first introduced in the 1970s. These early CDS were rudimentary, had limited clinical logic, and were largely used for research purposes.[23] Despite these challenges, the value proposition of CDS was strong as it was the most direct application of Charles Friedman’s fundamental theorem of “biomedical informatics,” defined as a person (clinician) working with an information resource (computer knowledge) that together should be able to do a better job than that person alone.[29]

The practice and delivery of modern medicine has become a high complex endeavor, in part, due to exponentially growing bodies of medical knowledge.[30] For instance, a simple search for “cirrhosis” in PubMed resulted in 130,791 publications published prior to 2000: this total doubled by 2015 and is anticipated to double again this year (2023). Interest in CDS as a strategy to improve care surged since the 2000s due to the rapid adoption of EHRs in the United States, catalyzed by the Health Information Technology for Economic and

Clinician Health (HITECH) Act of 2009.[23] The routine use of automated CDS systems is a component of national health care reform strategy propagated by the Centers for Medicare and Medicaid Services (CMS) and the Office of the National Coordinator (ONC).[31] In addition, with the explosive growth of artificial intelligence and personalized/personalized health care,[32–34] CDS could be a mechanism to incorporate both into routine clinical care.

CDS classifications and functions

CDS systems are frequently categorized based on knowledge source (knowledge-based or non–knowledge-based), functionality, and mode of delivery (active or passive). In knowledge-based systems, binary decision-tree rules are used to retrieve data, which are then evaluated by the system to produce an action or output. Rules could be based on literature, routine practice, expert-guidance, or specified by the CDS creator. In non–knowledge-based systems, the decision does not follow discrete or pre-programmed rules, but are generated based on statistical pattern recognition, and/or modeling. Although these CDS systems are a growing use case for incorporation of artificial intelligence in clinical practice, they have not been widely implemented.[23]

Aside from knowledge source, CDS systems are also categorized based on the function and action performed. The National Institutes of Health Pragmatic Trials Collaboratory and the Agency for Healthcare Research Quality has six broad categorizations of CDS systems based on functions and actions: alerts and reminders, dashboards, dynamic guidelines and workflow support, info buttons and reference guides, tailored forms and flowsheets, and order sets (Table 1).[31] Moreover, CDS systems can have multiple functions—for example, an alert that delivers information regarding a guideline and is linked with an order set. The delivery of CDS actions and functions to an end user is conceptualized under the “5 rights of CDS” framework. This was first developed by Osheroff et al in 2007 and states that CDS should deliver “the right information, to the right person, in the right format, through the right channel, at the right time in the workflow.”[39]

CDS USE-CASES IN HEPATOLOGY

Alerts and reminders

The most common application of CDS systems in hepatology care thus far has been in chronic hepatitis B and C screening. Common implementations include sticky notes, flags, and best practice advisory (BPA) alerts in the EHR.[35,40–44] For instance, the implementation of a BPA that prompted primary care providers to perform chronic HCV screening for patients seen in the primary care clinics at the University of Michigan increased HCV screening from 8% to 72% over 1 year. Fifty-three patients were newly diagnosed with HCV from this initiative, and all were referred for specialty care. Of particular note, 21% of these 53 newly diagnosed individuals had advanced fibrosis or cirrhosis on evaluation by hepatology.[35] In addition, as EHR systems have become increasingly more sophisticated with patient phenotyping, Chak and colleagues were able to develop a personalized health maintenance alert for chronic HBV screening in patients of Asian/Pacific Islander race or ethnicity. In a double-blind randomized controlled trial (RCT) of the health maintenance alert in 2 populations (the first privately insured and the second with patients with Medicare or Medicaid insurance), > 8299 Asian/Pacific Islanders were not screened in accordance to guideline; those randomized to the alert group were more than twice as likely to complete screening.[45]

