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# Prescription Real-Time Benefit Tools: Clinicians Receive Frequent Alerts Yet Rarely Accept The Suggested Changes

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**ABSTRACT Health systems are increasingly integrating real-time benefit tools into their electronic health records (EHRs). These tools are designed to improve the affordability of and adherence to medications by alerting clinicians to out-of-pocket prescription price estimates and lower-price alternatives. Clinicians' engagement with real-time benefit tools is critical to the tools' success, yet it has not been comprehensively examined. Using 2019–22 EHR data from 803 ambulatory clinics and 4,894 clinicians in a large health system, we found that clinicians received a median of 19 alerts per 100 orders; of the 87 percent of clinicians who received at least one alert, 91 percent changed an order in response to an alert at least once. Clinicians made changes in response to 11 percent of all alerts they received, but they rarely accepted the alternatives originally suggested by the tool. Changes most often involved the pharmacy (60 percent), followed by quantity (39 percent), formulation (6 percent), and medication (4 percent). Primary care clinicians received the most alerts per month, while medical and surgical subspecialists made changes for a larger share of alerts. For these tools to be successfully implemented, leaders must consider the quality and usability of alerts, time burdens, and alert fatigue.**

Patients commonly face high out-of-pocket prescription drug prices that present barriers to drug initiation and adherence. Patients often want to discuss these costs with their clinicians,[1] and clinicians want to prescribe medications that their patients can afford; however, such conversations are limited by the lack of accurate pricing information resulting from the complexity of plan benefit designs.[2] In an effort to provide clinicians with accurate, individualized information on prescription prices and, in turn, to mitigate high costs and associated harms of nonadherence, health systems increasingly use real-time benefit tools embedded in electronic health records (EHRs).[3,4] These tools interrupt a medication order to show the prescribing clinician patient-specific out-of-pocket price estimates for the drug they are ordering, as well as estimates for any available lower-cost alternatives. These individualized estimates consider similar inputs to those used at the point of sale, including negotiated retail price, pharmacy, and the patient's deductible and cost-sharing arrangement; they represent what the patient would pay for the medication if they obtained it from a pharmacy at that moment. Alternatives suggested by a real-time benefit tool may differ from the original order on medication type, formulation, quantity, and/or pharmacy. After the alert, the prescribing clinician can proceed with the original order, choose one of the suggested alternatives, or search for another option altogether.

Federal policy supports the implementation of real-time benefit tools. A 2019 regulation issued by the Centers for Medicare and Medicaid Services (CMS), reinforced by legislation enacted the following year, required Medicare Part D plans to provide accurate and timely estimates to real-time benefit tools by 2021.[4,5] Access to such tools has increased since then, with two-thirds of health systems using an EHR-based real-time benefit tool as of 2022.[6] Although basic standards exist regarding the tools' functionality,[7] there are no explicit guidelines for or expectations around frequency of alerts, number and type of lower-cost alternatives, or frequency of use by clinicians.

Although real-time benefit tool alerts have the potential to reduce patients' out-of-pocket spending and, in turn, improve adherence and outcomes, they may also carry unintended consequences such as alert fatigue among clinicians.[8,9] In support of this concern, early evidence shows that alerts are often ignored, with one study finding that primary care clinicians changed the drug order in response to only one in eight alerts.[10] In that study, primary care clinicians were more likely to make changes in response to alerts that were associated with greater potential savings or were for certain drug classes versus others, but the likelihood of change did not vary by patients' characteristics.[10]

It is not yet known how clinicians engage with real-time benefit tools more broadly (for example, including actions beyond the initial response), nor how responses to the tools' alerts may vary by clinicians' characteristics. In this study, we examined the use of real-time benefit tools at 803 ambulatory clinics affiliated with a large health system to answer the following questions: How frequently were clinicians exposed to alerts, and how did they respond? What clinician factors predicted the rate at which they made changes in response to alerts?

## Study Data And Methods

The Harvard University and University of Colorado Health System (UCHealth) Institutional Review Boards approved this study and waived the use of informed consent per 45 CFR 46.116(f). We followed Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines.

