

Research and Applications

Development and application of Breadth-Depth-Context (BDC), a conceptual framework for measuring technology engagement with a qualified clinical data registry

Emma Kersey , MPH¹, Jing Li , MPH¹, Julia Kay , BA¹, Julia Adler-Milstein , PhD^{2,3}, Jinoos Yazdany , MD^{1,2}, Gabriela Schmajuk , MD, MS^{1,2,4,*}

¹Department of Medicine, Division of Rheumatology, University of California San Francisco, San Francisco, CA 94143, United States, ²Institute for Health Policy Studies, University of California San Francisco, San Francisco, CA 94158, United States, ³Department of Medicine, Division of Clinical Informatics and Digital Transformation, University of California San Francisco, San Francisco, CA 94143, United States, ⁴San Francisco Veterans Affairs Medical Center, San Francisco, CA 94121, United States

*Corresponding author: Gabriela Schmajuk, MD, MS, Department of Medicine, Division of Rheumatology, San Francisco VA Medical Center, 4150 Clement St, Mailstop 111R, San Francisco, CA 94027, United States (gabriela.schmajuk@ucsf.edu)

Abstract

Objectives: Despite the proliferation of dashboards that display performance data derived from Qualified Clinical Data Registries (QCDR), the degree to which clinicians and practices engage with such dashboards has not been well described. We aimed to develop a conceptual framework for assessing user engagement with dashboard technology and to demonstrate its application to a rheumatology QCDR.

Materials and Methods: We developed the BDC (Breadth-Depth-Context) framework, which included concepts of breadth (derived from dashboard sessions), depth (derived from dashboard actions), and context (derived from practice characteristics). We demonstrated its application via user log data from the American College of Rheumatology's Rheumatology Informatics System for Effectiveness (RISE) registry to define engagement profiles and characterize practice-level factors associated with different profiles.

Results: We applied the BDC framework to 213 ambulatory practices from the RISE registry in 2020-2021, and classified practices into 4 engagement profiles: not engaged (8%), minimally engaged (39%), moderately engaged (34%), and most engaged (19%). Practices with more patients and with specific electronic health record vendors (eClinicalWorks and eMDs) had a higher likelihood of being in the most engaged group, even after adjusting for other factors.

Discussion: We developed the BDC framework to characterize user engagement with a registry dashboard and demonstrated its use in a specialty QCDR. The application of the BDC framework revealed a wide range of breadth and depth of use and that specific contextual factors were associated with nature of engagement.

Conclusion: Going forward, the BDC framework can be used to study engagement with similar dashboards.

Lay Summary

In many healthcare settings, dashboards are implemented to monitor quality of patient care. Yet, little is known about how these digital tools are used in real-world practice. We developed the BDC (Breadth-Depth-Context) framework to evaluate how clinicians engage with quality performance dashboards. Our framework captures users' dashboard sessions (breadth) and actions (depth) as well as factors that may influence these behaviors (context). To illustrate the utility of our framework, we applied it to an example analyzing clinician audit log data obtained from a quality performance dashboard within a national rheumatology registry (American College of Rheumatology's Rheumatology Informatics System for Effectiveness [RISE]). Using the BDC framework, we classified RISE dashboard users into 4 groups based on their dashboard use. Our analysis revealed that larger practices and practices with less complex electronic health record systems were more likely to engage with the RISE dashboard. In our future work, this framework can be used to help us understand how quality performance dashboards might help improve patient outcomes.

Key words: framework; user engagement; user profiles; audit log data; clinical dashboard.

Introduction

There are more than 100 qualified clinical data registries (QCDRs) designed for medical and surgical specialties in the United States. These registries, many of which are electronic-health-record (EHR)-enabled, have assumed an increasingly vital role in reporting quality of care to federal pay-for-performance programs, especially in ambulatory care. As a result, QCDRs require substantial investment to create and

maintain the data and measurement infrastructure required for accurate quality measure reporting. Beyond quality reporting, a core value proposition of QCDRs is to make performance measure data more readily available to practices to guide internal quality improvement efforts. Specifically, many registries have developed web-based dashboards to enable practice personnel to monitor quality measure performance, benchmark their performance against registry or

Received: October 16, 2023; Revised: May 24, 2024; Editorial Decision: June 10, 2024; Accepted: June 19, 2024

© The Author(s) 2024. Published by Oxford University Press on behalf of the American Medical Informatics Association.

This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial License (<https://creativecommons.org/licenses/by-nc/4.0/>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited. For commercial re-use, please contact journals.permissions@oup.com

national means, and explore patient-level data to identify gaps in care.

The utility of QCDR dashboards hinges on their real-world use by practice personnel; however, the patterns and extent of engagement with these dashboards has not been well described. Examining QCDR dashboard engagement is complex and requires knowledge of both the specific dashboard technology and the context in which use occurs. As highlighted by previous research, the interplay of individual and institutional beliefs, goals, and resources influence how digital clinical tools are used and quality improvement efforts are maintained.¹⁻¹³

Objectives

Given the limited research regarding user log data for QCDRs, we incorporated concepts derived from clinical dashboard literature to develop a framework for evaluating engagement with a QCDR dashboard. We illustrate our framework’s use by applying it to users of a national rheumatology QCDR.

Specifically, we created metrics within each domain of the framework to classify practices according to their level of engagement and applied these metrics to a specialty-care QCDR. Finally, we assessed the contextual factors associated with each engagement group.

Methods

Conceptual framework for engagement with a QCDR dashboard

We undertook a scoping review of assessments of clinical dashboard use published between 2005 and 2023 (n = 1800;

Supplementary Appendix 1A). Articles were screened for key words synonymous with the use of clinical dashboards or other electronic clinical feedback tools. Additional articles were identified via forward and backward searching citations of the literature reviewed. Drawing upon this body of literature, we identified relevant concepts for defining engagement with a QCDR dashboard.¹⁴⁻⁵⁶ Concepts included dimensions of use, context of use, and measurement considerations (Table 1; Figure 1). We identified 2 dimensions of dashboard use, “breadth” (derived from dashboard sessions) and “depth” (derived from dashboard advanced actions), as well as other core concepts for defining practice engagement.

Integrating domains to define engagement metrics and profiles for users of a QCDR dashboard

To create metrics and profiles for users of a QCDR dashboard, we developed the following general approach:

DOMAIN: measurement considerations

Step 0: User log data availability. The scope of user engagement analysis and construction of user profiles is contingent upon the components within user audit log data. Available audit log data will depend on the specific QCDR dashboard structure and functions and will be limited by the registry vendor’s ability to track and extract various data elements. Recognition of inherent data constraints should be considered in initial analytic protocols.

Step 1: Determine unit of analysis. Depending on the outcome of interest, engagement metrics can be assessed at the individual user-level or aggregated to the practice-level. Practices typically have multiple individual dashboard user accounts. Some accounts may be affiliated with designated

Table 1. Breadth-Depth-Context (BDC) framework: customizable domains for defining practice engagement with a QCDR dashboard.

Domain	Concept	Considerations for measurement
Measurement considerations	Data availability	Depending on the registry vendor and QCDR structure, there may be different data elements available for extraction and analysis.
	Unit of analysis	Dashboard use can be assessed at the individual user-level or aggregated to the practice-level depending on the research goal and outcome of interest.
	Quality measure priority allocation	QCDR dashboards monitor numerous quality measures that reflect various aspects of patient care. In alignment with an a priori hypothesis, engagement with clinically significant measures or measures relevant to the research question can be prioritized in engagement analysis in lieu of analyzing all quality measure interactions uniformly.
Dimensions of use	Breadth	Number of unique dashboard sessions represents one aspect of engagement.
	Depth	Use of additional, advanced functions available through the dashboard represent another aspect of engagement. Users can access advanced functions such as generation of patient-level reports or data exports. These can be performed for selected quality measures or for all quality measures.
	Patterns of breadth or depth	Patterns of breadth or depth, such as consistency of sessions or actions (how regularly sessions or actions occur) or temporality (what time of year sessions or actions occur), can also be assessed.
Context of use	Individual setting	Characteristics specific to individual users, such as user roles, years of dashboard use, and personal beliefs about dashboard accuracy, accessibility, and utility.
	Inner setting	Characteristics specific to the practice that individual users are affiliated with, such as practice infrastructure, availability of personnel to review practice data, EHR vendor, and patient-case mix characteristics.
	Outer setting	Characteristics of the sociopolitical environment in which the practice operates, such as policies that incentivize population health management.
Engagement profiles	From the integration of the aforementioned domains, a versatile array of user profiles can be constructed based on the dimensions of use metrics employed and contextual factors. These profiles can be customized to fit the research goals and available data.	