While less common, BPA alerts have also been deployed for the diagnosis and management of nonviral liver diseases and cirrhosis. For instance, a single-center prospective pre-post study of a pop-up screen with guidelines for ceruloplasmin use by Tapper et al[46] reduced orders in the outpatient setting by 82% and in the inpatient setting by 40%. Finally, BPAs have also been used in quality improvement in cirrhosis care. In a single-center intervention, Louissaint and colleagues deployed a BPA to increase rifaximin prescribing for patients with a history of HE admitted and discharged from the inpatient setting. The study team developed and deployed 2 one-time alerts that fired on opening the record of a chart after lactulose was ordered and the other during discharge planning. Rifaximin use increased from 53% to 71% after intervention on nonhospitalist and nongastroenterology services. More importantly, 30-day readmissions fell from 17.4% to 9.3% during the intervention period, demonstrating the potential cost savings and improved outcomes due to intervention.[47]

Dashboards

Clinical dashboards are defined as interactive data visualization tools that provide a summary of decision-related clinical information displayed in graphs, charts, or tables.[48] Dashboards have been developed both for HCV treatment and cirrhosis care. In 2012, Fathauer and Meek developed a clinical dashboard for HCV treatment, which included treatment-specific order sets (defined according to guidelines), automated treatment length calculation, quality indicators, and lab results. Items in need of intervention were incorporated or addressed by means of order sets. Actions taken were transferred to the chart. Pilot testing and implementation of this intervention showed active user engagement and equivalent rates of quality indicator completion.[49]

Utilizing the US Veterans Health Administration Corporate Data Warehouse (VHACDW), Kanwal and colleagues built the Population-Based Cirrhosis Identification and Management System (P-CIMS) to identify all patients with potential cirrhosis in the health system and to facilitate linkage to specialty liver care. P-CIMS extracted EHR data from VHACDW and identified patients who had at least 1 documented cirrhosis diagnosis or possible cirrhosis based on previous records. After implementation, ~30% of identified patients with cirrhosis without liver care were linked to hepatology clinics due to P-CIMS. The annual cost of maintaining P-CIMS was determined to be cost-effective, at <$100,000.[36]

Dynamic guidelines and workflow support

Dynamic guidelines are defined as multistep tools embedded into clinical workflows to guide clinicians to the appropriate decision. Weersink and colleagues constructed a CDS guideline system to help with medication management in patients with cirrhosis. The group classified 218 drugs into categories of “safe,” “no additional risks known,” “additional risks known, and “unsafe” for use in patients with cirrhosis. This system was introduced nationally throughout EHR systems throughout the Netherlands, but no formal evaluation has been conducted with regard to effectiveness.[50]

In an example of workflow support for NAFLD, Spann and colleagues created a comprehensive CDS system to identify care gaps in this patient population. Patients were identified based on previously documented diagnostic code and care gaps, defined as having missing laboratory values (such as aspartate transferase, alanine transferase, and platelet count) to calculate the Fibrosis-4 Index for Liver Fibrosis. In their evaluation, Spann and colleagues demonstrated significant care gaps in patients with NAFLD diagnoses, with 52% of patients missing screening labs. Moreover, only 3% of patients with abnormal liver enzymes were referred to hepatology.[37]

Finally, the Veterans Administration Health Services Research and Development Service (VAHRDS) developed a combined clinical decision-making and workflow support tool for cirrhosis management, called the Cirrhosis Order Set and Clinical Decision Support (CirrODS). This tool consists of 2 primary frames/interfaces with relevant patient clinical data and potential evidence-based tests and treatments to be ordered. The CirrODS system is intended to be a web-based interface accessed through and read/write to the Veterans Health Information Systems and Technology Architecture (VistA).[51] As of April 2022, CirrODS has been approved with constraints, and has been listed in the VA Technical Reference Model an available software system for VistA.[52] So far, however, there have not been any published effectiveness or implementation evaluations of cirrhosis-specific workflow support tools.

Order sets

Electronic order sets are predefined templates that standardize and expedite management for a specific condition or a set of conditions. The most common uses of order sets have been for single, discrete clinical decisions. For instance, a 3-hospital academic health system implemented and evaluated an electronic order set governing albumin use. An interrupted time-series analysis of the intervention showed an increase in the amount of albumin appropriately administered and a reduction in the overall use of albumin across the health system.[53] In addition, a single-center implementation of an electronic order set for antibiotics and octreotide for patients with known or suspected cirrhosis who presented with signs and symptoms of upper gastrointestinal bleeding significantly reduced the time to administration of these medications but did not improve time to procedure.[54]

