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**Review**

# Clinical Decision Support for Laboratory Testing

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**BACKGROUND:** As technology enables new and increasingly complex laboratory tests, test utilization presents a growing challenge for healthcare systems. Clinical decision support (CDS) refers to digital tools that present providers with clinically relevant information and recommendations, which have been shown to improve test utilization. Nevertheless, individual CDS applications often fail, and implementation remains challenging.

**CONTENT:** We review common classes of CDS tools grounded in examples from the literature as well as our own institutional experience. In addition, we present a practical framework and specific recommendations for effective CDS implementation.

**SUMMARY:** CDS encompasses a rich set of tools that have the potential to drive significant improvements in laboratory testing, especially with respect to test utilization. Deploying CDS effectively requires thoughtful design and careful maintenance, and structured processes focused on quality improvement and change management play an important role in achieving these goals.

## Introduction

Improving test utilization is a key healthcare priority, as both the underuse and overuse of laboratory tests lead to diagnostic errors and unnecessary costs (1–7). The underlying drivers of inappropriate testing are complex and involve provider education, rapid advances in technology, and professional incentives (8, 9). Addressing these effectively requires a comprehensive strategy incorporating multiple tools, and, as healthcare data are increasingly digital, approaches that leverage information technology are of particular interest (10–13).

Clinical decision support (CDS) refers to a collection of tools that layer clinically relevant information over standard healthcare data interfaces—including electronic health records (EHRs) and computerized physician order entry (CPOE) systems—to enhance patient care and improve clinical workflows (14). Common examples include critical value alerts, medication interaction warnings, and duplicate order notifications. CDS has been successfully deployed in diverse clinical settings, ranging from outpatient clinics to intensive care units (15–18). In addition, CDS has been shown to improve test utilization throughout laboratory medicine (19–24). Nevertheless, many CDS interventions fail to meet their objectives or have unintended consequences, and understanding these failure modes is critical for designing effective applications (25–27).

In this review, we describe the basic structure of common CDS tools as well as the processes underlying successful implementation. By building expert knowledge directly into healthcare data interfaces, well-designed CDS has the potential to play a central role in improving test utilization. In addition, given their expertise in both quality improvement and quality assurance, laboratory professionals have an opportunity to be leaders in this space (28).

## Overview of CDS Tools

While the architectures of different CDS interventions vary, they generally consist of a user interface, a clinical database, and a knowledge base (13). The most common user interfaces are EHRs and CPOEs, although some CDS tools are implemented as separate web or mobile applications and/or communicate with users via text messages or e-mail (29). The clinical database is typically the EHR, which allows the system to execute tasks based on patient-specific information. The knowledge base refers to the rules that determine how the system responds to user actions and patient data streams. Currently, most knowledge bases consist of rules that are explicitly programmed by human experts. Alternatively, there is growing interest in using machine learning to extract clinically relevant patterns from large healthcare datasets to inform decision making. Conventionally, these two approaches (manual vs automated) are designated "knowledge-based" and "non-knowledge–based" CDS.

In practice, CDS interprets user interactions with the interface in the context of patient-specific data and executes predefined actions based on the logic encoded

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**Table 1. Common CDS interventions.**

| Group | Tool | Strengths | Limitations |
|---|---|---|---|
| Data entry and ordering | Test names and aliases | Integrates into workflow; high impact | Lack of national standards for identifiers |
| | Preference lists | Integrates into workflow; high impact | Risk of adding inappropriate orders |
| | Test menu search | Integrates into workflows; high impact | Non-alphanumeric order can make search results difficult to navigate |
| | Order sets | Integrates into workflow; promotes standardization and appropriate use | Fixed components; risk that design errors lead to inappropriate use |
| | Diagnostic algorithms | Integrates into workflow; promotes standardization and appropriate use; promotes interpretability and cost-effectiveness | Increased turnaround time; providers may desire tests run in parallel |
| | Order alerts | Immediate intervention for errors that impact patient safety | Disrupts workflow; risk of alert fatigue; can lead to reactive behavior |
| | Documentation templates | Integrates into workflow; promotes standardization; limits transcriptional errors | Risk of overreliance on templates |
| Data review | Flowsheets | Organizes raw data clearly to facilitate efficient review; trends over time | Complex tests may require custom displays |
| | Dashboards | Summarizes raw data clearly to facilitate efficient monitoring | Fixed components |
| | Result alerts | Immediate notification of results impacting patient safety; promotes appropriate follow-up | Risk of alert fatigue, false positives |
| Provider education | Test information | Promotes appropriate use | May be ignored |
| | Practice guidelines | Promotes appropriate use | May be ignored |
| | Provider feedback | Provides quantitative insight into ordering habits; enables targeted education | May be ignored |