EHR, electronic health record; QCDR, Qualified Clinical Data Registry.

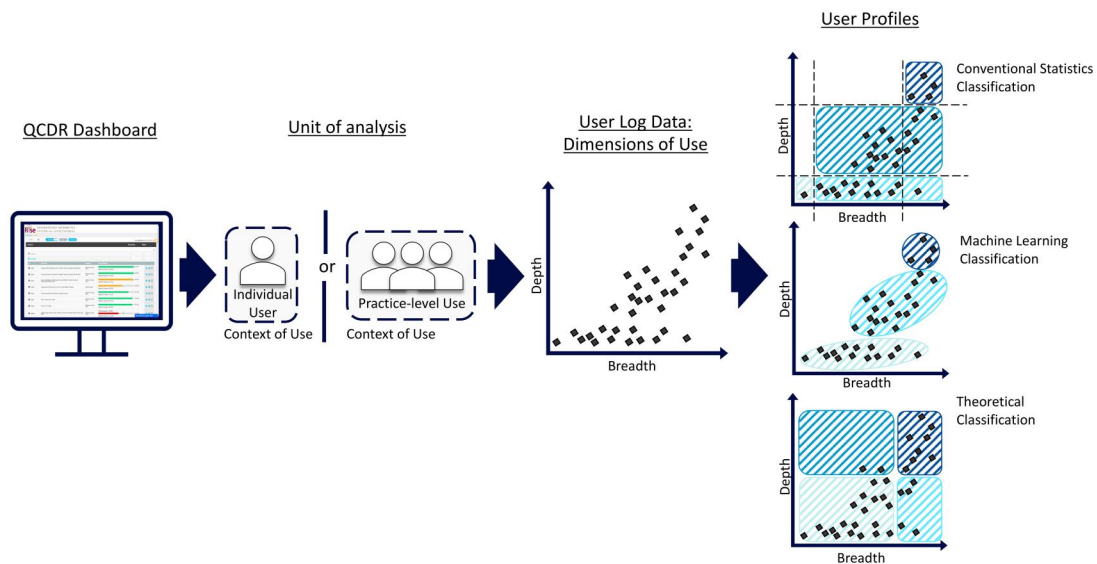


Figure 1. Domains for defining engagement with a QCDR dashboard. User log data can be assessed for individual users or aggregated to the practice-level. Users operate the dashboard within a context, including practice infrastructure, EHR vendor, and patient case-mix, which should be considered as potentially influencing engagement. Dashboard user log data are utilized to construct engagement metrics: breadth of use is defined by the number of unique sessions with the dashboard and consistency of sessions over the observation period; depth of use is defined using additional, advanced functions available through the dashboard such as generation of patient-level reports or data exports, and consistency of actions over the observation period. Thresholds of breadth and depth to define different user profiles can be derived theoretically or identified empirically through conventional statistics or other techniques, such as machine learning. Theoretical classification involves defining user groups based on established hypotheses or prior knowledge (eg, more than 12 sessions per year). Conventional statistical classification involves grouping users based on the inherent distribution of metrics (eg, above the 75th percentile of breadth and depth). Other classification techniques could involve machine learning to identify patterns and underlying structure within the data (eg, cluster analysis).

practice managers or personnel responsible for monitoring quality measure performance on behalf of all clinicians, while other accounts may be affiliated with individual clinician users. Although clinical dashboard usage is specific to individual users, a single user's engagement does not reflect the entirety of dashboard interactions that may impact quality performance within a practice. Thus, for research questions related to practice-level outcomes, such as quality of care, practice-level aggregation of user log data should be considered.

DOMAIN: dimensions of use

Step 2: Create metrics to assess engagement. Using the dimensions of use domain listed in Table 1, we can generate metrics for assessing breadth and depth of dashboard interactions. Measures of breadth and depth can be operationalized in various ways, contingent on the specific functions of the dashboard, available user log data, and research objective. Measures of breadth can include session count, session duration, and session consistency to capture the overall frequency, duration, and regularity of dashboard use. Depending on specific actions available through the dashboard, some actions may provide a granular view of practice performance (eg, viewing patient-level data on selected measures—defined as a “measure-level” action), while others may offer an overview of practice performance (eg, generating a summary report of overall measure performance—defined as a “summary-level” action). With this information in mind, measures of depth can include the count of distinct action types, number of quality measures interacted with during a measure-level action, and action consistency (see Table 2).

The breadth and depth metrics above can be defined as continuous or categorical values (eg, high vs low breadth or

depth). Cut-offs for categories of breadth and depth can be (1) derived theoretically (eg, “more than 12 sessions per year”), (2) derived from conventional statistics (eg, “above median number of sessions”), or (3) derived through other analytical techniques, such as machine learning (eg, cluster analysis).

Step 3: Define dashboard engagement profiles. Breadth and depth metrics can be assessed independently or combined in numerous ways to define engagement profiles. The specific metrics to be combined will depend on data availability and the specific goals for constructing engagement profiles. In some situations, it may be appropriate to define engagement by session count or session duration and measure-action count, while in other cases, engagement may be better reflected by session consistency or measure-action consistency.

DOMAIN: context of use

Step 4: Identify contextual factors. To define contextual factors that can influence the motivation and ability of users to engage with the dashboard, we built upon the Consolidated Framework for Implementation Research (CFIR) concepts of outer, inner, and individual settings of use.⁵⁷ The outer setting includes the broader social, economic, and political environment in which the user and practice operate. For QCDR dashboards, this can include the existence of policies, such as pay-for-performance programs, that may incentivize population health management. The inner setting encompasses institutional (practice) characteristics that may influence the quantity and quality of data displayed on the dashboard, and hence, the utility of the dashboard itself, including the number of users, practice size (number of clinicians), practice type (single- vs multi-specialty), years participating in the registry, EHR vendor, and patient case-mix. The individual setting is

Table 2. BDC (Breadth-Depth-Context) framework dimensions of use domain: sample metrics for assessing breadth and depth of engagement.

Metric	Metric calculation	Example
Breadth		
Session count	The total number of sessions logged by a user during the period of interest. Multiple sessions are possible on a given day.	If a user logs into the dashboard twice on Monday and once on Thursday, then their session count is 3 for the week.
Session duration	Total or average time spent accessing the dashboard, across all sessions during the period of interest.	If a user logs into the dashboard for a 2-hour session on Monday and a 1-hour session on Thursday, then their average session duration is 1.5 hours for the week.
Session consistency	The percentage of time (months, weeks, etc) during the period of interest for which a user had a given number of sessions.	If a user logs into the dashboard on Monday and Thursday, then their session consistency is calculated as 2/5 of days in a workweek (40%).
Depth		
Measure-action count	Since measure-level actions can be applied to any number of user-selected quality measures, a measure-action count quantifies the number of quality measures interacted with during a given action. Thus, a measure-action count equals the number of measure-level actions multiplied by the number of quality measures it was applied to, per session or period of interest. A measure-action count does not apply to a summary-level action (ie, generation of performance summary report). Summary-level actions automatically compile all aggregated quality performance data without requiring a user to individually select measures or examine patient-level data.	If a user viewed patient-level data for 3 <i>quality measures</i> and exported patient-level data for 1 <i>quality measure</i> , then they completed 4 measure-actions (3 quality measures viewed + 1 quality measure exported) during the session.
Action-type count	A count of the different types of actions that occurred, per session or period of interest for all measure-level or summary-level actions performed.	If a user <i>viewed patient-level</i> data for 3 quality measures, <i>exported patient-level</i> data for 1 quality measure, and <i>generated a performance summary</i> report, then they completed 3 distinct action-types (view + export + summary report) during the session.
Action consistency	The percentage of time (month, weeks, etc) during the period of interest for which a user completed a given number of action-types or measure-actions.	If a user viewed patient-level data for 3 quality measures on Monday and exported patient-level data for 2 quality measures on Thursday, then this can be calculated as a measure-action consistency of ≥ 3 measure-actions 1/5 (20%) of days in a workweek or a measure-action consistency of ≥ 2 measure-actions 2/5 (40%) of days in a workweek. Alternatively, these actions could represent an action-type consistency of ≥ 1 action-type 2/5 (40%) of days in a workweek.

comprised of features specific to users themselves. These are characteristics such as years of dashboard use and personal beliefs about dashboard accuracy, accessibility, and utility that may affect the likelihood of using more advanced functions within the dashboard.^{58,59} Understanding the context for engagement with a QCDR dashboard is an important aspect of the BDC framework since contextual factors may have important effects on metrics of breadth or depth.