Order sets governing multiple aspects of clinical care have also been evaluated in cirrhosis. Tapper and colleagues implemented an electronic checklist with goal-directed lactulose therapy and rifaximin for overt HE and antibiotic prophylaxis for spontaneous bacterial peritonitis. The checklist items were incorporated into the electronic provider order entry system for Beth Israel Deaconess Medical Center, and outcomes were assessed preintervention and postintervention. During the electronic phase of the study (there was a hand-held checklist phase in addition to the electronic phase), study participants had 40% lower adjusted odds of 30-day readmissions compared to the control period.[38]

The most ambitious implementation and evaluation of standardized order sets governing multiple aspects of cirrhosis care thus far is the Cirrhosis Care Alberta (CCAB) trial organized by the Alberta Health Services (AHS). CCAB is a 4-year multicomponent pragmatic type 1 hybrid effectiveness-implementation trial with the intervention being the CCAB intervention, defined as a standard clinical information system order set governing 3 domains: management of cirrhosis complications, management of broader health needs, and preparation for transition into the community (Table 2).[55] These order sets will be implemented into eight medical centers in Alberta. The primary effectiveness outcome assessed will be cumulative 90-day hospital length of stay. Secondary effectiveness outcomes include admission rates, readmissions, emergency room visit rates, outpatient visit rates, health care utilization, quality of care, and patient and caregiver experiences. Unique to this trial, this is one of the first trials within hepatology that will concurrently assess implementation outcomes using the reach, effectiveness, adoption, implementation, and maintenance framework.[55,56]

POTENTIAL PITFALLS OF CDS

Although certain use-cases of CDS in hepatology care have proven to be effective, systematic reviews and meta-analyses of CDS systems across the entirety of clinical medicine have shown mixed results. One of the first such pooled analyses of CDS systems on clinician performance and patient outcomes was published in 1994 assessed available studies from 1983 through February 1992. In this critical appraisal by Johnston and colleagues, the authors found 28 controlled trials that met their inclusion criteria and reviewed in detail, of which only 10 studies assessed patient outcomes. Of those 10 studies that assessed patient outcomes, only 3 reported significant improvements.[57]

In 2005, Garg and colleagues reviewed 100 trials examining > 3826 practitioners or practices prior to March 1998. The authors found that of the 97 controlled trials assessing clinician performance, 64% improved care processes. Fifty-two of the 100 trials assessed patient outcomes, often in a limited capacity without adequate statistical power to detect clinically important differences. With these limitations, only seven out of the 52 trials that assessed patient outcomes reported improved outcomes.[58] In 2012, Bright and colleagues reviewed 148 RCTs of CDS systems. The authors grouped studies that assessed the same outcomes in the same manner and found that both commercially and locally developed CDS improved health care processes related to performing preventative services, ordering clinical studies, and prescribing therapies.[59] Finally in 2020, Kwan and colleagues conducted a systematic review and linked meta-analysis of 122 trials of CDS systems embedded in EHRs from the earliest available date in Medline to August 2019 without language restrictions. The authors showed that CDS systems increased the proportion of patients receiving desired care by 5.8% (95% CI, 4.0%–7.6%) with substantial heterogeneity. More significantly, in the subset of 30 trials that included clinical outcomes, the authors found no significant improvements.[22,60] Factors thought to be contributing to the mixed efficacy of CDS systems reported include the lack of interoperability across EHR platforms, lack of patient engagement, and lack of human factors engineering in CDS design.[61]

The development, timely maintenance, and upkeep of CDS systems have also been described as potential barriers to adoption and implementation.[23] Most state-of-the-art CDS systems require compliant EHR systems, such as EPIC or Cerner, for implementation, which may be prohibitive in low-income or middle-income countries and care settings.[62] Upfront implementation costs for specific CDS systems are variable based on preexisting institutional infrastructure and could range from hundreds of thousands to millions depending on the specific setting.[63] Ongoing maintenance and upkeep could pose an indefinite challenge as updates may be required to reflect new clinical knowledge and staff may need to be continuously trained to fully use CDS systems. As the potential effectiveness of CDS interventions often depends on adoption and usability, there are concerns that low familiarity with digital technologies may be a substantial impediment to effective deployment.[23] Finally, previous cost-effectiveness analyses of CDS systems have been mixed and sparse due to heterogeneity in measurements and accounting of costs. Despite these concerns, however, the overall consensus is that CDS systems have substantial potential to reduce clinical costs.[23,63,64]