**SETTING AND DATA** UCHealth is a large integrated health system that provides care to nearly three million patients across fourteen hospitals and more than 800 ambulatory clinics spanning Colorado, Wyoming, and Nebraska; it uses the Epic Systems EHR. Since being introduced in June 2019, UCHealth's real-time benefit tool has displayed drug price estimates by clinician request or via a pop-up alert for patients whose insurance plans' pharmacy benefit managers contract with one of two vendors (Surescripts and Arrive Health). The estimates interrupt clinicians' medication orders at the point of prescribing if an alternative exists that meets the system's criteria, based on factors such as potential savings above a certain threshold (for example, $0.15) or options for switching to an on-site pharmacy. We linked Epic prescription order data to real-time benefit tool data, EHR patient data, and clinician data (via National Provider Identifiers in the CMS National Plan and Provider Enumeration System).

**ORDER COHORT** We examined order data and linked real-time benefit tool price estimates for all medication orders placed across 803 ambulatory care clinics at UCHealth from July 2019 through June 2022 for patients who had one or more chronic conditions and were in plans that participated in the real-time benefit tools (48.6 percent of patients with a chronic condition were covered by such a plan) (see online appendix exhibit A1 for a list of chronic conditions).[11] We excluded price estimates that were displayed by clinician request, which accounted for fewer than 1 percent of all price estimates in a prior study,[10] because our objective was to understand exposure and response to pop-up alerts.

**CLINICIAN COHORT** We included all clinicians (physicians and advanced practice clinicians) across the 803 ambulatory care clinics at UCHealth who placed at least one of these medication orders. Each clinician was attributed to the practice in which they placed the plurality of their orders; when there were ties (fifty-four clinicians, 1.1 percent), clinicians were randomly assigned to one of the two practices.

**MEASURES** Our primary outcome was the clinician-level change rate, defined as the percentage of alerts that resulted in clinicians making a change to a medication order. We also examined adoption, defined as clinicians making at least one medication change in response to an alert during the observation period.

We examined clinicians' characteristics: sex, clinician type (credential), specialty, years of US practice, primary practice setting, and mean medication orders per encounter. Clinician types were physicians and advanced practice clinicians (nurse practitioners, clinical nurse specialists, certified registered nurse anesthetists, certified nurse midwives, and physician assistants). Specialties were primary care, medical subspecialty, and surgical subspecialty, based on the department from which the clinician placed the plurality of their orders (appendix exhibit A2).[11] We defined years of US practice as years between the clinician's enumeration date (from the National Plan and Provider Enumeration System) and the beginning of the study period, and we created three categories (0 to <5 years, 5 to <10 years, and 10 or more years; appendix exhibit A1).[11] Primary practice settings included metropolitan and nonmetropolitan settings, based on rural-urban commuting area.[12]

Medication order characteristics were prescription drug class (cardiovascular, antihyperglycemic, psychotherapeutic, and anti-asthmatic; see appendix exhibit A3), as well as refill versus new medication.[11] New medication orders were those in which no medications with the same name were ordered in the prior six months; all other orders were refills. We characterized real-time benefit tool alerts by type of suggested change: medication (for example, a different drug in the same therapeutic class), formulation (dose, strength, or mode of delivery), quantity (for example, thirty days' supply versus ninety days' supply), or pharmacy (for example, between retail and mail-order pharmacies or between retail pharmacies including those located on site). Each order could have multiple suggested alternatives, and a given alternative could represent more than one of these change types. A formulation change was only possible if the proposed alternative was the same medication. A quantity change was only possible if the proposed alternative was the same medication with the same formulation. Finally, we calculated thirty-day out-of-pocket potential cost savings by comparing the costs of the originally selected prescriptions with their lowest-cost alternatives.

**ANALYSES** We described clinicians' characteristics, alerts received per 100 orders across clinicians and across practices, clinicians' adoption of the suggested changes, clinicians' engagement with alerts, the change rate among clinicians (overall and by drug class, alert type, and clinicians' characteristics), and thirty-day out-of-pocket potential cost savings. We also described alert types by specialty. Adoption was weighted by the number of months in which each clinician placed at least one medication order.

In our primary model, we assessed the association of clinician sex, credential, specialty, years of US practice, and primary practice location with the change rate, using a multivariable Poisson model with offset for number of alerts and adjustment for potential overdispersion by scaling according to the Pearson residuals. To assess how competing demands may influence alert responses, we then added to the model the mean clinician-level number of medication orders made per encounter (preliminary analyses showed that this number was higher for primary care clinicians than for other specialists; appendix exhibit A4).[11] We conducted sensitivity analyses in which we restricted the models to new medication prescriptions alone. All models included practice random effects to account for unobserved differences between practices and for correlation within practices. We used multiple imputation[13] to handle low rates (<1–8 percent) of missingness in clinician sex, credential, and years of practice (appendix exhibit A1).[11] We also performed a sensitivity analysis using complete case analysis. We used Holm-Bonferroni correction to account for multiple comparisons in our primary model and held statistical significance at $p < 0.05$.[14] We used R, version 4.3.2.