Example application of the BDC framework to assess engagement with a QCDR dashboard

We applied the BDC conceptual framework and general approach described in the prior section to the RISE registry, a national EHR-enabled QCDR that automatically extracts data collected during routine clinical care from participating rheumatology practices' EHRs (see [Supplementary Appendix 1B](#) for additional details).^{60,61}

Data source. The RISE web-based dashboard is designed to facilitate quality improvement activities and submission of quality measure performance information to the Center for Medicaid Services (CMS). Practice personnel are provided a

user account when the practice is onboarded to the registry. They can access their clinician dashboard through a web-based interface to view practice and clinician-level performance on their selected quality measures benchmarked against national and registry means. Quality measure data are updated nightly (see [Supplementary Appendix 1C](#)). To be included in the study, practices were required to have at least one practice personnel with an active RISE dashboard account throughout 2020 and 2021. This requirement ensured practices had the ability to access the dashboard for the duration of the study period, regardless of whether they logged any sessions. Practices with limited clinical data and some practice settings were excluded from the analysis (see attrition table, [Supplementary Appendix 1D](#)).

We explored distribution of sessions and actions over time, and patterns of sessions and actions throughout the year, by dashboard engagement profile. We also assessed changes in engagement profiles between 2020 and 2021. To examine the association of practice contextual factors and engagement profile, we used generalized estimating equations (GEE) accounting for the multiple observations across practices.

Additional details of the statistical analysis are provided in [Supplementary Appendix 1E](#). Predictive margins and 95% confidence intervals were reported. *P*-values less than .05 were considered statistically significant. Given that the study period spanned the onset of the COVID-19 pandemic, which had profound impacts on clinical practice and patient visit volume, we repeated the analyses above stratified by year due to possible changes in practice engagement due to the COVID-19 pandemic (2020 data only; 2021 data only).^{62,63} In another sensitivity analysis, we restricted the sample to practices using NextGen, the most common EHR vendor (N = 87). The analytic dataset was created with SAS Version 9.4 (SAS Institute) and analyses were performed using Stata 16 (StataCorp. 2017. College Station, TX: StataCorp LLC). All figures were created in RStudio (R Core Team. 2022. Vienna, Austria: R Foundation for Statistical Computing). The Western IRB and UCSF Committee on Human Research approved this study.

Results

Application of the BDC framework to assess engagement with a QCDR dashboard

Step 0: User log data availability. We obtained user audit log files comprised of lists of unique users, and records of every session and action (and corresponding quality measures) on the RISE dashboard between January 2020 and December 2021. User-level data included affiliated practice, account type (clinician or administrator), account creation date, and account inactivation date. Session-level data included session date, session start time, measure-level dashboard actions (drilldown view, drilldown export) along with the quality measures to which these actions were applied, and a summary-level dashboard action (performance summary report). In addition, users could mark measures as “favorites” to ensure that measure performance was visible at the top of the measure list on the dashboard landing page for easy viewing. Of note, session duration was not captured in available user log data and was therefore not included in this analysis.

Step 1: Determine level of analysis. We elected to aggregate metrics to the practice-level since many RISE practices have practice managers or personnel who monitor quality measure performance on behalf of all practice clinicians. Aggregating engagement metrics to the practice-level accounts for the quality monitoring efforts of all users within a practice and provides a more realistic view of the collective dashboard engagement that affects quality of care. Sessions and actions from each user within a given practice, regardless of role, were counted equally.

Step 2: Metrics to assess engagement. Several measures of breadth and depth were calculated for all included practices. Of the metrics calculated, we selected session consistency to assess breadth and measure-action consistency to assess depth. We made this choice based on our clinical experience with quality improvement programs, the most successful of which are those that monitor performance on a regular recurring basis (eg, monthly) and use patient-level reports to identify and correct gaps in care. The “high breadth” metric was defined as at least 2 sessions per month and the “high depth” metric was defined as at least 1 measure-action per month. These cut-offs were empirically selected via conventional statistics to capture the top quartile for the average number of sessions and average number of measure-actions per month (among practices that had at least 1 session).

Step 3: Dashboard engagement profiles. We classified practices into 1 of 4 engagement profiles (none, minimal, moderate, and most engagement) by combining metrics for breadth (as measured by session consistency) and depth (as measured by measure-action consistency) utilizing the high breadth and high depth metrics defined above in step 2 ([Figure 2](#)). “No engagement” was defined as practices with zero sessions and zero drilldown measure-actions. “Minimal engagement” was defined as practices with any number of sessions per month and zero drilldown measure-actions (low or high breadth, but no depth). “Most engagement” was defined as practices that had $\geq 50\%$ of months with at least 2 sessions (high breadth) AND $\geq 50\%$ of months with at least 1 drilldown measure-action (high depth). “Moderate engagement” was a heterogeneous group that comprised the remaining forms of engagement, including instances characterized by high breadth but low depth ($\geq 50\%$ of months with at least 2 sessions and $< 50\%$ of months with at least 1 drilldown measure-action), low breadth but high depth ($< 50\%$ of months with at least 2 sessions and $\geq 50\%$ of months with at least 1 drilldown measure-action), OR low breadth and low depth ($< 50\%$ of months with at least 2 sessions and $< 50\%$ of months with at least 1 drilldown measure-action).

Step 4: Contextual factors associated with engagement. We identified several potentially relevant practice contextual factors that could be associated with dashboard engagement. Outer setting factors were not considered because all practices were subject to the same MIPS pay-for-performance programs through CMS. Inner setting factors included the number of rheumatology clinicians (which we derived by linking clinician NPIs to the publicly available “Medicare Physician & Other Practitioners—by Provider and Service” file),⁶⁴ practice type (rheumatology only vs multi-specialty, based on associated clinicians’ NPIs who had rheumatology as their specialty), having more than 1 dashboard user in the practice (yes/no), and EHR vendor. Additional inner setting variables included patient count, defined as the number of unique patients with at least 1 visit between 2018 and 2021 (dichotomized as ≥ 5000 vs < 5000 based on the median number of patients across practices), and a patient case-mix characteristic of the proportion of patients with Medicare insurance (dichotomized at $\geq 30\%$ vs $< 30\%$ based on the 25th percentile). Notably, EHR vendor and proportion of patients with Medicare insurance were hypothesized to be particularly salient inner setting factors. Practices equipped with EHRs that have built-in tools available for population health management may exhibit lower levels or markedly different forms of engagement with a QCDR offering comparable capabilities than practices with less robust EHRs. Through pay-for-performance programs, the Center for Medicaid Services (CMS) financially incentivizes healthcare clinicians to meet quality standards for Medicare-covered patients, thus motivating practices with a higher proportion of Medicare patients to regularly engage with the dashboard to maximize their success in these programs. Since engagement was analyzed at the practice-level, individual factors such as new vs experienced users were approximated by the number of years a practice participated in the registry and dichotomized based on whether their first user’s account creation date was within 2 years of the study start date in 2020.

