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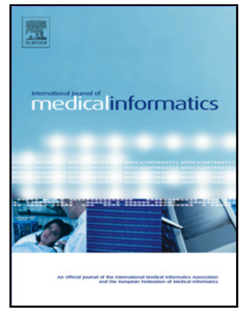

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The Effect of Provider Characteristics on the Responses to Medication-Related Decision Support Alerts

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Background: Improving the quality of prescribing and appropriate handling of alerts remains a challenge for design and implementation of clinical decision support (CDS) and comparatively little is known about the effects that provider characteristics have on how providers respond to medication alerts.

Objectives: To investigate the relationship between provider characteristics and their response to medication alerts in the outpatient setting.

Design and Participants: Retrospective observational study using **a** prescription log from the automated electronic outpatient system for each of 478 providers using the system at primary care practices affiliated with 2 teaching hospitals, from 2009-2011 for six types of alerts. Provider characteristics were obtained from the hospital credentialing system and the Massachusetts Board of Registration in Medicine.

Main Measures: Override rates per 100 prescriptions and 100 alerts.

Results: The providers' mean override rates per 100 prescriptions and per 100 alerts were 0.52 [95% confidence interval (CI), 0.46–0.58] and 0.42 (95% CI, 0.38–0.44) respectively. The physicians (n=422) on average overrode drug alerts with rates of 0.48 per 100 drugs and 0.44 per 100 warnings. Univariate analysis revealed that six physician characteristics (physician type, age, number of encounters, medical school ranking, residency hospital ranking, and acceptance of Medicaid) were significantly related to the override rate. Multiple regression showed that house staff were more likely to override than staff physicians (p<0.001), physicians with fewer than 13 average daily encounters were more likely to override than others with more than 13 encounters [p (range), <0.001–0.05], and graduates of the top 5 medical schools were more likely to override than the others (p=0.04). All six predictors together explained 30% and 50% of the variance in override rates, respectively.

Conclusions: Consideration of six specific physician characteristics may help inform interventions to improve prescriber decision-making.

INTRODUCTION

Despite the promise that computerized medication-related clinical decision support (CDS) systems will improve medication safety, there is wide variability in their use and in the responses to provider recommendations generated by these systems. Investigators have reported wide variations in override rates, ranging from 25% to 96% depending on the site, settings, and alert type.[1-5] The reported proportion of inappropriate overrides also varies widely, from 8% to 82%.[4, 5]

This variability in provider responses to medication-related CDS recommendations could be due to many factors, including the knowledge base used, how the alerts are displayed and where they occur in the workflow, the setting in which the system is deployed, and the provider characteristics.[6] In 2008, investigators working with the Leapfrog Group set up a "flight simulator" approach to computerized provider order entry (CPOE) aimed at estimating a system's potential effect on safety by examining how it handles dangerous ordering scenarios implemented in hospitals.[7] They evaluated 81 US hospitals and found wide variation in the frequency with which medication orders judged likely to cause serious harm to adult patients were detected by CPOE decision support.[8] The key finding of that work was the wide variation among hospitals in terms of which decision support they implemented, and there was also wide variation within vendor--in fact little correlation with vendor, suggesting that many key decisions must be made at the hospital level. Several systematic reviews [6, 9, 10] of CDS systems across a range of clinical domains and review studies [3, 11-14] have identified key steps that organizations should take to ensure the successful implementation and maintenance of a CDS system.

However, there have been few explorations of provider-level variation in terms of how prescribers respond to alerts, or what provider attributes affect override rates. Some studies have evaluated physician characteristics associated with alerting medication CDS and researchers have addressed the possibility of provider influence on alerts compliance [6, 13, 15-17], but relatively little empiric work has been done in routine clinical practice. If overrides of important warnings are clustered by physician, it might be possible to intervene with the high over-riders, and this information might also be used for credentialing, for example.

The present study was designed to assess the effect of provider-level characteristics on variation in prescribing patterns, with two specific aims: (i) to describe provider prescribing patterns relative to the rates of triggering alerts and overriding the alerts, and (ii) to determine the effects of provider characteristics on alert and override rates. We investigated 3 years of logs of the prescriptions of individual providers and responses to multiple domains of medication CDS alerts obtained from primary care practices.