**LIMITATIONS** We acknowledge several limitations. The generalizability of our study is limited by the single health system setting, although UCHealth is a large health system with diverse patients and clinicians across three states. Unobserved competing demands faced by clinicians while ordering medications may also influence clinicians' engagement with alerts. We were unable to measure all aspects of clinicians' responses to medication price estimate alerts, such as how the information affects their conversations with patients or other clinical team members, even in the absence of medication order changes. Finally, although our study focused on clinicians' engagement with real-time benefit tool alerts for the 49 percent of UCHealth patients who were in plans with available real-time benefit tool data, future research could examine whether having a higher proportion of patients enrolled in plans with available data might change clinicians' use of these tools.

## Study Results

Among the 4,894 clinicians in our study sample, 4,241 (86.7 percent) received at least one alert. Clinicians who received at least one alert had characteristics similar to those of clinicians who never received an alert. In the full cohort, 56.6 percent were female, 60.9 percent were physicians, 27.6 percent had a primary care specialty, 49.3 percent had ten or more years of US practice, and 93.8 percent were working in metropolitan areas. These clinicians placed a mean 1.5 (standard deviation: 0.38) total medication orders per encounter (appendix exhibit A5)[11] and received a median of 19 (interquartile range: 10–33) alerts per 100 orders (data not shown). Medical practices received a median of 22 (IQR: 15–31) alerts per 100 orders (data not shown). Overall, 91.2 percent (weighted) of clinicians who received one or more alerts made a change at least once during the study period (appendix exhibit A7).[11] We estimated the median out-of-pocket potential cost savings across these alerts to be $0.77 (IQR: 0.00–5.00) for a thirty-day supply (data not shown).

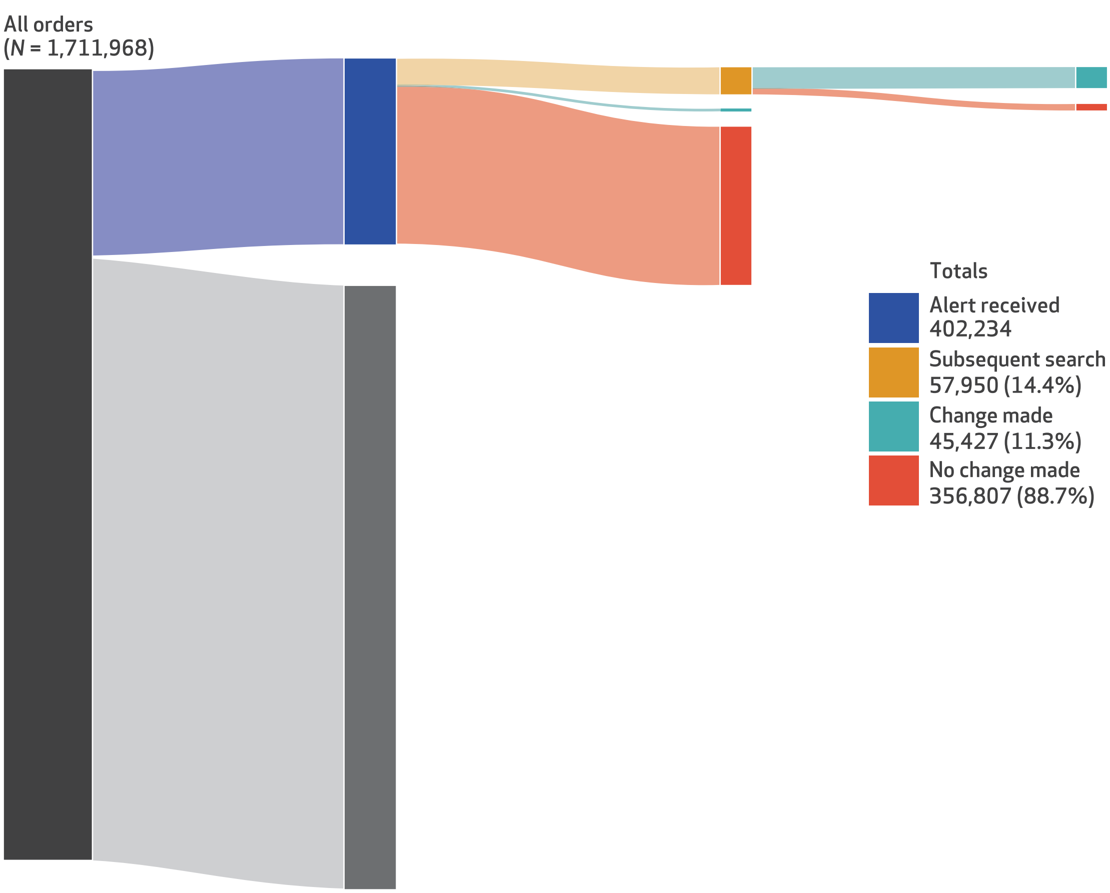
**CLINICIANS' ENGAGEMENT WITH ALERTS** When we examined actions taken by clinicians in response to an alert, we found that most alerts (85.4 percent) were immediately rejected in favor of the clinician's original order (exhibit 1). A small share of alerts (0.15 percent) resulted in the clinician accepting the presented alternative with no subsequent search. For the remaining 14.4 percent of alerts, clinicians closed the real-time benefit tool window and then searched for one or more additional medications within the EHR; in 77.3 percent of these instances, these additional searches ultimately resulted in a medication change.