Findings from the application of the BDC framework to assess engagement with a QCDR dashboard

During 2020 and 2021, there were 379 active RISE-dashboard individual user accounts affiliated with 213

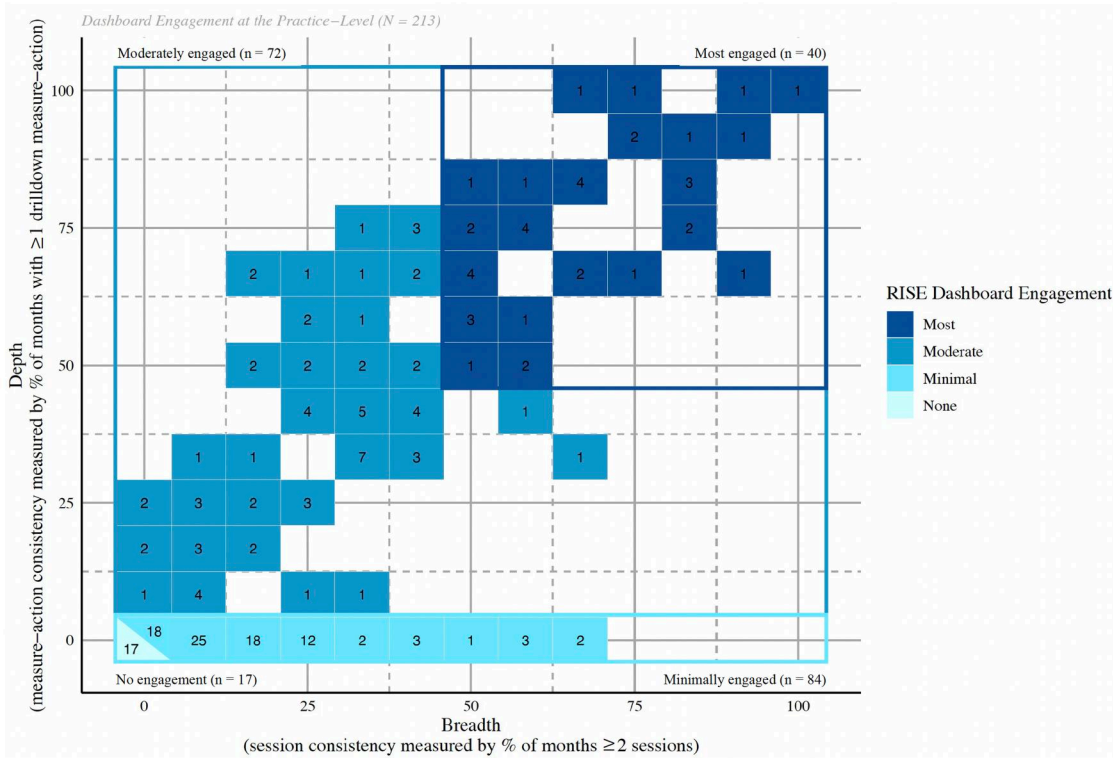


Figure 2. RISE dashboard engagement by breadth (consistency of sessions) and depth (consistency of measure-actions) metrics in 2020. Engagement profiles of the RISE dashboard by breadth and depth of use in 2020. Breadth of use is measured by session consistency within 2020 and defined by the percent of months with at least 2 sessions. Depth of use is measured by measure-action consistency within 2020 and defined by the percent of months with at least 1 measure-action. The units of the breadth and depth axes are percent of months, whereby 0% represents 0 months, 25% represents 3 months, 50% represents 6 months, 75% represents 9 months, and 100% represents 12 months in a year. Engagement profiles are defined as (1) most engaged: $\geq 50\%$ of months with at least 2 sessions AND $\geq 50\%$ of months with at least 1 drilldown measure-action, (2) moderately engaged: $\geq 50\%$ of months with at least 2 sessions and $< 50\%$ of months with at least 1 drilldown measure-action, $< 50\%$ of months with at least 2 sessions and $\geq 50\%$ of months with at least 1 drilldown measure-action, OR $< 50\%$ of months with at least 2 sessions and $< 50\%$ of months with at least 1 drilldown measure-action, (3) minimally engaged: any percent of months with any sessions and 0% of months with at least 1 drilldown measure-action, and (4) no engagement 0% of months with sessions and 0% of months with drilldown measure-actions.

practices. Most practices were rheumatology-only practices (single-specialty or solo practitioners; 90%) and had the EHR vendor NextGen (40%). The majority of practices had fewer than 5000 patients and a patient case-mix that consisted predominantly of female, non-Hispanic White patients, under the age of 65 (Supplementary Appendix 2).

Metrics to assess engagement. We observed a total of 6889 dashboard sessions across all practices during 2020 and 2021. Sessions, measure-actions, and action-type counts from 2020 and 2021 are shown in Supplementary Appendix 3.

Dashboard engagement profiles. By breadth and depth dimension of use metrics, 8% of practices had no engagement, 39% had minimal engagement (breadth, no depth), and 19% had most engagement (high breadth, high depth) in 2020. A similar distribution of engagement was observed in 2021. Sessions were most common at the end of the calendar year during both 2020 and 2021 (Figure 3). We observed similar patterns for drilldown measure-actions and performance summary actions. These trends held across all engagement groups. The majority of practices (63%) stayed in the same profile from 1 year to the next (Figure 4). Only 9% of practices moved into a more engaged profile; 28% moved into a less engaged profile.

Contextual factors associated with engagement. Practices with 5000 or more patients had a significantly higher likelihood of being in the most engaged group compared to

practices with fewer patients, even after adjusting for other factors (24% vs 9%, $P < .05$) (see Supplementary Appendix 4). Practices utilizing the EHR vendor eClinicalWorks or eMDs had a significantly increased probability of most engaged dashboard use compared to practices using Nextgen (25% and 33% vs 10%, respectively, $P < .05$). In all adjusted models, practices were more likely to be most engaged with the dashboard during the year 2020 compared to 2021 (19% vs 14%, $P < .05$).

A sensitivity analyses that examined the association between most engaged dashboard use and practice characteristics in a single year, and an analysis restricted to NextGen practices yielded similar results to the primary analysis (see Supplementary Appendix 4).

Discussion

In this study, we developed the BDC (Breadth-Depth-Context) framework to measure engagement with a QCDR dashboard. By adapting concepts from clinical dashboard literature, we constructed a versatile framework that encompasses both breadth and depth dimensions, and a feasible, step-by-step guide for implementing the framework to assess engagement. Next, we demonstrated the application of the BDC framework to classify engagement at the practice-level using audit log data from the RISE registry, a specialty-care

