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Enhancing diagnosis through technology: Decision support, artificial intelligence, and beyond

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Introduction

Critical care settings are complex environments that are well-suited for diagnostic clinical decision support (CDS). First, the patients are critically ill and decisions need to be made quickly in order to avoid rapid patient deterioration, morbidity and mortality.[1] Second, the clinical issues are often quite complex with involvement of multiple organ systems and surgical procedures.[2] Finally, the variety, velocity, and volume of the data generated in these settings can be very large--pushing the limits of human cognitive abilities to process all the relevant data in a timely fashion. For these reasons, clinical decision support is a set of promising approaches that can allow technology to partner with clinicians to provide high-quality, safe, and effective care.

Types of Clinical Decision Support

A clinical decision support (CDS) system is defined as one that “provides clinicians, staff, patients, or other individuals with knowledge and person-specific information, intelligently filtered or presented at appropriate times, to enhance health and health care.”[3] The breadth of this definition encompasses a wide range of potential systems. Wright and colleagues developed a taxonomy of CDS interventions that spans this range.[4] In Table 1, we briefly introduce those categories with direct relevance to diagnostic decision support.

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Categories of diagnostic decisions & applications of CDS

Diagnostic tasks in critical care

The diagnostic process in critical care involves multiple different activities as described in earlier chapters. Figure 1 shows one potential model to organize these activities into five broader categories. Each of these diagnostic steps has the potential to be supported by different types of CDS and we describe a few examples to highlight these possibilities—recognizing that evolving CDS capabilities set the stage for ongoing innovation.

Recognize indication for intensive care unit (ICU)—The first step to appropriate care in intensive care units is to recognize the indication for ICU admission. When patients require ICU care at their initial presentation, this triage requires an accurate assessment of illness severity during the initial evaluation. This triage can be supported by illness-specific and/or general severity of illness scores. Illness-specific scores (such as CURB65 for community-acquired pneumonia[5]) can perform well in targeted scenarios, but performance is somewhat variable.[6,7] General severity of illness scores and early warning systems (such as APACHE IV[8], pSOFA[9], SIRS[10], MEWS[11]) characterize overall physiologic derangements and have also shown mixed results when implemented into workflows.[6,12] However, if validated through well-designed studies, data-driven triaging tools may help ensure that critically-ill patients are brought to the attention of ICU teams soon after initial presentation.

Another high-risk group of critically-ill patients is those who do not require ICU level of care at initial presentation to the hospital, but deteriorate during their stay. Early recognition of this deterioration is crucial to prompt intervention to rescue these patients. Rapid response teams (RRTs) have been instituted to extend critical care expertise outside of ICU. Failure to activate the RRT is one of the biggest contributors to failure to rescue.[13] As with severity of illness scores for initial presentation to the hospital, several data-driven deterioration scores have been developed for hospitalized patients. These systems for early detection of deterioration within the hospital have promise, but the true impact on outcomes remains unclear.[14,15]

For both the initial severity of illness models and the deterioration scores, the scores will be most useful when integrated directly into EHRs.[16] The score may be presented in the overview of groups of patients for prioritizing evaluation. In addition, the scores could be used to trigger specific alerts to prompt consideration of additional diagnostic and therapeutic interventions. For example, a general deterioration score can be shown as a column on a patient list and sorted to help teams see higher-scoring patients earlier in the day. These scores may also trigger “proactive rounding” by rapid response teams with the goal of preempting the need to transfer patient to a higher level of care.

Formulate plan—Once the patient has been triaged for evaluation for ICU admission, that evaluation requires a rapid collection of relevant clinical data. Providers face significant challenges gathering these data as they are often scattered across many sources and not well-organized.[17] When surveyed about chart review workflow during initial evaluation, half of providers described their process as haphazard or disorganized. In addition, they noted that their diagnostic and therapeutic strategy was often established by chart review alone.[18] Findings such as these highlight opportunities to improve data aggregation, summarization and visualization for critical care providers. Efforts are underway to develop data displays that of better aligned to clinician cognitive processes,[19,20] but these displays have not yet had widespread adoption. Documentation templates have also been used to improved data gathering by prompting clinicians to obtain a complete set of clinical data for initial evaluation. In addition, these templates can automatically import data from the EHR into the note to facilitate review.