**CHANGE RATES OVERALL AND BY ALERT AND ORDER CHARACTERISTICS** In adjusted analyses, we found that clinicians made changes in response to an average of 11.4 percent (95% confidence interval: 11.3, 11.5) of the real-time benefit tool alerts they received (data not shown). Among those who made at least one change, change rates in response to subsequent alerts were nearly the same (11.3 percent; 95% CI: 11.2, 11.4). Nearly all clinicians made changes in response to 25 percent or fewer of the alerts they received (exhibit 2).

The majority of real-time benefit tool alerts suggested a change in pharmacy ($n$ = 353,480, 88.7 percent). One-third suggested a change in quantity ($n$ = 130,465, 32.7 percent). Fewer suggested changes in formulation ($n$ = 33,346, 8.4 percent) and medication name ($n$ = 59,869, 15.0 percent). Among the changes made in response to alerts, the majority included changes

**EXHIBIT 1**

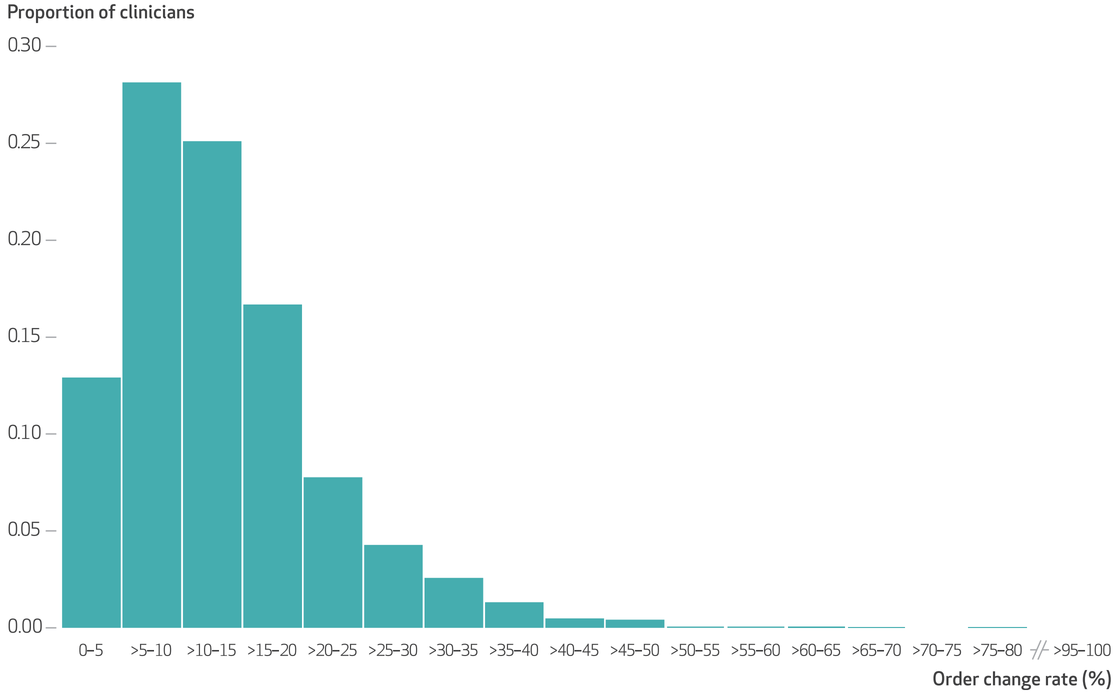
**Actions taken by clinicians in response to real-time benefit tool alerts in a large health system, July 2019–June 2022**