in the knowledge base. In general, CDS actions present providers with clinically relevant information, which can be displayed passively or require additional user interaction. Regarding applications, CDS tools can be broadly grouped into those related to data entry and ordering, data review, and provider education (Table 1) (14).

### DATA ENTRY AND ORDERING

While CDS is commonly associated with reactive tools (e.g., alerts), some of the most effective interventions occur through the design and organization of the interface. For example, electronic test menus often contain nonstandard names or abbreviations as well as tests with

similar names, both of which disrupt clinical workflows and lead to incorrect orders (30). These sources of ambiguity can be resolved by assigning tests names that are clear, descriptive, and distinct. In addition, many CPOEs allow frequently used tests to be collected in facility- or provider-specific preference lists for convenience, but this can exacerbate inappropriate orders if the wrong tests are inadvertently added. For example, one study found that simply removing 25-hydroxyvitamin D from non-specialist preference lists decreased the rate of inappropriate orders from 44% to 30% over a 6-month period (31). Similarly, the order in which tests appear in search results can have a significant impact on test utilization, as shown by a study demonstrating that switching the default order of 1,25-dihydroxyvitamin D and 25-hydroxyvitamin D reduced 1,25-dihydroxyvitamin D test volume by 90% (32). In general, optimizing how orders are presented to users is a powerful (and underused) approach for improving test utilization.

CDS tools designed to assist with test ordering often require the collection of additional patient information, which can be achieved by building structured data entry into individual orders. At our institution, this type of CDS played a critical role in our response to the COVID-19 pandemic. The rapid emergence of SARS-CoV-2 in early 2020 required many laboratories, including ours, to validate multiple molecular testing platforms (e.g., batched and random-access tests) in parallel to accommodate massive demand in the face of global supply constraints. Accordingly, we included a series of multiple-choice questions in our COVID-19 RNA order to collect information about patient symptoms, exposures, and specific indications to route specimens to the appropriate assay format (Fig. 1). This same approach has been used to promote appropriate test utilization in other settings. For example, requiring providers to enter a clinical risk score (4Ts) when ordering anti-heparin/platelet factor 4 antibody tests was found to reduce inappropriate testing for heparin-induced thrombocytopenia from 66% to 56% (33). Likewise, including questions about patient presentation and risk factors in orders for *Clostridium difficile* nucleic acid testing was shown to reduce overall test volume by 41% (34).

Another CDS tool that can be used to structure the ordering process is order sets, which combine orders for multiple tests in selectable templates based on patient presentation (e.g., chest pain), diagnosis (e.g., heart failure), or events (e.g., hospital admission). Order sets are a highly effective form of CDS that integrate smoothly