Beyond merely obtaining all relevant clinical data, critical care providers must integrate and interpret these data to properly assess the patient's current clinical state and trajectory and to drive appropriate diagnostic and therapeutic interventions. Well-designed data displays can highlight important information[21] and enable interactive exploration of clinical data.[22–24] The latter capability is important as there is sufficient variability among critically ill patients to require a personalized approach to data review.[23] Studies in simulated environments have shown significant impact, but translation of these results into real-world settings has remained elusive.[22] At least one study using a simulated EHR environment demonstrated decreased search time and fewer errors using a problem-oriented view of clinical data.[25]

A key step in diagnostic evaluations is to have an appropriately broad differential diagnosis (prioritized list of potential diagnoses) early in the process. Different forms of CDS can be used to facilitate the creation of the differential diagnosis. The organization may provide links within the clinician workflow to curated clinical references (e.g., DynaMed, UpToDate, etc.) to enable point-of-care review of relevant knowledge and diagnostic guidelines. Checklists are another potential intervention and several critical care-specific checklists have been created.[26] These checklists can be linked as references or some may be incorporated directly into the assessment and plan sections of documentation templates.

Expert systems can also be used to provide additional support both for development of differential diagnoses and for identifying the additional clinical information that would help narrow down the diagnosis (i.e., the best next test). Briefly, expert systems rely on a large corpus of "if-then-else" rules derived from clinical experts and the scientific literature to help clinicians identify the correct diagnosis.

Preliminary data suggests an expert system can be useful in the general medical inpatient setting[27], but robust evaluation within critical care settings is currently unavailable. Better integration of expert systems into EHRs could help reduce the data entry requirement that is often cited as a barrier to their use.

When infections are considered, one aspect of diagnosis is to consider the potential causative organisms. Expert systems can be used to ensure that the appropriate spectrum of potential infectious causes is considered and consequently that appropriate antimicrobial therapy is selected. One such system was shown to improve both patient outcomes and lower costs.[28]

Critical care settings, as with many others, often involves a substantial number of care handoffs. Therefore, proper documentation of clinical reasoning and certainty around the working diagnosis is an important step to continuity of care across these transitions.

Documentation templates have been used to prompt the recording of diagnostic reasoning, although there is limited published literature describing their impact in critical care settings.

Execute plan—CDS has a clear role in supporting the execution of diagnostic plans. One function of CDS during this stage is to ensure that the intended workup includes all relevant orders. Order facilitators, such as indication-based order sets, can serve as evidence-based or standard of care collections of related orders to avoid inadvertent oversight. For example, these order sets can include related diagnostic tests for samples collected during procedures such as paracentesis, thoracentesis or lumbar puncture or a set of tests to work up anemia. These order sets may also include consultations to specialists in certain circumstances.[29]

In addition to prompting consideration of tests, CDS may also be used to highlight potentially low-yield or inappropriate tests as part of diagnostic stewardship programs. Examples include alerts highlighting when laboratory tests are ordered more frequently than likely to be clinically useful[30,31] and when tests for *Clostridioides difficile* are ordered on patients lacking clear indications[32]. Initial studies of these approaches have suggested decreased test utilization can be achieved without adversely affecting patient outcomes.

CDS during ordering can also be used to suggest alternative tests that may be more appropriate for that particular patient. This approach has been used for advanced imaging studies. Based on the indication for the test and patient-specific criteria, the system can present the ordering provider with alternative imaging that may be more appropriate.[33] It has yet to be seen whether this approach leads to substantial changes in imaging or whether clinicians alter their interaction with the system to satisfy the appropriateness check and to obtain their initially-desired test.