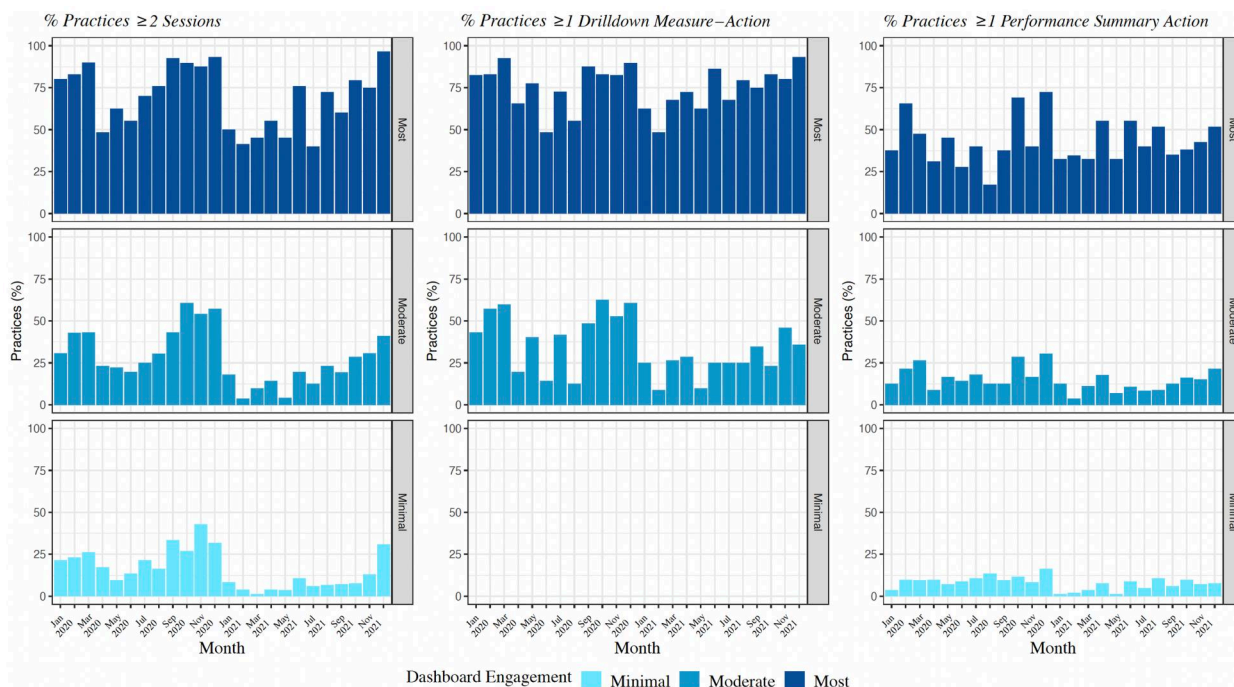


Figure 3. RISE dashboard session and action consistency by month, stratified by engagement profile. Seasonality of session consistency, measure-action consistency, and performance summary action consistency by engagement profile across 2020 and 2021. Session consistency is defined as the percent of months with ≥ 2 sessions, measure-action consistency is defined as the percent of months with ≥ 1 drilldown measure-action (measure-level actions), and performance summary action consistency is defined as the percent of months with ≥ 1 performance summary report generation (summary-level action). Engagement profiles are defined as (1) most engaged: $\geq 50\%$ of months with at least 2 sessions AND $\geq 50\%$ of months with at least 1 drilldown measure-action, (2) moderately engaged: $\geq 50\%$ of months with at least 2 sessions and $< 50\%$ of months with at least 1 drilldown measure-action, $< 50\%$ of months with at least 2 sessions and $\geq 50\%$ of months with at least 1 drilldown measure-action, OR $< 50\%$ of months with at least 2 sessions and $< 50\%$ of months with at least 1 drilldown measure-action, (3) minimally engaged: any percent of months with any sessions and 0% of months with at least 1 drilldown measure-action, and (4) no engagement: 0% of months with sessions and 0% of months with drilldown measure-actions.

(rheumatology) QCDR. These data show that in the case of the RISE registry, many practices had little to no engagement. Practices with larger patient volumes and those utilizing EHRs with less specialty-specific embedded software were more likely to be highly engaged with the RISE dashboard. Perhaps not surprisingly, these findings imply practices most driven to engage with the dashboard may be those with opportunity (personnel resources available) and need (lacking native EHR tools).

Analysis of user audit log data in healthcare is an emerging field, and there are a limited number of studies that have examined clinician engagement with dashboards (none with QCDRs specifically). Prior studies did not consider the broader range of breadth and depth metrics elucidated above and rarely addressed the contextual factors in which various dimensions of use occur.^{17,18} The majority of existing literature focused on the breadth dimension of use, usually defined by session count or session time, and infrequently explored depth of use.^{19–34} Of the studies that explored both breadth and depth dimensions of use, most inadequately captured depth of engagement and did not integrate these dimensions to effectively define more complex forms of engagement.^{27,35–48} A subset of studies employed both dimensions of use to create user profiles and evaluated use within specific contexts.^{49–55} Nevertheless, the profiles of engagement described in these studies are not established within a defined framework nor are the profiles easily applicable to different settings. To our knowledge, there is only one pre-existing framework for evaluating user engagement with a clinical

dashboard; however, this evaluative framework focused on interaction effectiveness, user experience, and system efficacy and did not emphasize the actual usage of the tool itself as our BDC framework does.⁵⁶ Thus, our study extends this literature in important ways by conceiving a multi-dimensional approach for assessing engagement that permits us to gain deeper insight into how users utilize and derive value from dashboard features.

In applying the BDC framework to the rheumatology QCDR dashboard audit log data, we faced many decisions about how to operationalize specific dimensions of breadth and depth, and how to effectively combine these metrics to generate robust user profiles of engagement. In the RISE registry example, we specifically selected session consistency and measure-action consistency as metrics for breadth and depth, respectively. This choice was based on the understanding that improving population health is an on-going endeavor, so regular sessions and utilization of additional dashboard functionality to monitor quality measure performance are more likely to result in meaningful gains in quality. However, it is possible that by emphasizing consistency of use, we may have missed practices who focused their dashboard engagement around the time of MIPS (national pay-for-performance program) submissions, as suggested by the calendar time analysis in Figure 4 that showed a peak in engagement across all profiles at the end of the calendar year. An alternate classification of user profiles could have highlighted different user goals, for instance, a “population health” profile for practices with consistent use versus a

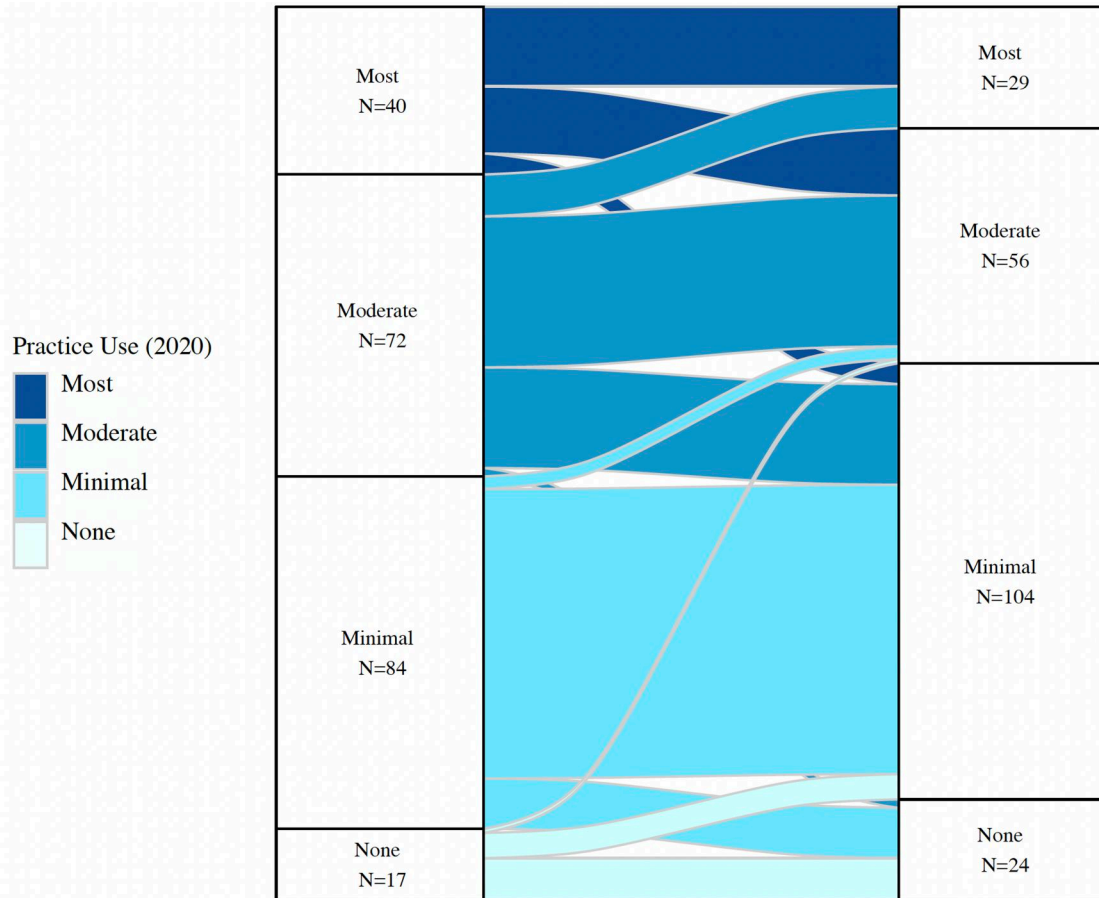


Figure 4. Change in practice dashboard use (practice-level) between 2020 and 2021. Change in engagement profile from 2020 to 2021. The left-hand column displays practices' profile of engagement in 2020 and the right-hand column displays practices' profile of engagement in 2021. The color of the flow corresponds to the initial engagement profile in 2020 and the width of the flow corresponds to the number of practices transitioning from a given profile in 2020 to a given profile in 2021. Engagement profiles are defined as (1) most engaged: $\geq 50\%$ of months with at least 2 sessions AND $\geq 50\%$ of months with at least 1 drilldown measure-action, (2) moderately engaged: $\geq 50\%$ of months with at least 2 sessions and $< 50\%$ of months with at least 1 drilldown measure-action, OR $< 50\%$ of months with at least 2 sessions and $< 50\%$ of months with at least 1 drilldown measure-action, (3) minimally engaged: any percent of months with any sessions and 0% of months with at least 1 drilldown measure-action, and (4) no engagement: 0% of months with sessions and 0% of months with drilldown measure-actions.