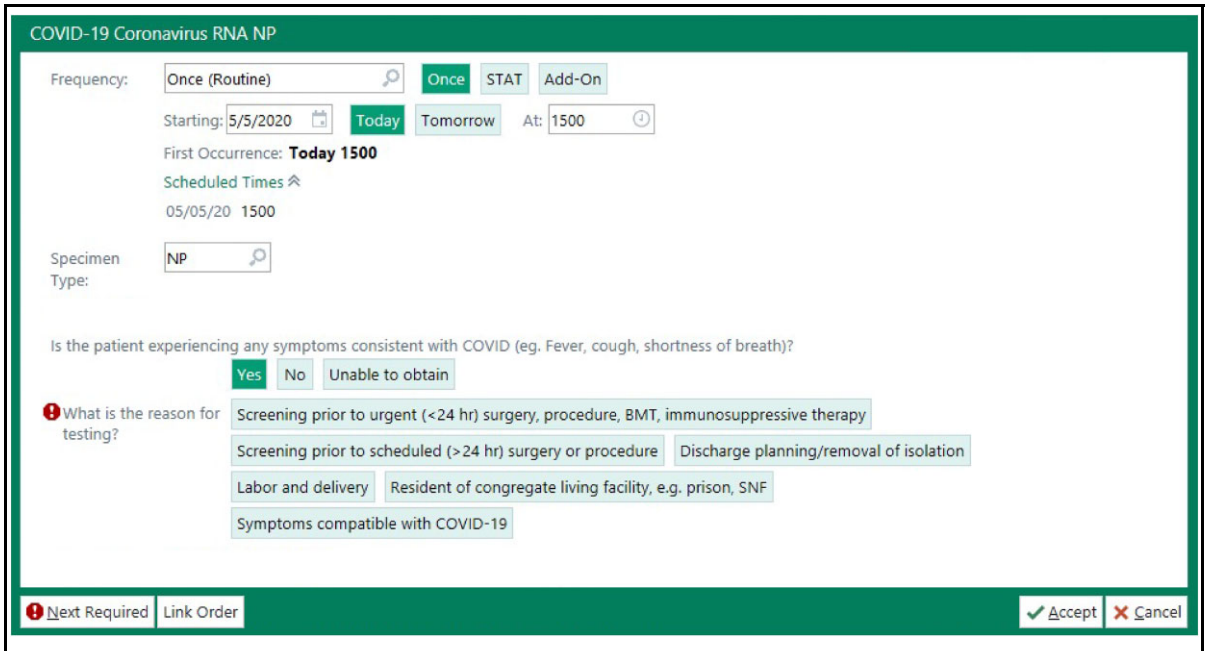


**Fig. 1. COVID-19 RNA order template.**
**An order template for COVID-19 molecular testing (designed in the Epic electronic health record at our institution) collects patient information to route specimens to appropriate assay formats. At the time of the order build (May 2020), a limited number of random-access COVID-19 tests were available and reserved for urgent indications; all other specimens were directed to batched platforms.**

into clinical workflows to promote standardized care and appropriate test utilization. For example, implementing an order set for patients presenting to the emergency department in septic shock was shown to improve antibiotic administration and fluid resuscitation, leading to significant decreases in mortality and length of stay (35). In addition, a recent randomized controlled trial of nearly 10 000 primary care patients showed that using order sets for a variety of common indications reduced inappropriate tests from 62% to 42% (36). Importantly, the specific tests included in order templates—and which elements are pre-selected—are powerful drivers of provider behavior, meaning that order sets must be designed carefully to avoid amplifying undesired practices (37).

An alternative approach to combining test orders is to offer them via diagnostic algorithms (or cascades), in which tests are performed in series depending on the results at each step. As a simple example, one study described implementing an algorithm for thyroid function testing in which free triiodothyronine and free thyroxine were run exclusively as reflex tests in patients with abnormal thyroid stimulating hormone concentrations, which led to significant reductions in inappropriate orders for both free triiodothyronine and free thyroxine (38). By arranging informative tests in logical sequences, diagnostic algorithms often yield results that are easier to interpret while promoting evidence-based utilization and controlling costs, as opposed to the common practice of "shotgun" testing, in which many tests are performed simultaneously. The main limitations of these tools are that they tend to increase turnaround time and that providers need to be oriented to order the algorithm instead of its component tests.

Finally, some of the most common CDS interventions are alerts, which display relevant patient information in response to specific user actions. Alerts can be either interruptive (e.g., pop-up windows) or non-interruptive (e.g., appear in a sidebar), and interruptive alerts can be further subdivided into those that can be overridden (soft stops) and those that cannot (hard stops). In general, hard stops are more effective than soft stops at reducing inappropriate orders, but they risk delaying appropriate care if implemented incorrectly (22, 39). In the context of ordering tests, alerts are frequently used to reduce duplicate orders and promote appropriate utilization (40, 41). For example, an alert conditioned on patient hemoglobin concentrations >7.0 g/dL was shown to durably reduce unnecessary red blood cell transfusions by 25% over a 2-year period (42). Similarly, an alert triggered by an international normalized ratio below 1.7 was shown to reduce inappropriate plasma transfusions by 5% (43).