METHODS

Setting

We evaluated primary care practices affiliated with two Harvard teaching hospitals, Brigham and Women's Hospital and Massachusetts General Hospital (Boston, MA. USA). These sites are part of a regional integrated healthcare delivery system, called the Partners HealthCare System. Most of the clinical sites evaluated in this study are community-based practices, and the study included several community health centers. All providers in the Partners network use the same electronic health records (EHRs) with medication-related CDS alerts with exactly the same set of rules in their outpatient primary care clinics. The medication related alerts have six types of warnings: patient allergies, drug−drug interactions, duplicate drugs, age-based suggestions, renal suggestions and formulary substitutions.

Provider characteristics relevant to responses on medication alerts

As in prior work[5], we analyzed the reasons for provider overrides; the most common reasons were those associated with their clinical uncertainty about warnings, even which were based on current evidences, such as "*patient has taken previously without adverse reaction,*" "*will monitor as recommended,*" and "*patient has tolerated this drug in the past.*" Regarding uncertainty and physician behavior in clinical practice, Gerrity et al.[18] proposed a conceptual model for identifying factors affecting how physicians react to uncertainty and how reactions to uncertainty might influence their behavior (Figure 1). The model highlighted five major elements: the patient, the medical problem or illness, the physician, test and treatment characteristics, and the organizational structure.

<Figure 1 here>

Several previous studies have identified the following factors as being associated with the decision to override alerts: prescriber type[4], knowledge and training[6], preferences[6], the degree to which a physician believes that health information technology will contribute to medication safety[17, 19], and workload[17] such as the number of patients cared for, the staffing of the department, and the duration of the shift or the time of the day.

Based on the model of Gerrity et al. and other previous work, we explored the variables that were available in the Partners HealthCare databases, including provider type, gender, age, race, specialty, practice site, medical school attended, graduation year, board certification, board certification year, academic degree, and the number of clinical encounters. We also retrieved data from the physician profiles of Massachusetts Board of Registration in Medicine (http://profiles.ehs.state.ma.us/Profiles/Pages/FindAPhysician.aspx). The profile of each physician contains a host of information, including about his or her specialty, medical school, residency training, insurance plans accepted, honors/awards, publications, instances of Board-related and hospital discipline, criminal convictions, and medical malpractice payments reported to the Board. Among these variables we discarded variables containing missing values or too small a number of events (e.g., race, practice site, criminal convictions, and medical malpractice payments) or having redundant information with other variables (e.g., age and graduation year). We selected 14 variables for the final analysis: gender, age, medical school, academic degree, residency hospital, fellowship, type of physician, hospital specialty, Medicaid, average number of encounters per day, number of prescriptions, number of alerts, override ratio, and override rate. We used the average number of daily patient encounters to estimate providers workload according to the previous studies.[20, 21] We excluded visits for prescription refill only. The rank of the medical school the physician graduated from and the residency training hospitals attended were classified into two categories: (i) in US top 5 and (ii) not in US top 5 or non-US (with reference to the list of best medical schools in research rank in 2012 released by US News and World Report [22]).

Study design and subject selection

The present study used a cross-sectional, observational approach that included data from a 3-year period between January 1, 2009, and December 31, 2011. The dependent variables were the primary care physician's override rates for specific types of alert.

After obtaining institutional review board approval from Partners HealthCare Systems, we collected data on provider overrides from the automated electronic outpatient system. We restricted our evaluation to primary care because more than 95% of the prescriptions were issued by approximately 500 primary care providers, even though the specialists are also all on-line. In total, there were 1,718 prescribers in primary care. We included primary care clinicians with prescribing authority, staff physicians, residents and non-physicians with independent prescribing authority such as nurse practitioners (NPs).