STRATEGIES TO IMPROVE CDS ADOPTION AND USE

Interoperable application programming interfaces

The trend of EHR vendor market consolidation has resulted in individual and proprietary terminologies and ontologies for data with EHRs, which may differ from commonly accepted standards.[65,66] The emergence of individual standards could create problems with interoperability and deployment of CDS systems across different EHR platforms. The Substitutable Medical Applications and Reusable Technologies on Fast Health Interoperability Resources (SMART-on-FHIR) application programming interface is a standard-based interoperable platform for EHR systems.[67,68] SMART-on-FHIR allows for the development of more complex and prospective CDS systems by securely and automatically pulling in relevant patient data from the EHR.[67,68]

SMART-on-FHIR applications are designed to be platform agnostic and could be deployed in multiple EHR implementations, such as EPIC and Cerner. Moreover, a robust "app gallery" has been established for SMART-on-FHIR to display publicly available applications for the most popular EHR platforms. SMART-on-FHIR-based CDS systems have historically been shown to have excellent usability and improved process outcomes.[25] The use of the SMART-on-FHIR application programming interface is a strategy to overcome barriers to creating, implementing, and sharing CDS approaches across institutions and platforms.

Human-centered design

The most common criticism of and perhaps the greatest vulnerability of CDS systems is incompatibility with clinician workflows and decision needs. Clinicians work in complex information environments that include multitudes of related information objects, such as laboratory studies, biometric readings, radiographic imaging, and clinical notes. The design of CDS systems to support clinicians' ability to rapidly comprehend prompted information and convert it into action is challenging at best.[69] The most common manifestation of this challenge is "alert fatigue," defined as where clinicians become desensitized to alerts and as a result ignore, bypass, or fail to respond to them.[27] Other workflow issues may include misalignments between established care workflows, patients' clinical conditions, and deployment/timing of CDS recommendations.[23]

Failures of human factor engineering in CDS often results in the inability to deliver the "5 rights of CDS." To overcome this issue, user experience and the human-computer interface should be actively considered in CDS design.[61] Human-centered design (HCD) is an approach that systematically engages with and prioritizes the needs and preferences of end users in the development of a service or intervention. Key aspects of HCD in health care settings include understanding clinicians, how they think and behave, and how they are influenced by their work environments. By addressing the functional and usability aspects, HCD helps to construct interventions that end users will actually use.[70–72]

One of the most widely used, applied, and adapted visualizations of the HCD process is the "Double Diamond Model" developed by the British Design Council in 2004.[73] The Double Diamond model divides the HCD process into 4 main activities: discover, define, develop, and deliver (Figure 1). Activities included in the HCD process may include user observations, interviews, focus groups, co-creation, and prototyping.[71] HCD has been used in CDS design for multiple clinical scenarios, such as in management of massive transfusions,[74] hypertension in chronic kidney disease,[75] and pulmonary embolism.[76]

CDS design for cirrhosis care is a unique test case for HCD for multiple reasons. First, cirrhosis and its complications indirectly or directly impact multiple non-hepatic organ systems. The delivery of guidelines-based cirrhosis care requires integrating data from multiple disparate sources throughout the EHR. Moreover, clinical workflows for cirrhosis care often rely on multiple clinical specialties working collaboratively to deliver the necessary care. Designing a CDS system for chronic liver disease and/or cirrhosis care, therefore, must consider not only the informatics considerations, but also the human factor needs, and disease-specific knowledge (Figure 2).