By design, interruptive alerts disrupt clinical workflows, which makes them particularly useful for addressing issues that impact patient safety, such as prescribing medications that are contraindicated due to allergies or drug–drug interactions. However, multiple studies have shown that the effectiveness of alerts decays rapidly as providers encounter repeated notifications, and the impact of "alert fatigue" has to be weighed carefully in the decision to deploy specific CDS interventions (44, 45). In our experience, interruptive alerts almost always impair the user experience and dilute the impact of other interventions while failing to achieve their goals, because the user is either too busy to process the information, disagrees with the recommendation, or is not the person making the decision (46). Accordingly, we work to limit the use of interruptive alerts to rare situations in which orders are clearly inadvertent mistakes, and we resist the impulse to substitute alerts for broader educational initiatives.

### DATA REVIEW

Another major application of CDS is ensuring that test results are presented to providers in formats that are easy to access and interpret. For individual tests, this means preparing reports that are clear and complete. However, clinical decision-making almost always requires providers to integrate results from multiple tests collected at different time points, and tools that automate this process are valuable. For example, flowsheets are dynamic tables that aggregate test results and other clinical data as they are reported, which allows providers to evaluate trends in multiple variables over time. By default, flowsheets organize results into informative groups (e.g., by laboratory section or disease process), but they also allow users to customize the tests that are shown as well as the time range. In addition, flowsheets often use color or special characters (e.g., exclamation points) to highlight abnormal or critical values, and most platforms support both tabular and graphical displays.

Similar to flowsheets, dashboards summarize information from multiple patients via an array of interactive tables and graphs presented on a single page. For clinical care, dashboards are often used to follow the status of groups of patients in acute settings, such as emergency departments and intensive care units (47, 48). Dashboards can also be used to track metrics related to hospital operations, including census, length of stay, and readmissions (49, 50). In addition, dashboards can be used to monitor data immediately relevant to clinical laboratories, such as local patterns of antimicrobial resistance, blood bank inventories, and workflow management (51–54). In general, there is significant interest in using modern data visualization to generate intuitive summaries of healthcare data that can be used to improve both patient care and hospital processes (48, 55). However, efforts to study the impact of these tools have not yielded clear results—primarily due to their novelty,

lack of standardization, and lack of consensus as to how their utility should be measured—and further research is needed to establish how they can best be used (56, 57).

In addition to the role of alerts in placing orders (described above), they also contribute to data review by notifying clinicians of important results. For example, some institutions use automated alerts to report critical values (58–61). Similarly, automated notifications have been shown to improve rates of follow-up for abnormal test results that are reported after patients have been discharged or that are obtained in ambulatory settings, although the effectiveness of contemporary systems is relatively understudied (62, 63). Finally, the interpretive comments included in individual reports can be another powerful form of CDS. These can include rules-based structured comments as well as patient-specific reports prepared by laboratory experts (i.e., diagnostic management teams) (64, 65).

#### PROVIDER EDUCATION

CDS can also be used to provide clinicians with general information about how to use individual tests effectively, including collection requirements, turnaround time, and practice guidelines. Within EHR environments, these details can be displayed as part of test orders, presented as alerts, or made available through links to internal or external references (66). Importantly, educational initiatives that occur outside of EHRs (via e-mail, informational posters, or structured didactics) also play a significant role in many CDS interventions. With respect to practice guidelines, most specialty societies publish evidence-based recommendations for diagnosing and monitoring specific conditions. The *Choosing Wisely* campaign is an ongoing project led by the American Board of Internal Medicine and Consumer Reports that focuses specifically on resource utilization and recruits specialist societies to identify overused tests in their fields (5, 67). *Choosing Wisely* launched in 2012 with 5 recommendations each from 9 professional societies based in the United States, and it has since grown into an international campaign with nearly 700 recommendations from over 80 organizations.