Recognize events and changes in clinical status—The large volume of data collected on patients while they are in the intensive care units presents a challenge to the care teams. They must process these data to promptly respond to new test results, clinical events and changes in patients' status. A key role for CDS is to facilitate this process. The approaches mentioned above to improve data summarization and visualization are likely to be helpful in enabling clinicians to recognize important events and changes in status.[19–21]

Diagnosis in intensive care settings involves many team members and therefore the CDS systems can target a wide range of providers. Nurses likely have the most time directly at patients' bedsides and are key partners in diagnostic processes. The effectiveness of CDS for ICU nurses has not been fully evaluated. This area represents a substantial opportunity to support diagnostic excellence.[34] One approach that has been well-studied is the use of daily screening checklists (often facilitated within EHRs) for the identification of delirium in the ICU[35], although early diagnosis of this condition does not always lead to effective intervention.[36]

Respiratory therapists are also crucial members of the diagnostic team in ICUs. There can be substantial overlap between diagnosis and optimal treatment for patients receiving invasive and non-invasive ventilation. For example, adjustment of ventilator settings involves diagnosis of an opportunity to wean ventilation or a need for adjustment to provide effective therapy. Systems have been developed to analyze mechanical ventilation pressures, flows and settings and make recommendations to providers regarding potential patient-specific adjustments.[37,38]

Checklists can represent a manual process to identify patients at high risk of events. Developing models that automatically calculate risk scores based on EHR data can add powerful options for early detection of important conditions in ICUs. These models may be based on traditional methods such as logistic regression. Examples include models to identify risk of acute respiratory distress syndrome after trauma[39] or development of acute kidney injury[40].

More complex artificial intelligence predictive algorithms have the potential to improve the performance of these predictions. As Yu and colleagues describe, "with deep-learning algorithms, raw patient-monitoring data could be better used to avoid information overload and alert overload while enabling more accurate clinical prediction and timely decision-making."[41] These approaches are being applied to predict a variety of intensive care conditions such as hypotension[2] or the onset of sepsis[42]. The scores from checklists or predictive models can be shown directly to providers and used to trigger alerts or additional protocols.

Transition out of ICU—Similar to other settings in the hospital, the transition at the time of discharge from the ICU requires effective communication of the status of the diagnostic workup and any diagnosis-related follow-up required.[43] This communication should involve both the patient and subsequent providers.[43] The transfer of ICU patients to the general wards is a vulnerable process and is often not standardized.[44] From a CDS standpoint, documentation templates have been used to improve the completeness of information transfer.[44] While opportunities remain to improve information transfer during this transition, we lack evidence regarding the most effective support of this process.[45]

Diagnostic feedback for calibration—We expect clinicians to improve the calibration of their diagnostic decision-making with experience. This process requires ongoing feedback of the outcomes of their decisions, but this feedback is often lacking[46–48]. Improving patient data visualization to enable clinicians to "close the loop" on their decisions has the potential to meet this need and improve diagnostic performance over time. One example of such a system may include provider-specific dashboards that highlight recent patients and their outcomes after care was handed off to other providers, such as the Post-Handoff Reports of Outcomes (PHAROS) system.[49] In an ICU setting, such a system could be modified to highlight specific downstream outcomes or events of interest, including return to ICU, urgent/emergent surgical procedures, death, etc. These dashboards could be coupled with dedicated time to reflect on the care of recent patients to identify both individual and organizational opportunities for improvement.

Implementation issues

Clinical decision support is one component of a complex care environment.[50] In addition to the quality of the data and the accuracy of any predictions, the implementation of CDS systems can greatly affect their impact[51]. Prior experience with CDS across a variety of settings has provided best practices regarding the development of CDS—encapsulated by the "5 Rights of CDS"[52] (Table 2).

As artificial intelligence (AI), machine learning and other predictive models become more widespread, one key aspect of increasing their impact is to ensure that the output of these models is directly tied to a specific clinical workflow[53]. That is, if a patient is found to be at risk of a significant clinical outcome, who gets notified and what action is then taken? Without clear delineation of these aspects of the workflow, the identification of high-risk scenarios may not lead to improved patient care.