“MIPS submission” profile for practices with more seasonal engagement.

Considering the context of dashboard users can offer valuable insights for enhancing the utility of the dashboard. In the case of the RISE registry, we examined factors within the inner and individual setting.

Our analysis revealed that practices with a larger number of patients were more inclined to engage with the dashboard. This could be attributed to larger practices having more resources dedicated to quality improvement and federal quality-related reporting activities. On the contrary, smaller practices without additional staff may lack the time and resources necessary to address quality improvement via dashboard use or actively participate in pay-for-performance programs.^{2,65-67} Differences in engagement were also noted for practices with different EHR vendors. EHR vendors can have different native tools available for population health management that serve a similar purpose to the QCDR clinician dashboard. Consequently, practices utilizing these EHRs may have alternative means to identify patient subsets and target them for quality improvement, while practices using EHRs with few or less functional tools may be highly motivated to

access a QCDR dashboard.⁶⁸ This could explain why practices with particular EHR vendors show lower or higher engagement with the QCDR. Indeed, our findings that eClinicalWorks and eMDs practices had a higher likelihood of being engaged users could be explained by the fact that these EHRs are known to lack rheumatology-specific software modules and quality reporting features that are present in other EHR vendors like Nextgen.^{69,70} Taken together, our findings can be used to drive investment into dashboard modifications aimed at enhancing usability for smaller practices and optimizing dashboard features for larger practices who currently use the dashboard more frequently.

The strengths of this work include a robust conceptual framework and step-by-step guide for creating metrics, and developing user profiles in this novel application to clinician-facing health IT tools. The metrics within the framework were purposely designed to be flexible to allow adaptation and application to different use cases. The BDC framework can be implemented to assess engagement with many medical or subspecialty IT tools, of which a subspecialty ambulatory QCDR (RISE registry) is just one example. Nevertheless, the application of the framework to the RISE registry highlights

some limitations of the framework itself: first, the efficacy of the framework in constructing user engagement profiles relies on the availability of user log data. Our RISE data analysis was limited by missing information on session duration, which made a more nuanced evaluation of breadth of use impossible. Second, understanding contextual factors requires detailed information about the setting in which use occurs, which is not always feasible: as seen with the RISE analysis, the existence or lack thereof of tools for quality improvement within the EHR may have impacted practice engagement and motivation to use the QCDR dashboard.

Conclusion

In summary, we developed a comprehensive framework that classifies engagement with clinician-facing health IT tools and is also flexible enough to be applied to other tools where audit log data are collected. When applying this framework to the RISE registry, we discovered significant variation in dashboard engagement and identified important contextual factors that are associated with engagement, such as the availability of personnel or access to existing EHR-based tools. While we can hypothesize that being most engaged with the dashboard enables quality improvement, additional study is needed to understand whether engagement profiles mediate the improvement in quality of care that is observed with participation in a QCDR.⁷¹ Such research will not only improve our understanding of how dashboard engagement may translate into tangible improvements in healthcare quality but inform stakeholder funding in the design and development of future clinician-facing health IT tools.

Acknowledgments

The data were supported by the American College of Rheumatology's RISE Registry. However, the views expressed represent those of the authors and do not necessarily represent the views of the American College of Rheumatology. This study protocol was prepared by and the data analysis was executed by the RISE data analytic center at UCSF.

Author contributions

Julia Adler-Milstein, Jinoos Yazdany, and Gabriela Schmajuk (Conceptualization), Emma Kersey, Jing Li, and Julia Kay (Data curation), Emma Kersey and Jing Li (Formal analysis), Jinoos Yazdany and Gabriela Schmajuk (Funding acquisition), Julia Adler-Milstein, Jinoos Yazdany, and Gabriela Schmajuk (Methodology), Jinoos Yazdany and Gabriela Schmajuk (Resources), Gabriela Schmajuk (Supervision), Emma Kersey and Gabriela Schmajuk (Writing—original draft), Emma Kersey, Jing Li, Julia Kay, Julia Adler-Milstein, Jinoos Yazdany, and Gabriela Schmajuk (Writing—review and editing), Emma Kersey, Jing Li, Julia Adler-Milstein, Jinoos Yazdany, and Gabriela Schmajuk (Final approval of the version to be published).

Supplementary material

Supplementary material is available at JAMIA Open online.

Funding

This work was supported by National Institute of Health, National Institute of Arthritis and Musculoskeletal and Skin Diseases [grant R01AR079566] with additional support from National Institute of Health, National Institute of Arthritis and Musculoskeletal and Skin Diseases [P30AR070155]. J.Y. is supported by K24 AR074534.

Conflicts of interest

Emma Kersey: None declared, Jing Li: None declared, Julia Kay: None declared, Julia Adler-Milstein: None declared, Jinoos Yazdany: AstraZeneca (consultant), Aurinia (grant/research support), Bristol-Myers Squibb (BMS) (consultant), UCB (consultant), Gabriela Schmajuk: None declared.

Data availability

The data underlying this article is owned by the American College of Rheumatology and cannot be shared publicly due to data use agreements with practices that contributed data.

References

1. Barbazza E, Ivanković D, Davtyan K, et al. The experiences of 33 national COVID-19 dashboard teams during the first year of the pandemic in the World Health Organization European Region: a qualitative study. *Digit Health*. 2022;8:20552076221121154. Published August 29, 2022. <https://doi.org/10.1177/20552076221121154>
2. Ye J, Zhang R, Bannon JE, et al. Identifying practice facilitation delays and barriers in primary care quality improvement. *J Am Board Fam Med*. 2020;33(5):655-664. <https://doi.org/10.3122/jabfm.2020.05.200058>
3. Barnes GD, Sippola E, Ranusch A, et al. Correction: implementing an electronic health record dashboard for safe anticoagulant management: learning from qualitative interviews with existing and potential users to develop an implementation process. *Implement Sci Commun*. 2023;4(1):25. Published March 13, 2023. <https://doi.org/10.1186/s43058-023-00412-8>
4. Effken JA, Brewer BB, Logue MD, Gephart SM, Verran JA. Using cognitive work analysis to fit decision support tools to nurse managers' work flow. *Int J Med Inform*. 2011;80(10):698-707. <https://doi.org/10.1016/j.ijmedinf.2011.07.003>
5. Dowding D, Merrill J, Russell D. Using feedback intervention theory to guide clinical dashboard design. *AMIA Annu Symp Proc*. 2018;2018:395-403. Published December 5, 2018.
6. Jeffries M, Keers RN, Phipps DL, et al. Developing a learning health system: insights from a qualitative process evaluation of a pharmacist-led electronic audit and feedback intervention to improve medication safety in primary care. *PLoS One*. 2018;13(10):e0205419. Published October 26, 2018. <https://doi.org/10.1371/journal.pone.0205419>
7. Korst LM, Aydin CE, Signer JM, Fink A. Hospital readiness for health information exchange: development of metrics associated with successful collaboration for quality improvement. *Int J Med Inform*. 2011;80(8):e178-e188. <https://doi.org/10.1016/j.ijmedinf.2011.01.010>
8. Gude WT, Roos-Blom MJ, van der Veer SN, et al. Health professionals' perceptions about their clinical performance and the influence of audit and feedback on their intentions to improve practice: a theory-based study in Dutch intensive care units. *Implement Sci*. 2018;13(1):33.
9. Khairat S, Marc D, Crosby W, et al. Reasons for physicians not adopting clinical decision support systems: critical analysis. *JMIR Med Inform*. 2018;6(2):e24.