One class of educational interventions that has received significant attention is embedding price information in ordering interfaces to improve cost awareness. For example, one study showed that displaying Medicare allowable fees alongside diagnostic laboratory tests at a tertiary care hospital decreased test utilization by approximately 9% over a 6-month period (68). As summarized by 2 systematic reviews, the majority of published studies report that cost display is associated with modest reductions in test volume (69, 70). However, nearly all of the studies included in these reviews examined relatively short post-intervention periods (6 months or less). In contrast, a more recent multicenter randomized controlled trial found that presenting cost data had no impact on clinician ordering behavior when followed over the course of a full year (71). Additional work is therefore needed to determine if cost display leads to durable changes in test utilization. In general, the quality of evidence used to guide CDS implementation would be enhanced by reporting the impact of interventions over longer periods of time.

A complementary approach to general education initiatives to improve test utilization is to offer providers summaries of their ordering behavior at regular intervals, which is known as audit and feedback. For example, a randomized controlled trial of 85 primary care practices showed that combining educational messages targeting 9 tests with quarterly feedback on practice-level test utilization reduced order volumes by 10% to 15% (72). Similarly, a study of 200 predominantly general practice physicians found that providing individual clinicians with summaries of their test volume compared to their peers decreased tests per visits by approximately 8% over the course of 2 years (73). In general, studies suggest that audit and feedback approaches yield modest but durable reductions in test orders, although their reported impact has been variable across care settings (74).

## Emerging CDS Applications

In general, the dynamic CDS interventions described above evaluate relatively simple relationships among small numbers of variables to determine when to fire and what information to display. In contrast, the increasing amount of data captured by EHRs, combined with advances in computer algorithms and hardware, are enabling CDS tools to recognize more complex situations and perform more sophisticated tasks. The technology driving these applications can be broadly described as machine learning—a collection of computational and statistical methods that automate the discovery of patterns in data. Recently, 2 classes of machine learning models in particular, deep neural networks (or deep learning) and methods based on decision trees, have demonstrated dramatic improvements in predictive performance across multiple healthcare disciplines, with some studies reporting accuracy comparable to human experts (75, 76). Importantly, while several prominent studies have described successful applications of machine learning in radiology and histopathology, compelling use cases are not limited to image analysis (77–79). Clinical applications of machine learning have been reviewed in detail previously, but we provide the following examples to illustrate some of the opportunities and challenges related to the use of machine learning for CDS (80, 81).

One of the most active areas of research in healthcare-related machine learning is the development of early warning systems—tools that monitor EHR data continuously to estimate the risk of a range of clinically significant events. For example, a recent systematic review identified over 100 machine learning models that have been developed to predict the onset of sepsis in hospitalized patients (82). One of the most widely implemented sepsis prediction models is a proprietary tool developed by the EHR vendor Epic (Epic Systems Corporation), which uses penalized logistic regression to estimate the probability of sepsis from patient demographics, vital signs, laboratory data, procedures, and comorbidities (83). If the predicted risk exceeds a set threshold, an alert is triggered and presents an appropriate order set (e.g., intravenous fluids, blood cultures, antibiotics, lactate) if evaluation and treatment for sepsis are clinically indicated.

Similar tools have been developed to predict the risk of acute kidney injury. For example, investigators from the University of Chicago developed a model based on decision trees to estimate the probability of inpatients developing stage 2 acute kidney injury and/or receiving kidney replacement therapy within 48 hours using approximately 60 clinical variables, including demographics, vital signs, laboratory data, and nursing assessments (84). In a prospective multicenter validation study, this model achieved areas under the receiver operating characteristic curve (ROC AUCs) of 0.85 to 0.86 for predicting acute kidney injury and 0.95 to 0.96 for predicting the need for renal replacement therapy (85). In a separate study, a group from DeepMind (DeepMind Technologies) and University College London developed a deep learning model incorporating 620 000 variables to predict the risk of acute kidney injury (any stage) within 48 hours and achieved an ROC AUC of 0.92 in a retrospective cohort (86).

As these studies suggest, machine learning enables rich representations of patient data that can be used to estimate the risk of clinical deterioration and—potentially—alert providers with sufficient notice to pursue meaningful interventions. Nevertheless, implementing these tools in practice presents several challenges, many of which are general challenges for CDS. First, many of the input variables used by CDS tools are assigned different names at different institutions or at different sites within institutions, and these need to be harmonized to be accessible and interpretable for both humans and machines (e.g., by adopting standards such as Logical Observation Identifiers Names and Codes, or LOINC) (87). Similarly, EHRs need to implement standardized data structures and information exchange protocols, namely those maintained by Health Level 7 International (HL7), to support programmatic access and interoperability. Notably, early HL7 standards, including Clinical Document Architecture, were organized around medical documentation and lacked flexibility (88). More recently, HL7 developed Fast Healthcare Interoperability Resources, which is based on a more granular data model and optimized for web applications (89).