OPPORTUNITIES RELEVANT TO AND ENABLED BY CDS IN HEPATOLOGY CARE

Pragmatic RCTs

The first is for evaluating interventions, specifically conducting electronically enabled pragmatic RCTs. While the RCT generally provides the highest level of evidence for clinical practice, it is also a highly controlled exercise in practice and may not reflect real-world conditions. EHRs can now support RCT-related tasks, such as electronically assessing eligibility, stratified and blocked randomization, and intervention delivery according to randomized assignment. CDS systems are an intervention that could be tested in this way, with enrollment and randomization occurring automatically, and delivery of the CDS to the clinician during usual clinical workflows such that the trial can be fully embedded into the EHR with minimal disruption to the clinical workflow.[77,78] The unit of randomization would have to be chosen carefully to balance power considerations versus the risk of contamination, where patients may be exposed to factors associated with the alternative randomization assignment.[79,80]

Operationalization of complex algorithms

There has been tremendous excitement about applications of machine learning (ML) in the care of liver diseases and liver transplantation. ML algorithms have been trained and developed in multiple aspects of hepatology care—a few limited examples include the early detection of NASH,[81] treatment recommendations in HCC,[82] and determining post-transplant outcomes in patients with acute-on-chronic liver failure.[83]Yet, while predictive modeling and ML have the potential to impact care—in practice, implementation and evaluations of these algorithms have been difficult. Clinical utility, financing, technology, data requirements, and integration into clinical workflows have been identified as significant barriers to incorporation into clinical use.[84] CDS systems may be a potential solution to some of these barriers, specifically being able to automatically assess and retrieve complex data for computation of potential outcomes (Figure 3). Moreover, the use of application programming interfaces and standards such as SMART-on-FHIR eases dissemination across institutions.[67,68] Delivery of the information, such as the clinical decision recommendation or modeling outcome, into an integrated environment to the clinician through CDS would facilitate actual use. Finally, pragmatic RCTs as described above and implemented through CDS, would be a logical mechanism to evaluate the validity of predictive models and ML algorithms.[77,78]

Patient-facing portals

Patient-facing portals, such as “MyChart” systems, can serve as vital tools for the management of chronic liver diseases. One particularly relevant use-case is the efficient and effective gathering of patient-reported outcomes like health-related quality of life, which are diminished in patients with chronic liver diseases and cirrhosis.[85] Health-related quality of life measurement tools, such as the Chronic Liver disease Questionnaire, Short Form-36, and Patient-Reported Outcomes Measurement Information System-29, have all been studied previously in patients with liver diseases.[85–87] Measurement tools could be deployed through patient portals prior to appointments to collect data that then could be integrated into CDS systems to guide clinicians. This integration could improve the tracking of disease progression and manage complications and decompensations in a timelier manner.[88] Another use-case is the deployment of patient decision support and education tools, which have been pilot tested in shared-decision-making in the liver transplantation,[89] treatment of HCC,[90] and treatment of chronic hepatitis C in patients with chronic kidney disease.[91] Despite these advantages, patient-facing portals also pose several significant challenges for clinicians. One significant concern is the possibility of patients receiving critical test results prior to an opportunity to discuss the findings with their health care providers. Mis-interpretation of raw clinical data is another risk as medical information could be difficult to understand without proper context and explanation.[23,92] Moreover, direct patient messages to clinical teams have been identified as a potential driver of clinician burnout.[93] Patient-facing portals, therefore, pose unique challenges and rewards for the future development and deployment of hepatology-specific CDS systems.

Generative artificial intelligence

Since the release of ChatGPT in November 2022,[94] there has been significant technological innovation and advancement in the generative artificial intelligence (GAI) space. We have previously demonstrated potential use-cases for ChatGPT and other GAI technologies in clinical hepatology.[95] Several institutions have trained or are in the process of creating large language models trained specifically on clinical data to allow mining of unstructured clinical narratives in EHRs. GaterTron, a large language model trained on more than 90 billion words of text in the University of Florida Health EHR, is one such example of a clinically focused GAI model.[96] The presentation, delivery, and implementation of GAI technologies, however, will likely be through CDS and EHR-based interventions. Already, ChatGPT has been used to fine tune CDS by improving the specificity of alert logic.[97] Initial applications of GAI will likely be in drafting and editing notes and reports, but will ultimately shift toward improving the quality of information for tasks. Ultimately, GAI is expected to be integrated into clincial workflows and help augment clinicial decision-making.[98]

Toward precision and personalized medicine

Finally, the ultimate application of CDS would be for the facilitation and actualization of precision and personalized medicine (the logical conclusion of precision medicine). Precision medicine is commonly described as the elucidation of disease at a more detailed level through the integration of multiomic data and tools.[32,99,100] Genomic sequencing has been used in many applications to better understand the biological underpinning of NAFLD and HCC, as well as to generate prediction models that stratified patient groups.[32] Integration of advanced genomic data may facilitate the delivery of targeted interventions in patient management through CDS.