Given the complexities of incorporating CDS systems into ICU settings and their potential impact on providers and patients, having clear governance of CDS portfolios is recommended[54]. This governance involves careful consideration of how new CDS will affect the care environment and its participants before implementation. It is also important to develop tools and processes to monitor CDS interventions over time and to promptly adjust, optimize or deactivate them if the clinical scenarios warrant.[54]

Future directions and opportunities for CDS in ICUs

Intensive care settings are well-suited for on-going innovation and additional diagnostic CDS interventions. Artificial intelligence and various forms of predictive modeling using the full spectrum of available electronic data are likely to play a prominent role in this area. Some use cases may involve systems to suggest specific diagnoses based on full record review[55] and models to better identify and highlight unexpected clinical trajectories. Much of the information related to clinician assessments and reasoning is contained in free text notes. For this reason, more extensive use of natural language processing (NLP) will be important to push diagnostic CDS forward[41,56].

There are continued opportunities to improve the display of patient-specific relevant information to reduce the cognitive load on providers and facilitate faster and more accurate clinical assessments. In particular, it will be important to effectively display and model the temporal aspect of diagnostic information. Potential functionality to support this goal includes display of trends with highlighting of substantial changes in vital signs, laboratory values, or other numerical trends[23] as well as using established interactive features such as graphical zoom, pan, and filtering.[24] One specific area that may benefit from this type of approach is the assessment of intravascular fluid status and subsequent fluid management[57,58].

To support reflective practice and ongoing diagnostic calibration, CDS systems should be developed to provide systematic feedback of diagnostic outcomes to clinicians. Functionality that has been used to support clinical care and reporting can be harnessed to augment on-going learning. Improvement opportunities from the systems can be provided at both the individual clinician and organizational levels.

Conclusions

Patient care in intensive care environments is complex, time-sensitive and data-rich--factors that make these settings particularly well-suited to clinical decision support. A wide range of CDS interventions have been used in ICU environments. However, robust data on their impact on patient outcomes is often lacking. The field is in need of well-designed studies to identify the most effective CDS approaches. The continued evolution of artificial intelligence and machine learning models may reduce the information-overload and enable teams to take better advantage of the large volume of patient data available to them. It will be vital to effectively integrate new CDS into clinical workflows and to align closely with the cognitive processes of frontline clinicians.

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Key Points

- Critical care settings are well-suited to diagnostic clinical decision support due to high clinical acuity, time pressure and large volumes and variety of data.
- There are multiple types of clinical decision support that can be helpful at many points in the diagnostic process in critical care settings.
- Evolving approaches using artificial intelligence, machine learning and natural language processing hold promise to improve patient care and provider experiences.
- Diagnostic decision support interventions require careful integration into clinical workflows to have the highest impact and avoid unintended consequences.

Synopsis:

Patient care in intensive care environments is complex, time-sensitive and data-rich--factors that make these settings particularly well-suited to clinical decision support (CDS). A wide range of CDS interventions have been used in ICU environments. The field is in need of well-designed studies to identify the most effective CDS approaches. Evolving artificial intelligence and machine learning models may reduce information-overload and enable teams to take better advantage of the large volume of patient data available to them. It will be vital to effectively integrate new CDS into clinical workflows and to align closely with the cognitive processes of frontline clinicians.