Of the 1,718 prescribers, we limited the sample to providers who had received 20 or more alerts (opportunity to override), resulting in the exclusion of 438 prescribers. The 498 prescribers who had left their institution were also excluded. Furthermore, the 190 prescribers for whom complete clinical- encounter data were not available because they joined the system after the beginning of the study period were also excluded. An additional 81 providers with limited information and 33 providers who had issued less than 20 prescriptions were excluded from the sample (Figure 2). Thus, the final sample included 478 providers, 422 physicians and 56 NPs. We calculated the statistical power with a type-III F test in multiple regression with partial correlations of 0.17 ~ 0.49, an alpha value of 0.05, and a sample size of 422. The calculated statistical power was 94 ~ 99.7% , suggesting adequate sample size.

<Figure 2 here>

Statistical analysis

The analyses were carried out with the prescriber as the unit of analysis. The override ratio was calculated using the alerts overridden and total alerts triggered, but this did not take into account differences in the total number of medication prescriptions among providers. We therefore recalculated the override ratio into the forms of override rate per 100 prescriptions

(prescriptions OR) and override rate per 100 alerts (alerts OR). Pearson correlation was used to assess the determinants of override behavior by examining the relationships among the number of prescriptions, number of alerts, override ratio, and number of encounters. We hypothesized that a large number of encounters would cause a large number of medication prescriptions based on the finding that 76 ~81% of patient visits received a drug prescription in a primary care setting[23] ,which would increase the probability of triggering alerts and overriding them. The provider characteristics were compared using the *t*-test, chi-square statistic, and Fisher's exact test. Univariate analysis and generalized linear regression model with maximum likelihood estimates ($p < 0.05$) were used to identify factors associated with physicians' decision to write prescriptions and to respond to the alerts generated. We used SAS 9.3 software (SAS Institute, Cary, NC, USA) for the analyses.

RESULTS

Provider Groups

The nurse practitioners were older and more often female than the physicians (both $p< 0.0001$; Table 1). The physician group had more academic degrees than nurse practitioners. The average number of daily encounters did not differ between the groups.

Table 1. Characteristics of the subjects

Variable	*n* (%)			χ^2 (p)
		Provider type		
	All providers (*n*=478)	Physicians (*n* =422)	Nurse practitioners (*n*=56)	
Gender				
Female	270 (56.5)	216 (51.2)	54 (96.4)	

Male	208 (43.5)	206 (48.8)	2 (3.6)	41.17¶ (<0.0001)
Age, years				
< 33	126 (26.4)	120 (28.4)	6 (10.7)	26.58¶ (<0.0001)
33 ~ 37	79 (16.5)	76 (18.0)	3 (5.4)	
38 ~ 42	60 (12.6)	55 (13.0)	5 (8.9)	
43 ~ 52	95 (19.9)	79 (18.7)	16 (28.6)	
53 ~ 59	57 (11.9)	43 (10.2)	14 (25.0)	
>59	61 (12.8)	49 (11.6)	12 (21.4)	
Academic degree				
Ph.D.	56 (11.7)	55 (13.0)	1 (1.8)	6.05¶ (0.0139)
Not Ph.D.	422 (88.3)	367 (87.0)	55 (98.2)	
Daily clinical encounters				
≤4	127 (26.6)	119 (28.2)	8 (14.3)	5.58¶ (0.1337)
4 < and ≤ 8	132 (27.6)	116 (27.5)	16 (28.6)	
8 < and ≤ 12	130 (27.2)	110 (26.1)	20 (35.7)	
≥12	89 (18.6)	77 (18.3)	12 (21.4)	

¶Fisher's exact test

With respect to the numbers of prescriptions and alerts, the physician group had issued more prescriptions and NPs had received more alerts (Table 2). The override ratio was 0.44 and 0.48 in the NP and physician groups, respectively (p=0.14). The prescriptions OR did not differ significantly between NPs and physicians (0,83 vs. 0.48, p=0.08). The alerts ORs were 0.23 and 0.44 in the NP and physician groups, respectively (p< 0.0001).