**SOURCE** Authors' analysis of University of Colorado Health System electronic health record and real-time benefit tool data, July 2019–June 2022. **NOTES** In response to an alert, a clinician could either reject ("no change made") or accept ("change made") an alternative presented to them, or they could conduct a search for other alternatives ("subsequent search"). The percentages in the figure represent proportions of the prior category. Overall, 45,427 alerts (11.3%) resulted in changes, and 356,807 alerts (88.7%) resulted in no changes. Among the 57,950 alerts with subsequent searches, 7,842 (13.5%) resulted in 3 or more total searches (including the initial medication search), and 1,092 (1.9%) resulted in 4 or more total searches, with a maximum of 7 total searches on a single medication order (data not shown). Among the 1,711,968 clinician orders entered, 1,309,734 resulted in no alert.

**EXHIBIT 2**

**Distribution of rate of individual clinician changes to medication orders after a real-time benefit tool alert among clinicians in a large health system who received 10 or more alerts, July 2019–June 2022**




**SOURCE** Authors' analysis of University of Colorado Health System electronic health record and real-time benefit tool data, July 2019–June 2022. **NOTE** The bins from >80–85% through >95–100% had zero values.

**EXHIBIT 3**

**Rate of change to medication orders by clinicians in a large health system in response to alerts from a real-time benefit tool, by change type and medication class, July 2019–June 2022**

| Alert type | No. of alerts | No. of alerts resulting in a change | Order change rate[a] |
|---|---|---|---|
| All alerts | 402,234 | 45,427 | 11.3% |
| **CHANGE TYPE[b]** | | | |
| Change in medication | 60,978 | 1,593 | 2.6 |
| Change in formulation | 35,765 | 2,528 | 7.1 |
| Change in quantity | 142,230 | 16,451 | 11.6 |
| Change in pharmacy | 360,639 | 27,360 | 7.6 |
| **MEDICATION CLASS** | | | |
| Cardiovascular drugs | 105,562 | 10,830 | 10.3 |
| Antihyperglycemic drugs | 19,645 | 1,923 | 9.8 |
| Psychotherapeutic drugs | 49,199 | 5,593 | 11.4 |
| Anti-asthmatic drugs | 7,490 | 855 | 11.4 |

**SOURCE** Authors' analysis of University of Colorado Health System electronic health record and real-time benefit tool data, July 2019–June 2022. [a]Percent of all alerts of the given class or type that resulted in a change. [b]Alerts with a specific change type included all alerts with at least one alternative that offered that change type; formulation changes were only considered for alternatives with the same medication as the original order, and quantity changes were only considered with alternatives with the same medication and formulation. The numbers of alerts in each subcategory do not sum to the total number of alerts, as there can be multiple change types suggested in a given alert.

to pharmacy (60.2 percent), and smaller shares included changes to quantity (39.1 percent), formulation (5.6 percent), or medication (3.5 percent). The change rate varied by alert type, as well as by medication class (exhibit 3). The change rate, both overall and across suggested alert types or medication classes, was similar in analyses restricted to new prescriptions (appendix exhibit A6).[11]

**ROLE OF CLINICIAN FACTORS** Primary care clinicians received the highest number of alerts per month and had higher adoption than other specialties (exhibit 4); 95.5 percent of primary care clinicians made at least one change in weighted analyses, versus 91.5 percent of medical subspecialists and 84.7 percent of surgical specialists. However, other specialists had higher change rates than primary care clinicians (22.3 percent higher for clinicians in medical subspecialties and 21.1 percent higher for clinicians in surgical subspecialties; exhibit 4, multivariable model 1). Adjusted change rates were also higher for male clinicians and for clinicians with fewer years of practice in the US. In model 2, which additionally included mean medication orders per encounter, the associations of change rate with specialty and years of practice diminished, and the association with sex became in-