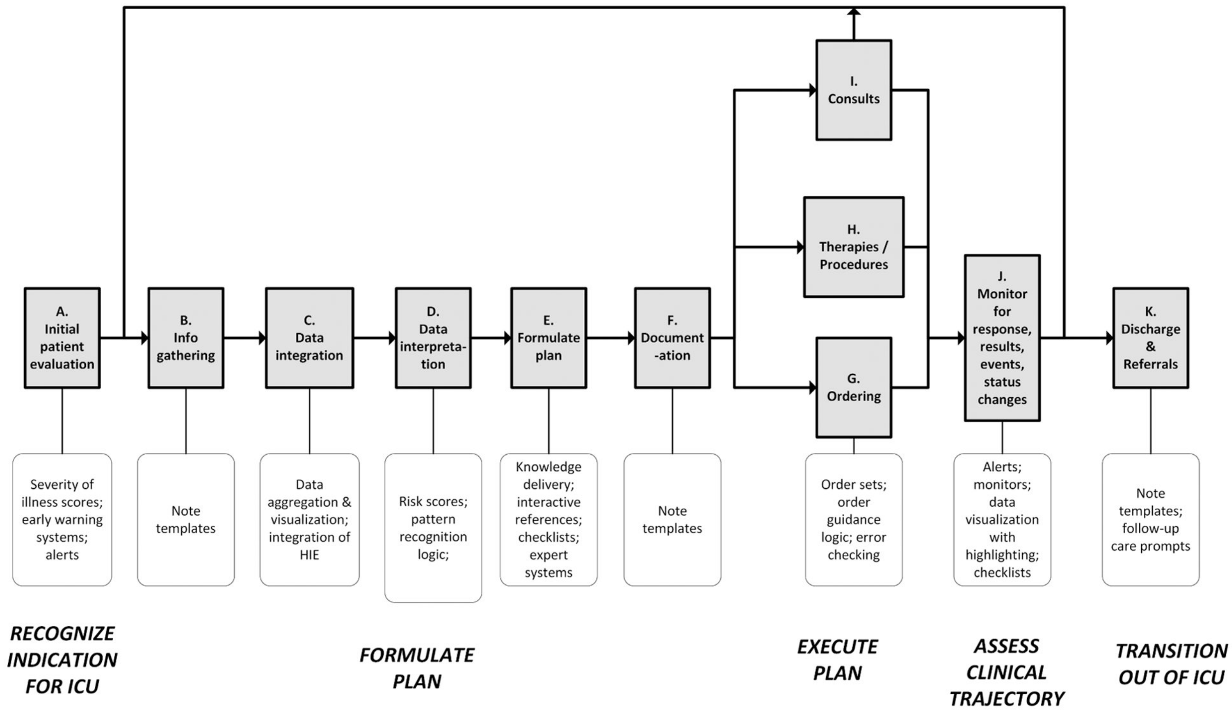

Figure 1.

Categories of Diagnostic Tasks and Potential Uses of Clinical Decision Support (ICU: intensive care unit)

Table 1.

Types of Clinical Decision Support (CDS) for Diagnosis

Type of CDS	Description
Order facilitators	These systems provide grouped sets of orders to streamline commonly ordered items. In addition, systems may request additional information from providers to ensure the proper order is initially selected.
Point-of-care alerts and reminders	These systems may alert providers to specific information using interruptive of passive means, depending on urgency. Examples of potential uses include prompting consideration of specific diagnostic tests, raising awareness of potential complications or interactions and highlighting critical test results.
Relevant information display	These displays may be targeted—such as displaying renal function when ordering a contrast-enhanced imaging study. They may also include more sophisticated data aggregation and visualizations that bring together several data elements to allow clinicians to see patterns and understand the patient's current status and trajectory.
Expert systems	These systems provide complex decision support using a wide range of electronic data. Examples include differential diagnosis generators and risk and prognosis models.
Workflow support	These interventions include support such as templates to facilitate reliable processes. Examples include support for registry functions across multiple patients and documentation aids.

Data from Wright A, Sittig DF, Ash JS, et al. Development and evaluation of a comprehensive clinical decision support taxonomy: comparison of front-end tools in commercial and internally developed electronic health record systems. J Am Med Inform Assoc. 2011;18(3):232–242.

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Table 2.

The Five Rights of Clinical Decision Support

Component	Description
Right information	evidence-based guidance, response to clinical need
Right person	targeting decision-makers– including the patient
Right CDS format	e.g., order sets, flow-sheets, dashboards, patient lists
Right channel	e.g., EHR, mobile device, patient portal
Right time in workflow	for decision making or action

Data from Osheroff JA, Teich JM, Levick D, et al. *Improving outcomes with clinical decision support: an implementer's guide.* CRC Press; 2012.