Table 2. Override ratios among the subjects

Variable	*n* (%Mean (95% CI))			χ^2 (p)
		Provider type		
	All providers (n=478)	Physicians (n =422)	Nurse practitioners (n=56)	
No. of prescriptions	216.9 (200.3, 233.4)	219.7 (199.1, 240.3)	195.5 (129.0, 262.1)	0.77 (0.4396)
No. of alerts	244.6 (225.5, 263.6)	240.0 (215.8, 264.4)	278.6 (212.9, 344.2)	–1.07 (0.2851)
Override ratio	0.47 (0.46, 0.49)	0.48 (0.46, 0.49)	0.44 (0.39, 0.50)	1.47 (0.1414)

Override rate per 100 prescriptions	0.52 (0.46, 0.58)	0.48 (0.43, 0.52)	0.83 (0.43, 1.22)	-1.75 (0.0848)
Override rate per 100 alerts	0.42 (0.38, 0.44)	0.44 (0.40, 0.48)	0.23 (0.19, 0.27)	7.70 (< 0.0001)

ˁFisher's exact test

Relationships among prescriptions, alerts, and overrides

The relationships among the number of encounters, number of prescriptions, number of alerts, and override ratio differed according to the provider group (Table 3). There were positive and significant correlations for a larger number of encounters, increased number of prescriptions, and large number of alerts, leading to a high override ratio in the physician group. However, there was a significant relationship only between encounter frequency and number of prescriptions for the NPs.

Table 3. Relationships among the average encounters, the annual number of prescriptions, the annual number of alerts, and the override ratio according to provider group

Variable	Correlation coefficient (probability value)					
	Physicians (n = 422)			Nurse practitioners (n = 56)		
	Average encounters per day	Total No. of prescriptions	Total No. of alerts	Average encounters per day	Total No. of prescriptions	Total No. of alerts
Average encounters per day	1	-	-	1	-	-
Total No. of prescriptions	0.58 (<0.0001)	1	-	0.46 (0.0004)	1	-
Total No. of alerts	0.57 (<0.0001)	0.54 (<0.0001)	1	–0.12 (0.3922)	0.26 (0.0524)	1
Override ratio	-0.06 (0.2097)	0.07 (0.1666)	0.33 (<0.0001)	–0.42 (0.0013)	–0.40 (0.002)	0.21 (0.128)

Univariate effects of physicians characteristics on the prescriptions OR

Univariate analyses revealed different results for the override ratio and the prescriptions OR (Table 4). In terms of the override ratio, staff physicians overrode 0.04 more than house staff (p=0.0145), but based on prescriptions OR, house staff overrode 0.31 more than staff physicians (p<0.0001). Furthermore, the override ratio was highest among those aged ≥59 years and lowest among those aged ≤38 years (0.75 vs. 0.46~0.47, p=0.0013), while the prescriptions ORs of those aged ≥59 years and <32 years were 0.37 and 0.71, respectively (p<0.0001). With regard to Medicaid acceptance, the override ratio was 0.04 higher for acceptance than for non-acceptance (p=0.0126), while the prescriptions OR was 0.30 lower for acceptance than for non-acceptance (p<0.0001). The average encounters, medical school ranking, and residency hospital ranking differed significantly only for prescriptions OR: the prescriptions OR was 0.59 higher for physicians with 4 or fewer encounters than for those with more than 12 encounters (p<0.0001), 0.18 higher for graduates from the top 5 medical school than for those graduating from non-top 5 medical school (p=0.0002), and 0.22 higher for the top 5 residency hospital trainees (p<0.0001). Fellowship and physician specialty were not significantly associated with either the override ratio or prescriptions OR.

Table 4. Results of univariate analyses of override ratio and prescriptions OR relative to physicians' demographics and educational, and clinical background (n=422)

Variable	n	Override ratio		Prescriptions OR	
		Mean (95% CI)	F (p)	Mean (95% CI)	F (p)
Type of physician					
Staff physician	299	0.49 (0.47, 0.51)	-2.45 (0.0145)	0.39 (0.34, 0.43)	42.90 (<0.0001)
House staff	123	0.45 (0.42, 0.48)		0.70 (0.61, 0.78)	