**EXHIBIT 4**

**Adoption and medication order change rate in response to real-time benefit tool alerts to clinicians in a large health system, by clinicians' characteristics, July 2019–June 2022**

| Characteristics | Sample size | Alerts per month, mean[a] | Alerts per 100 orders, mean | Clinician adoption[b] | Order change rate[c] | Difference in order change rate[d] Model 1 | Model 2 |
|---|---|---|---|---|---|---|---|
| All clinicians | 4,241 | 3.5 | 26.3 | 91.2% | 11.3% | —[e] | —[e] |
| Sex[f] | | | | | | | |
| Female | 2,409 | 3.5 | 26.7 | 92.1 | 11.5 | Ref | Ref |
| Male | 1,824 | 3.6 | 25.7 | 90.2 | 11.1 | 2.8%** | 2.3% |
| Credential[g] | | | | | | | |
| Doctor | 2,556 | 3.6 | 27.6 | 90.9 | 11.1 | Ref | Ref |
| APC[h] | 1,348 | 3.4 | 24.3 | 91.7 | 11.4 | −0.92 | −2.1 |
| Specialty | | | | | | | |
| Primary care | 1,281 | 6.6 | 23.6 | 95.5 | 10.3 | Ref | Ref |
| Medical subspecialty | 1,916 | 2.2 | 26.7 | 91.5 | 13.4 | 22.3*** | 18.1** |
| Surgical subspecialty | 1,044 | 2.1 | 28.6 | 84.7 | 11.3 | 21.1* | 13.3 |
| Years of US practice[i] | | | | | | | |
| 0–>5 | 935 | 3.2 | 28.1 | 89.8 | 11.8 | 6.1*** | 5.3** |
| 5–>10 | 1,121 | 3.3 | 27.2 | 91.2 | 11.8 | 3.5** | 1.3 |
| 10 or more | 2,177 | 3.8 | 25.0 | 91.7 | 11.0 | Ref | Ref |
| Primary practice location | | | | | | | |
| Metropolitan | 3,993 | 3.6 | 26.8 | 91.5 | 11.3 | Ref | Ref |
| Nonmetropolitan | 248 | 2.9 | 16.9 | 87.4 | 11.5 | −0.91 | −0.49 |

**SOURCE** Authors' analysis of University of Colorado Health System electronic health record and real-time benefit tool data, July 2019–June 2022. **NOTE** A version of this table with standard deviations and 95% confidence intervals is in appendix exhibit A7 (see note 11 in text). [a]Calculated by counting all alerts received by clinicians in a category and dividing by the sum of months with an order across all clinicians in that category. [b]Weighted percent of eligible physicians who made at least one change in response to an alert. [c]Percent of all alerts of the given class or type that resulted in a change. [d]Percent differences among eligible orders obtained from multivariate Poisson models, weighted by number of alerts. Model 1 had fixed effects for sex, credential, specialty, years of US practice, and practice location effects and practice random effects. Model 2 ("volume-adjusted") also included a clinician's average orders per encounter as a fixed effect. [e]Not applicable. [f]Missing for 8 clinicians. [g]Missing for 337 clinicians. [h]Advanced practice clinicians (nurse practitioners, clinical nurse specialists, certified registered nurse anesthetists, certified nurse midwives, and physician assistants). [i]Missing for 8 clinicians. Because registering with the National Plan and Provider Enumeration System only became mandatory for all clinicians in 2008, we grouped all physicians with 10 or more years between their enumeration date and the beginning of the study period. Missingness addressed using multiple imputation. *$p < 0.10$ **$p < 0.05$ ***$p < 0.01$

significant (exhibit 4). Medical subspecialists and surgical subspecialists made a larger share of pharmacy changes compared with primary care clinicians (appendix exhibit A7).[11] In sensitivity analyses restricted to new prescriptions only, associations between clinicians' characteristics and change rates were similar (appendix exhibit A8).[11] A complete case sensitivity analysis yielded results that closely mirrored those of the main analysis (appendix exhibit A9).[11]

## Discussion

In this analysis of real-time benefit tool use in a large, multistate health system, we found that clinicians frequently received real-time benefit tool alerts when entering medication orders in their patients' EHRs. Although most clinicians made at least one change in response to an alert, they made these changes in response to a minority of alerts and almost never chose the presented alternatives. Taken together, these findings reveal that although clinicians are receptive to the information presented via real-time benefit tools, they generally decide to follow their own judgment or gather additional information on their own, instead of following recommendations generated by the tools. These results suggest that implementers need to consider practical concerns about the quality of alert information and suggested alternatives, as well as the clinician time burden of making prescription changes after an alert.