In one notable example in pediatrics, Owen and colleagues developed “Genome-to-Treatment,” an automated, CDS system for genetic disease diagnosis and acute management guidance for childhood genetic disease. This system integrated rapid diagnostic whole genome sequencing with unstructured data extraction from the EHR by means of natural language processing to deliver guidance on initial treatment management for critically ill children in the intensive care setting at the time of diagnosis.[101] While “Genome-to-Treatment” is only one demonstration in neonatal critical care, the principles behind its construction could one day be applicable for hepatology care. For instance, one could foresee a day in the future when CDS systems utilizing artificial intelligence models to process genomic and real-time EHR data give more accurate, comprehensive, and real-time prediction of mortality with complications of cirrhosis and make recommendations on medical treatment and timing of transplantation.[102] This future is rapidly approaching and closer than we think in hepatology care.

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CONFLICTS OF INTEREST

Jin Ge consults for Astellas Pharmaceuticals/Iota Biosciences. He received grants from Merck. Valy Fontil owns stock in EngageRx. Jennifer C. Lai consults for Genfit. She advises Novo Nordisk. She received grants from Axcella Health, Flagship Pioneering, Lipocine, Pliant, and Vir Biotechnologies. The remaining authors have no conflicts to report.

Abbreviations:

AHS	Alberta Health Services
API	application programming interface
BPA	best practice advisory
CCAB	Cirrhosis Care Alberta
CDS	clinical decision support
CirrODS	Cirrhosis Order Set and Clinical Decision Support
CMS	Centers for Medicare and Medicaid Services
EHR	electronic health record
GAI	generative artificial intelligence
HCD	human-centered design
HITECH	Health Information Technology for Economic and Clinician Health
ML	machine learning
ONC	Office of the National Coordinator
P-CIMS	Population-based Cirrhosis Identification and Management System
RCT	randomized controlled trial
SMART-on-FHIR	Substitutable Medical Applications and Reusable Technologies on Fast Health Interoperability Resources
VAHRDS	Veterans Administration Health Services Research and Development Service
VHACDW	Veterans Health Administration Corporate Data Warehouse
VistA	Veterans Health Information Systems and Technology Architecture

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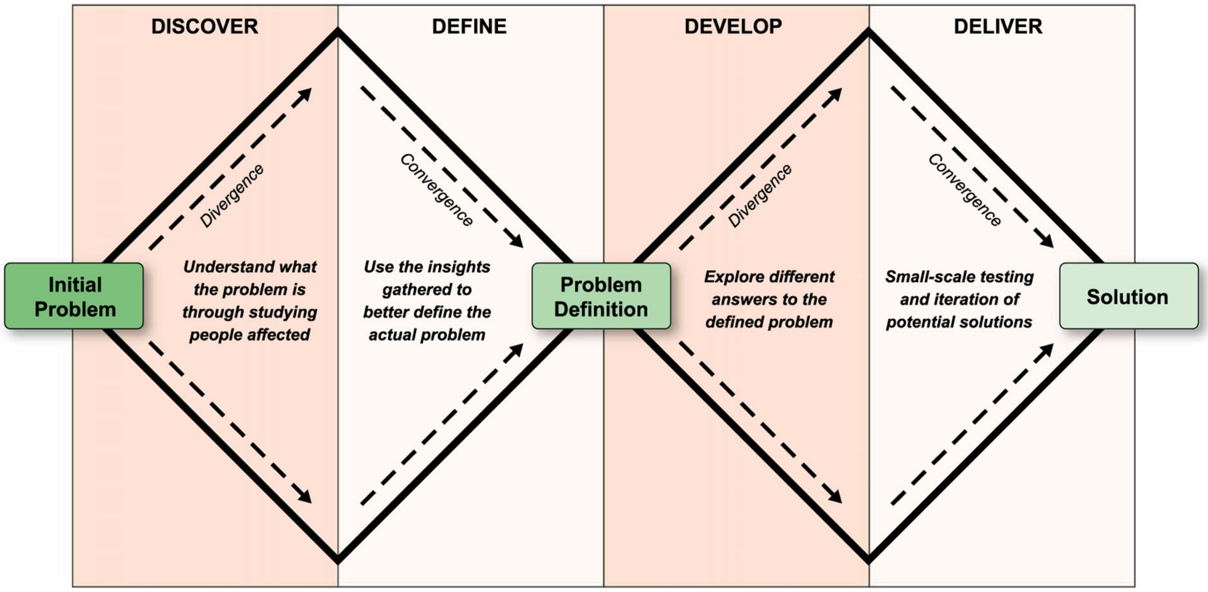