10. Coles E, Anderson J, Maxwell M, et al. The influence of contextual factors on healthcare quality improvement initiatives: a realist review. *Syst Rev*. 2020;9(1):94-93.
11. Laka M, Milazzo A, Merlin T. Factors that impact the adoption of Clinical Decision Support Systems (CDSS) for antibiotic management. *Int J Environ Res Public Health*. 2021;18(4):1901.
12. Brown B, Gude WT, Blakeman T, et al. Clinical Performance Feedback Intervention Theory (CP-FIT): a new theory for designing, implementing, and evaluating feedback in health care based on a systematic review and meta-synthesis of qualitative research. *Implement Sci*. 2019;14(1):40-45.
13. van Deen WK, Cho ES, Pustolski K, et al. Involving end-users in the design of an audit and feedback intervention in the emergency department setting—a mixed methods study. *BMC Health Serv Res*. 2019;19(1):270.
14. Miller RH, Sim I, Newman J. Electronic medical records in solo/small groups: a qualitative study of physician user types. *Stud Health Technol Inform*. 2004;107(Pt 1):658-662.
15. Wilcox A, Bowes WA, Thornton SN, et al. Physician use of outpatient electronic health records to improve care. *AMIA Annu Symp Proc*. 2008;2008:809-813.
16. Beal LL, Kolman JM, Jones SL, et al. Quantifying patient portal use: systematic review of utilization metrics. *J Med Internet Res*. 2021; 23(2):e23493.
17. Ismail M, Morden E, Hussey H, et al. Evaluation of a public COVID-19 dashboard in the Western Cape, South Africa: a tool for communication, trust, and transparency. *BMC Public Health*. 2022;22(1):2453. Published December 29, 2022. <https://doi.org/10.1186/s12889-022-14657-w>
18. Jeffries M, Gude WT, Keers RN, et al. Understanding the utilisation of a novel interactive electronic medication safety dashboard in general practice: a mixed methods study. *BMC Med Inform Decis Mak*. 2020;20(1):69. Published April 17, 2020. <https://doi.org/10.1186/s12911-020-1084-5>
19. Burningham Z, Latha RR, Duford-Hutchinson B, et al. Developing the VA geriatric scholars programs' clinical dashboards using the PDSA framework for quality improvement. *Appl Clin Inform*. 2022;13(4):961-970. <https://doi.org/10.1055/s-0042-1757553>
20. Connolly M, Selling MK, Cook S, Williams JS, Chin MH, Umscheid CA. Development, implementation, and use of an "equity lens" integrated into an institutional quality scorecard. *J Am Med Inform Assoc*. 2021;28(8):1785-1790. <https://doi.org/10.1093/jamia/ocab082>
21. de Lusignan S, Liyanage H, Sherlock J, et al. Atrial fibrillation dashboard evaluation using the think aloud protocol. *BMJ Health Care Inform*. 2020;27(3):e100191. <https://doi.org/10.1136/bmjhci-2020-100191>
22. Dorsch MP, Chen CS, Allen AL, et al. Nationwide implementation of a population management dashboard for monitoring direct oral anticoagulants: insights from the veterans affairs health system. *Circ Cardiovasc Qual Outcomes*. 2023;16(2):e009256. <https://doi.org/10.1161/CIRCOUTCOMES.122.009256>
23. Dixon BE, Grannis SJ, McAndrews C, et al. Leveraging data visualization and a statewide health information exchange to support COVID-19 surveillance and response: application of public health informatics. *J Am Med Inform Assoc*. 2021;28(7):1363-1373. <https://doi.org/10.1093/jamia/ocab004>
24. Joshi A, Amadi C, Katz B, Kulkarni S, Nash D. A Human-Centered platform for HIV infection reduction in New York: development and usage analysis of the Ending the Epidemic (ETE) dashboard. *JMIR Public Health Surveill*. 2017;3(4):e95. Published December 11, 2017. <https://doi.org/10.2196/publichealth.8312>
25. Hester G, Lang T, Madsen L, Tambyraja R, Zenker P. Timely data for targeted quality improvement interventions: use of a visual analytics dashboard for bronchiolitis. *Appl Clin Inform*. 2019;10(1):168-174. <https://doi.org/10.1055/s-0039-1679868>
26. Gremyr A, Holmberg C, Thor J, Malm U, Gäre BA, Andersson AC. How a point-of-care dashboard facilitates co-production of health care and health for and with individuals with psychotic disorders: a mixed-methods case study. *BMC Health Serv Res*. 2022;22(1):1599. Published December 30, 2022. <https://doi.org/10.1186/s12913-022-08992-2>
27. Alvarado N, McVey L, Elshehaly M, et al. Analysis of a web-based dashboard to support the use of national audit data in quality improvement: realist evaluation. *J Med Internet Res*. 2021;23(11):e28854. Published November 23, 2021. <https://doi.org/10.2196/28854>
28. Patel S, Rajkomar A, Harrison JD, et al. Next-generation audit and feedback for inpatient quality improvement using electronic health record data: a cluster randomised controlled trial. *BMJ Qual Saf*. 2018; 27(9):691-699.
29. Linder J, Schnipper J, Tsurikova R, et al. Electronic health record feedback to improve antibiotic prescribing for acute respiratory infections. *Am J Manag Care*. 2010; 16(12 Suppl HIT):e311-e319.
30. Twohig PA, Rivington JR, Gunzler D, et al. Clinician dashboard views and improvement in preventative health outcome measures: a retrospective analysis. *BMC Health Serv Res*. 2019;19(1):475.
31. Rogal SS, Yakovchenko V, Gonzalez R, et al. The hepatic innovation team collaborative: a successful population-based approach to hepatocellular carcinoma surveillance. *Cancers (Basel)*. 2021;13(9):2251. Published May 7, 2021. <https://doi.org/10.3390/cancers13092251>
32. Burningham Z, Jackson GL, Kelleher JL, et al. Use of a medication safety audit and feedback tool in the emergency department is affected by prescribing characteristics. *Appl Clin Inform*. 2023;14(4):684-692. <https://doi.org/10.1055/s-0043-1771393>
33. Schnock K, Roulier S, Butler J, et al. Engaging patients in the use of real-time electronic clinical data to improve the safety and reliability of their own care. *J Patient Saf*. 2022;18(2):e407-e413. <https://doi.org/10.1097/PTS.0000000000000831>
34. McCleary N, Desveaux L, Presseau J, et al. Engagement is a necessary condition to test audit and feedback design features: results of a pragmatic, factorial, cluster-randomized trial with an embedded process evaluation. *Implement Sci*. 2023;18(1):13-16.
35. Bersani K, Fuller TE, Garabedian P, et al. Use, perceived usability, and barriers to implementation of a patient safety dashboard integrated within a vendor EHR. *Appl Clin Inform*. 2020;11(1):34-45. <https://doi.org/10.1055/s-0039-3402756>
36. Kummer BR, Willey JZ, Zelenetz MJ, et al. Neurological dashboards and consultation turnaround time at an academic medical center. *Appl Clin Inform*. 2019;10(5):849-858. <https://doi.org/10.1055/s-0039-1698465>
37. Lim SL, Tay MHJ, Ong KW, et al. Association between mobile health app engagement and weight loss and glycemic control in adults with type 2 diabetes and prediabetes (D'LITE study): prospective cohort study. *JMIR Diabetes*. 2022;7(3):e35039. Published September 30, 2022. <https://doi.org/10.2196/35039>
38. Dolan JG, Veazie PJ, Russ AJ. Development and initial evaluation of a treatment decision dashboard. *BMC Med Inform Decis Mak*. 2013;13:51. Published April 21, 2013. <https://doi.org/10.1186/1472-6947-13-51>
39. Cochran JM, Fang H, Sonnenberg JG, Cohen EA, Lindenmayer JP, Reuteman-Fowler JC. Healthcare provider engagement with a novel dashboard for tracking medication ingestion: impact on treatment decisions and clinical assessments for adults with schizophrenia. *Neuropsychiatr Dis Treat*. 2022;18:1521-1534. Published July 28, 2022. <https://doi.org/10.2147/NDT.S369123>
40. Mulhall CL, Lam JM, Rich PS, et al. Enhancing quality care in Ontario long-term care homes through audit and feedback for physicians. *J Am Med Dir Assoc*. 2020; 21(3):420-425.
41. Patel MS, Kurtzman GW, Kannan S, et al. Effect of an automated patient dashboard using active choice and peer comparison performance feedback to physicians on statin prescribing: the PRESCRIBE cluster randomized clinical trial. *JAMA Netw Open*. 2018;1(3):e180818. Published July 6, 2018. <https://doi.org/10.1001/jamanetworkopen.2018.0818>
42. Hallgren KA, Cohn EB, Ries RK, Atkins DC. Delivering remote measurement-based care in community addiction treatment:

- engagement and usability over a 6-Month clinical pilot. *Front Psychiatry*. 2022;13:840409. Published April 7, 2022. <https://doi.org/10.3389/fpsyt.2022.840409>
43. Sanders JP, Gokal K, Thomas JJC, Snacktivity Investigators, et al. Development of a mobile health Snacktivity App to promote physical activity in inactive adults (SnackApp): intervention mapping and user testing study. *JMIR Form Res*. 2023;7:e41114. Published May 22, 2023. <https://doi.org/10.2196/41114>
 44. Shrestha R, Altice FL, Khati A, et al. Clinic-integrated smartphone app (JomPrEP) to improve uptake of HIV testing and pre-exposure prophylaxis among men who have sex with men in Malaysia: mixed methods evaluation of usability and acceptability. *JMIR Mhealth Uhealth*. 2023;11:e44468. Published February 16, 2023. <https://doi.org/10.2196/44468>
 45. Van Citters AD, Gifford AH, Brady C, et al. Formative evaluation of a dashboard to support coproduction of healthcare services in cystic fibrosis. *J Cyst Fibros*. 2020;19(5):768-776. <https://doi.org/10.1016/j.jcf.2020.03.009>
 46. Curtis HJ, Bacon S, Croker R, et al. Evaluating the impact of a very low-cost intervention to increase practices' engagement with data and change prescribing behaviour: a randomized trial in English primary care. *Fam Pract*. 2021;38(4):373-380. <https://doi.org/10.1093/fampra/cmaa128>
 47. Ho J, Corden ME, Caccamo L, et al. Design and evaluation of a peer network to support adherence to a web-based intervention for adolescents. *Internet Interv*. 2016;6:50-56. <https://doi.org/10.1016/j.invent.2016.09.005>
 48. Sullivan PS, Woodyatt CR, Kouzouian O, et al. America's HIV epidemic analysis dashboard: protocol for a data resource to support ending the HIV epidemic in the United States. *JMIR Public Health Surveill*. 2022;8(2):e33522. Published February 10, 2022. <https://doi.org/10.2196/33522>
 49. Chien I, Enrique A, Palacios J, et al. A machine learning approach to understanding patterns of engagement with internet-delivered mental health interventions. *JAMA Netw Open*. 2020;3(7):e2010791. Published July 1, 2020. <https://doi.org/10.1001/jamanetworkopen.2020.10791>
 50. Booth F, Potts C, Bond R, et al. A mental health and well-being chatbot: user event log analysis. *JMIR Mhealth Uhealth*. 2023;11:e43052. Published July 6, 2023. <https://doi.org/10.2196/43052>
 51. Wang JY, Yang CH, Liao WC, et al. Highly engaged video-watching pattern in asynchronous online pharmacology course in pre-clinical 4th-Year medical students was associated with a good self-expectation, understanding, and performance. *Front Med (Lausanne)*. 2021;8:799412. Published January 21, 2022. <https://doi.org/10.3389/fmed.2021.799412>
 52. Vest JR, Jaspersen 'S. How are health professionals using health information exchange systems? Measuring usage for evaluation and system improvement. *J Med Syst*. 2012;36(5):3195-3204. <https://doi.org/10.1007/s10916-011-9810-2>
 53. Jones JB, Weiner JP, Shah NR, Stewart WF. The wired patient: patterns of electronic patient portal use among patients with cardiac disease or diabetes. *J Med Internet Res*. 2015;17(2):e42. Published February 20, 2015. <https://doi.org/10.2196/jmir.3157>
 54. Greenberg KL, Poupko T, Sorotzkin D, Keidar O, Zwas DR. Development and usage of a health recommendation web tool (HearT) designed to inform women of personalized preventive health recommendations. *Internet Interv*. 2022;31:100599. Published December 24, 2022. <https://doi.org/10.1016/j.invent.2022.100599>
 55. Smit D, Vrijnsen JN, Broekman T, Groeneweg B, Spijker J. User engagement within an online peer support community (depression connect) and recovery-related changes in empowerment: longitudinal user survey. *JMIR Form Res*. 2022;6(11):e39912. Published November 2, 2022. <https://doi.org/10.2196/39912>
 56. Zhuang M, Concannon D, Manley E. A framework for evaluating dashboards in healthcare. *IEEE Trans Visual Comput Graphics*. 2022;28(4):1715-1731. <https://doi.org/10.1109/TVCG.2022.3147154>
 57. Damschroder LJ, Reardon CM, Widerquist MAO, et al. The updated consolidated framework for implementation research based on user feedback. *Implement Sci*. 2022;17(1):75.
 58. Venkatesh V, Bala H. Technology acceptance model 3 and a research agenda on interventions. *Decision Sci*. 2008;39(2):273-315.
 59. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Q*. 1989;13(3):319-340. <https://doi.org/10.2307/249008/>
 60. Yazdany J, Bansback N, Clowse M, et al. Rheumatology informatics system for effectiveness: a National Informatics-Enabled Registry for quality improvement. *Arthritis Care Res (Hoboken)*. 2016;Dec68(12):1866-1873.
 61. American College of Rheumatology (ACR). Electronic health record (EHR) compatible systems. American College of Rheumatology (ACR): RISE Registry. Accessed January 2022. <https://rheumatology.org/Portals/0/Files/RISE-EHR-Compatible-Systems.pdf>.
 62. Moynihan R, Sanders S, Michaleff ZA, et al. Impact of COVID-19 pandemic on utilisation of healthcare services: a systematic review. *BMJ Open*. 2021;11(3):e045343. Published March 16, 2021. <https://doi.org/10.1136/bmjopen-2020-045343>
 63. Li J, Ringold S, Curtis JR, et al. Effects of the SARS-CoV-2 global pandemic on U.S. rheumatology outpatient care delivery and use of telemedicine: an analysis of data from the RISE registry. *Rheumatol Int*. 2021;41(10):1755-1761.
 64. Centers for Medicare and Medicaid Services (CMS). *Medicare Physician & Other Practitioners by Provider and Service* [Dataset; Website]. 2021. Accessed November 2023. <https://data.cms.gov/provider-summary-by-type-of-service/medicare-physician-other-practitioners/medicare-physician-other-practitioners-by-provider-and-service>
 65. Morton S, Shih SC, Winther CH, Tinoco A, Kessler RS, Scholle SH. Health IT-enabled care coordination: a national survey of patient-centered medical home clinicians. *Ann Fam Med*. 2015;13(3):250-256. <https://doi.org/10.1370/afm.1797>
 66. Meunier PY, Raynaud C, Guimaraes E, Gueyffier F, Letrilliant L. Barriers and facilitators to the use of clinical decision support systems in primary care: a mixed-methods systematic review. *Ann Fam Med*. 2023;21(1):57-69. <https://doi.org/10.1370/afm.2908>
 67. Lin YJ, Ransusch A, Seagull FJ, Sussman JB, Barnes GD. Dynamic interplay between available resources and implementation climate across phases of implementation: a qualitative study of a VA national population health tool. *Implement Sci Commun*. 2023;4(1):74. Published June 29, 2023. <https://doi.org/10.1186/s43058-023-00460-0>
 68. Neprash HT, Vock DM, Hanson A, et al. Effect of integrating access to a prescription drug monitoring program within the electronic health record on the frequency of queries by primary care clinicians: a cluster randomized clinical trial. *JAMA Health Forum*. 2022;3(6):e221852. Published June 5, 2022. <https://doi.org/10.1001/jamahealthforum.2022.1852>
 69. Hammam N, Izadi Z, Li J, et al. The relationship between electronic health record system and performance on quality measures in the American College of Rheumatology's Rheumatology Informatics System for Effectiveness (RISE) registry: observational study. *JMIR Med Inform*. 2021;9(11):e31186.
 70. The Office of the National Coordinator for Health Information Technology (ONC). *Certified Health IT Product List (CHPL)*. Certified Health IT Product List: Compare Products. 2022. Accessed June 23, 2023. <https://chpl.healthit.gov/#/compare/11133&10850&11021>
 71. Izadi Z, Schmajuk G, Gianfrancesco M, et al. Significant gains in rheumatoid arthritis quality measures among RISE registry practices. *Arthritis Care Res (Hoboken)*. 2022;74(2):219-228.

© The Author(s) 2024. Published by Oxford University Press on behalf of the American Medical Informatics Association.

This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial License (<https://creativecommons.org/licenses/by-nc/4.0/>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited. For commercial re-use, please contact journals.permissions@oup.com

JAMIA Open, 2024, 7, 1–11

<https://doi.org/10.1093/jamiaopen/ooae061>

Research and Applications