Our findings raise concerns that real-time benefit tool alerts may often disrupt clinicians without meaningfully reducing medication costs. First, clinicians rarely made changes in response to these alerts—similar to the results of two earlier studies from the University of Colorado Health System and other academic health systems[9,10]—and clinicians who made a change in response to an alert one time were not any more likely to make a change in response to future alerts. Second, changes to medication and formulation, which tend to result in greater savings,[15] were rarely suggested by alerts or made by clinicians. The low change rate may be explained by clinicians worrying about the accuracy of the estimates[1,8] or by alerts identifying alternatives that clinicians or patients do not prefer (for example, a minimal cost savings when switching to a less convenient pharmacy). Finally, we found that the median potential cost reduction from switching to the lowest-cost alternative offered by the real-time benefit tool was less than a dollar per thirty-day supply, suggesting modest savings even if clinicians had made those changes.

Our results on clinicians' characteristics revealed further insights. Primary care clinicians received more alerts per month, yet they made changes at lower rates than medical subspecialists and surgical subspecialists. One potential explanation is that these subspecialists may be more comfortable changing prescriptions within their area of expertise, although our finding that most order changes (especially for these subspecialists) affected only quantity or pharmacy makes this less likely. These subspecialists may also prescribe more expensive drugs with higher patient cost sharing, which increases the motivation to search for lower-price options for their patients. Lower rates of change among primary care clinicians may also reflect the greater time pressures and competing demands they face. Although primary care visits are often scheduled for shorter durations than other specialist visits,[16] they typically involve discussion of a greater number of issues.[17,18] When we adjusted for number of medication orders (as a proxy for visit complexity), rates of change in response to real-time benefit tool alerts became more similar among specialties. Our findings of slightly greater adoption among male clinicians and those with less experience also diminished or disappeared when we controlled for medication orders per encounter, suggesting that greater competing demands for female[19,20] and more experienced clinicians may help explain these findings as well.

## Conclusion

By providing patient-specific estimates of medication out-of-pocket expenses offered at the point of care, real-time benefit tools offer salient price information at the time it is needed, which is a meaningful form of price transparency. However, more work is needed to increase understanding of the optimal frequency of alerts in primary care and subspecialty practices: Although too many alerts can cause alert fatigue, some alerts are likely necessary. Previous research examining real-time benefit tools activated only through active queries from clinicians (that is, no interruptive alerts) found that clinicians viewed price estimates in fewer than 1 percent of clinical encounters.[21] The low change rates we observed in this study suggest that clinicians did not find the real-time benefit tool alerts very useful; however, the ideal rate of order changes is unclear and is unlikely to be 100 percent, given the nuances of clinician and patient decision making. For example, some patients may decline a cost-saving pharmacy change because they prefer paying slightly more to pick up their medication on site or on their way home, instead of waiting for delivery from a mail-order pharmacy.

**Our findings raise concerns that real-time benefit tool alerts may often disrupt clinicians without meaningfully reducing medication costs.**

Given a new CMS regulation requiring inclusion of real-time benefit tools in all certified EHRs by January 2028,[22] it is important for these tools to work as intended. To make the alerts usable while minimizing alert burdens on clinicians, pharmacy benefit managers, real-time benefit tool developers, and EHR developers can improve the specificity of suggested alternatives to consider indications, contraindications, drug-drug interactions, and the patient's comorbidities. To maximize impact, real-time benefit tool developers and health system leaders making decisions about tool design and configurations should consider raising cost-saving thresholds at which clinicians are alerted and changing the specifications for which recommendations show up. For example, health systems could program their real-time benefit tool to be more likely to show suggested changes in medication and formulation when possible. To improve real-time benefit tool policy and implementation, it will be important to seek clinicians' input, especially from primary care clinicians. Such input can ensure that these tools provide useful information and avoid adding inefficiencies to already busy clinical days. ■

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