FIGURE 1.

Double diamond model for human-centered design. Adapted from the British Design Council under the CC BY 4.0 International License. https://creativecommons.org/licenses/by/4.0/.

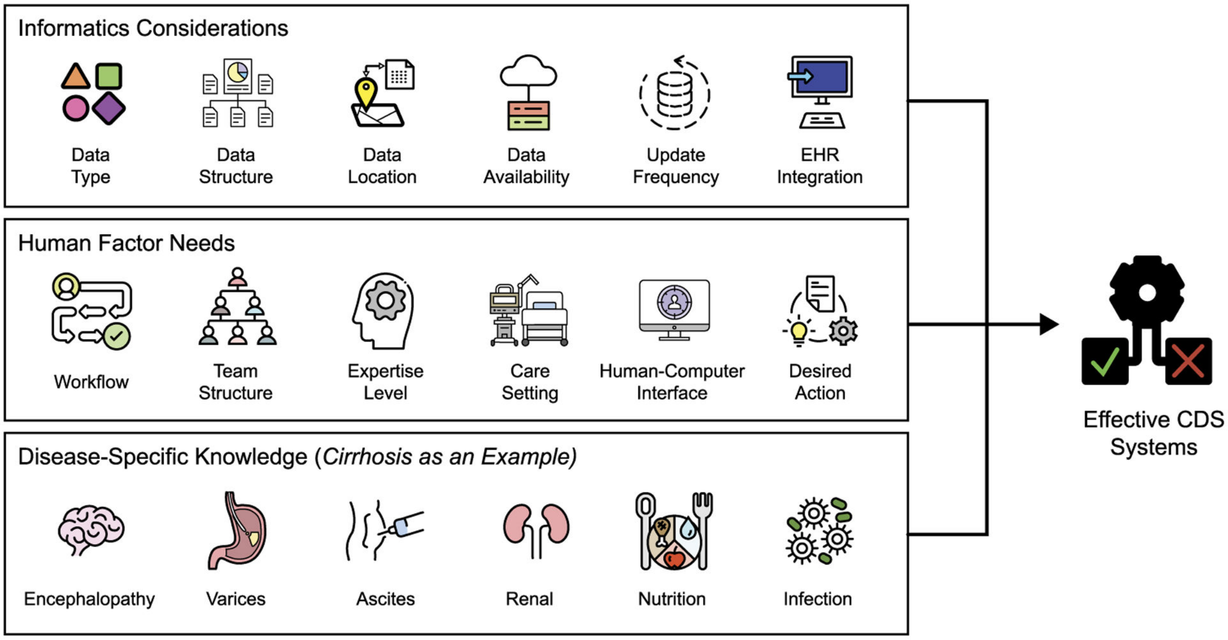

FIGURE 2.

Informatics, human, and disease-specific factors for CDS in hepatology. Abbreviation: CDS, clinical decision support; EHR, electronic health record.