In addition to building the required data infrastructure, deploying machine learning applications clinically requires careful consideration of model stability—i.e., the degree to which performance varies across institutions and/or over time. For example, one recent study performed an external validation of the Epic sepsis tool and found that the model achieved an ROC AUC of 0.63, which was significantly lower than the performance reported by the vendor (ROC AUC 0.76 to 0.83) (83). The authors attribute this discrepancy in part to differences in the case definition of sepsis, but the results suggest that institutions may need to perform local calibration and validation of machine learning tools prior to launch (as they do for any other diagnostic test). More generally, this study highlights the need for independent prospective validation studies for clinical prediction models, including those that are proprietary. Finally, even after machine learning tools are launched, continued monitoring is required, as the performance of models is often influenced by factors that change over time, such as available treatments, laboratory tests, patient demographics, and provider behavior (90).

## Effective CDS Implementation

### GENERAL GUIDELINES

Given the breadth and complexity of available CDS tools, several sets of guidelines have emerged to promote successful implementation. For example, "The Five Rights of CDS" is a classic framework, which states that sustainable CDS provides 1) the right information, 2) to the right person, 3) in the right CDS intervention format, 4) through the right channel, 5) at the right time in the workflow (91). Similarly, a group from Brigham and Women's Hospital in Boston, Massachusetts summarized their institutional experience with the "Ten Commandments for Effective CDS," which emphasizes the importance of minimizing disruptions to clinical workflows as well as monitoring the impact of interventions (92). More recently, an international collaboration developed a CDS checklist organized around context, content, system, and implementation domains (93). Finally, multiple systematic reviews have sought to identify factors associated with successful CDS (94–97). These studies have generally supported the guidelines described above, highlighting the importance of tools that are aligned with clinical workflows, provide actionable recommendations, and present information at the time of decision-making.

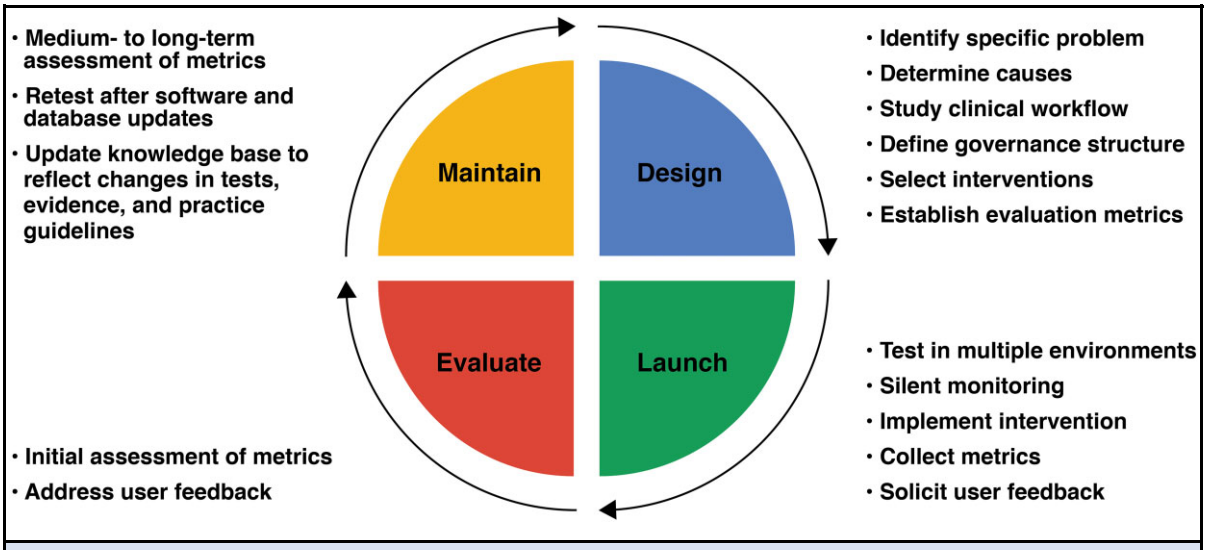


**Fig. 2.** The life cycle of effective clinical decision support.
The phases of deploying effective clinical decision support interventions are: design, launch, evaluate, and maintain (adapted from the Plan-Do-Study-Act cycle) (98).