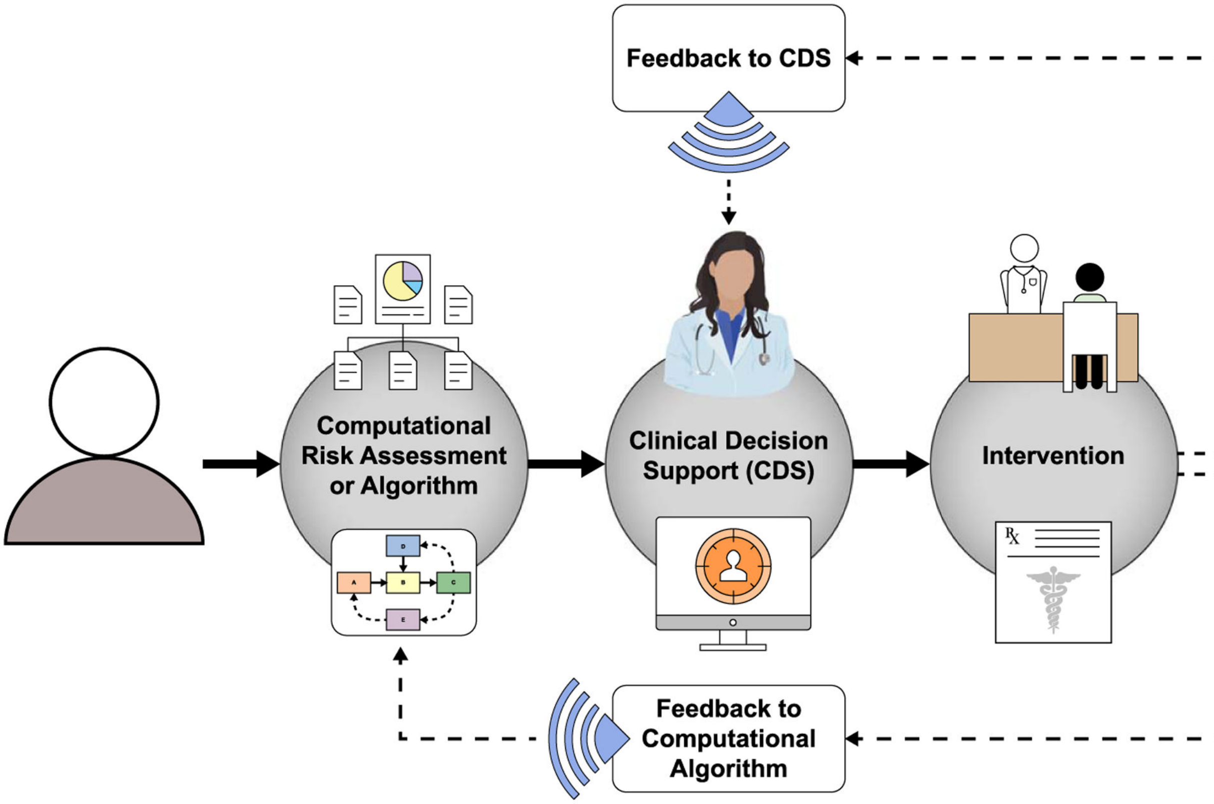

FIGURE 3.
Incorporation of complex algorithms in hepatology CDS.

TABLE 1

Most common types of clinical decision support

CDS type	Description	Example in hepatology
Alerts and reminders	Passive or active notifications that guide and provide more information regarding a clinical decision	Best Practice Advisory for hepatitis C screening[35]
Dashboards	Visualizations and tables for population-based decision-making and monitoring	Population-based Cirrhosis Identification and Management System (P-CIMS)[36]
Dynamic guidelines and workflow support	Multistep tool embedded in clinical workflow that results in a recommendation based on user responses	Care gap identification for NAFLD[37]
Infobutton and reference guides	Integrated resources to provide knowledge at the time of decision-making	Links to clinical reference knowledge
Tailored forms and structured documentation	Structured documentation templates	“Smartsets” and “Smartphrases”
Order sets	Predefined orders that standardize management around a specific condition	Goal-directed checklist and order sets for HE[38]

Adapted from NIH Pragmatic Trials Collaboratory.[31]

Abbreviation: CDS, clinical decision support.

TABLE 2

Cirrhosis care Alberta order set domains[55]

Domain #1—management of cirrhosis complications	Domain #2—management of broader health needs	Domain #3—preparation for transition into the community
Alcoholic hepatitis Ascites Hepatic hydrothorax spontaneous bacterial peritonitis Spontaneous bacterial pleuritis Renal dysfunction Hepatorenal syndrome Variceal bleeding HE	Alcohol use disorder physical frailty (nutrition, physical activity) Advance care planning and goals of care designations	Providing standardized patient education Providing postdischarge diagnostic imaging, labs, and procedure requisitions arranging follow-up with primary and specialty care providers