Our own experience has reinforced that CDS tools are most effective when deployed as part of broader quality improvement initiatives focused on defined goals. In this context, CDS is a continuous process similar to the Plan-Do-Study-Act model that was originally developed for industrial manufacturing and has since been widely adopted in healthcare (98–100). Building on this analogy, the life cycle of CDS tools consists of 4 phases—design, launch, evaluate, and maintain (Fig. 2). By identifying tasks required for implementation as well as maintenance, this framework promotes the development of CDS interventions that are both effective and durable.

## DESIGN

Effective CDS begins by identifying a specific problem and investigating its causes. Common examples related to test utilization include ordering tests that are not indicated, ordering tests at inappropriate frequencies, and failing to order related tests required to interpret results. Determining the drivers of these behaviors often entails working with providers to understand how tests are used in practice, including the clinical questions they are meant to answer, how orders are placed, who places them, and how results are reviewed. Another key step in the design phase is to engage stakeholders (e.g., clinicians, laboratory professionals, information technology specialists, and institutional representatives) to establish a governance structure over the clinical and technical elements of the project (101). Notably, in addition to directing individual projects, governance plays a key role in prioritizing problems to address (e.g., based on provider input, risk of patient harm, system-level goals, or threats to reimbursement). Governance structures vary significantly with respect to size, composition, and organizational style and can be tailored to meet the needs of individual institutions. Nevertheless, given their subject matter expertise, we find that CDS interventions are more likely to succeed when laboratorians play a central role in both the design and implementation of new initiatives. Ultimately, once specific problems are defined, stakeholders work together to develop appropriate interventions and define the metrics by which they will be evaluated.

A recent survey of chief medical information officers in the Unites States reported that 93% of respondents experienced CDS malfunctions at their institutions, and a follow-up study found that CDS failures were often due to errors in design (102, 103). For example, one randomized controlled trial showed that reminders to order laboratory tests based on patient medications (e.g., checking potassium in patients on angiotensin-converting enzyme inhibitors) had no effect on test utilization (104). However, the baseline compliance ranged from 94% to 98%, suggesting that the intervention did not address a genuine problem in the study population. In settings with lower baseline compliance, similar studies have shown that embedding testing guidelines in medication orders also had no impact on test utilization—most likely because this intervention format does not build the recommended action into the workflow (105, 106). Another study illustrating the importance of

CDS design described an attempt to reduce serum magnesium testing by developing a common order template for magnesium, calcium, and phosphate that displayed recent results as well as practice guidelines (107). However, by presenting these tests together, this intervention prompted many providers to order all three, which led to a 2- to 3-fold increase in test volume (the opposite of the intended effect).

### LAUNCH

The launch phase of CDS entails moving tools into production and initiating data collection to monitor their performance. Errors that impact the launch phase are typically technical issues related to application builds. For example, one case report described an alert reminding providers to prescribe beta blockers for patients admitted for myocardial infarction prior to discharge (108). The developer of this alert assumed that medications with combined alpha and beta blocker activity (e.g., carvedilol) would be classified as belonging to both classes, however, these were coded as belonging to a third category. As a result, one patient who was already taking carvedilol was discharged with an additional prescription for atenolol, which led to an episode of bradycardia and hypotension. Strategies to avoid these types of errors include close coordination between developers and subject matter experts during the build phase and extensive testing prior to launch. In general, CDS applications are built, tested, and launched in separate environments to prevent tools in development from impacting patient care—although another source of errors during the launch phase is inadvertently moving interventions into production before they are fully built (102). Once interventions are moved to a live environment, they should initially be run silently (not visible to users) for a sufficient period of time (days to weeks) to evaluate their performance as an additional quality control measure prior to full activation (109).

### EVALUATE

After CDS interventions launch, an initial assessment is needed to determine if they function as intended. Typical evaluation metrics include the number of times alerts fire, how often they are overridden, and changes in test volume. In addition, user feedback plays an important role in understanding how interventions impact clinical workflows and are perceived by providers. A common reason for CDS failure is provider nonacceptance, which can be driven by multiple factors (110). In particular, providers may not trust CDS recommendations because the system lacks transparency (especially in the case of difficult to interpret "black box" models) or presents inaccurate information (111). For example, a recent study described an alert for medication dosing based on renal function that fired inappropriately in almost 90% of cases (over 37 000 times in one year), leading to a 100% override rate (112). Another important factor contributing to provider nonacceptance is alert fatigue—i.e., presenting too many alerts leads to most being ignored. One study reported that individual primary care providers received a median of over 5000 best practice advisories and medication alerts per year, approximately 85% of which were ignored (45). Strategies to address provider nonacceptance include engaging clinicians early in the design process, minimizing the use of interruptive alerts, and responding effectively to user feedback. In addition, 2 recent studies focusing specifically on CDS for test utilization found that features including provider role, department, clinical setting, and length of stay were predictive of provider nonacceptance, which could be used to develop more targeted interventions in the future (46, 113).

### MAINTAIN

Given that EHRs, test menus, and practice guidelines are updated frequently, ensuring that CDS interventions function correctly over time requires ongoing monitoring. For example, one case report described an alert to prescribe aspirin for patients presenting with myocardial infarction, which was triggered by a troponin concentration >0.5 ng/mL (108). When this intervention launched, undetectable troponin was reported as 0.01 ng/mL, but this changed to <0.01 ng/mL with an instrument upgrade several years later. Unfortunately, the original CDS build interpreted the "<0.01" character string as a large number, leading to alerts firing for every patient with undetectable troponin. Another study described a reminder to monitor thyroid stimulating hormone concentrations in patients prescribed amiodarone, which failed after an internal code for amiodarone had been changed (102). As opposed to a dramatic increase in alert volume, this error led to a gradual decrease in notifications that went unrecognized for over 3 years. As these cases illustrate, CDS interventions need to be periodically retested, especially after updates to software and databases, which often accompany new instrumentation. In addition, several studies have shown that monitoring trends in firing rates over time can be an effective method for detecting CDS malfunctions (102, 114). This approach has been used to identify CDS errors due to software updates, changes in internal data structures (e.g., test and medication codes), bugs in CDS builds, and failures to activate seasonal alerts. Notably, multiple groups have reported that detecting anomalies in CDS firing rates can be automated (109, 115). Finally, maintaining CDS tools requires a process for updating the knowledge base as new tests become available and practice guidelines evolve. In general, the time and resources required to maintain CDS interventions can be significant, which emphasizes the

importance of establishing a clear governance structure as well as institutional support early in the course of projects.

## Conclusion

CDS encompasses a flexible set of tools that, when designed carefully, empower clinicians to use laboratory tests more effectively and deliver higher quality patient care. However, CDS is not an end in itself, and successful implementation requires developing teams and processes to build and maintain applications that address clinically relevant problems. Laboratory testing is traditionally partitioned into pre-analytical, analytical, and post-analytical phases, and, through a sustained focus on quality, clinical laboratories have reduced analytical errors to an estimated 5% to 10% of total errors (116, 117). By allowing clinical laboratories to directly access the pre- and post-analytical phases of testing, CDS has significant potential to drive further reductions in errors going forward. Finally, as the underlying technology continues to improve, future CDS tools will use more complex representations of EHR data—including contextual features related to patient history, provider role, and clinical setting—to deliver more effective and more personalized recommendations.

**Nonstandard Abbreviations:** CDS, clinical decision support; EHR, electronic health record; ROC AUC, area under the receiver operating characteristic curve

**Author Contributions:** *All authors confirmed they have contributed to the intellectual content of this paper and have met the following 4 requirements: (a) significant contributions to the conception and design, acquisition of data, or analysis and interpretation of data; (b) drafting or revising the article for intellectual content; (c) final approval of the published article; and (d) agreement to be accountable for all aspects of the article thus ensuring that questions related to the accuracy or integrity of any part of the article are appropriately investigated and resolved.*

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