Gender					
Female	216	0.47 (0.45, 0.49)	0.92 (0.3573)	0.45 (0.39, 0.51)	1.63 (0.2019)
Male	206	0.49 (0.46, 0.51)		0.51 (0.44, 0.57)	
Age, years					
< 33	120	0.46 (0.42, 0.50)	4.07 (0.0013)	0.71 (0.63, 0.79)	15.43 (<0.0001)
33 ~ 37	76	0.45 (0.41, 0.50)		0.57 (0.45, 0.69)	
38 ~ 42	55	0.50 (0.44, 0.55)		0.41 (0.30, 0.52)	
43 ~ 52	79	0.47 (0.43, 0.52)		0.27 (0.19, 0.34)	
53 ~ 59	43	0.46 (0.40, 0.53)		0.25 (0.16, 0.34)	
≥59	49	0.57 (0.51, 0.62)		0.37 (0.25, 0.47)	
Average encounters per day					
≤4	119	0.46 (0.43, 0.50)	1.05 (0.3699)	0.77 (0.69, 0.85)	45.78 (<0.0001)
>4 and ≤8	116	0.50 (0.46, 0.53)		0.56 (0.46, 0.65)	
>8 and ≤12	110	0.48 (0.44, 0.52)		0.28 (0.22, 0.34)	
>12	77	0.47 (0.42, 0.51)		0.18 (0.14, 0.22)	
Medical School					
Non top 5	300	0.48 (0.46, 0.50)	-0.36 (0.7226)	0.42 (0.37, 0.48)	13.77 (0.0002)
Top 5	122	0.47 (0.45, 0.50)		0.60 (0.52, 0.68)	
Residency hospital					
Non top 5	178	0.49 (0.47, 0.52)	-1.77 (0.0774)	0.35 (0.28, 0.42)	23.27 (<0.0001)
Top 5	244	0.47 (0.45, 0.48)		0.57 (0.51, 0.62)	
Medicaid					
Accepted	261	0.49 (0.47, 0.51)	-2.51 (0.0126)	0.36 (0.31, 0.41)	45.44 (<0.0001)
Not accepted	161	0.45 (0.43, 0.48)		0.66 (0.58, 0.73)	
Fellowship					
Absent	301	0.48 (0.46, 0.50)	0.47 (0.6411)	0.47 (0.42, 0.53)	0.01 (0.9369)
Present	121	0.47 (0.44, 0.50)		0.48 (0.40, 0.55)	
Hospital specialty					
None	41	0.46 (0.40, 0.52)	-0.71 (0.4816)	0.45 (0.32, 0.58)	-0.38 (0.7036)
Yes	381	0.48 (0.47, 0.50)		0.48 (0.43, 0.53)	

Effects of physician characteristics on override rates

The six significant variables identified in the univariate analysis were used to examine two regression models, one for override rates based on prescriptions and the second based on alerts. For the model of prescriptions OR, 3 physician characteristics were associated with higher override rates: physician type, number of average encounters, and medical school ranking (Table 5). House staff were more likely to override than staff physicians, physicians with 12 or fewer encounters per day were more likely to override than those having more than 12 encounters per day, and physicians who had graduated from a top 5 medical school were more likely to override than other physicians. The interaction between physician type and age group was significant for prescriptions. For the same age group, house staff overrode alerts less often than did staff physicians. In the alerts OR model, physicians younger than 38 years had significantly higher override rate than those older than 59 years. The R^2 *values* of the two models were 0.30 for prescriptions and 0.50 for alerts. There were no statistical significant associations between override rates and residency hospitals or Medicaid acceptance.

Table 5. Results of generalized linear regression analysis for the two override rates

	Prescriptions OR			Alerts OR		
	Coefficient estimate	95% CI	*p*	Coefficient estimate	95% CI	*p*
(Intercept)	0.13	-0.02, 0.28	0.0812	0.08	-0.01, 0.18	.0879
Type of physician: house staff	1.10	0.56, 1.64	<0.0001	0.37	-0.01, 0.75	.0560
Age, years						
≤32	0.04	-0.15, 0.23	0.6753	0.17	0.04, 0.30	0.0092
33~37	0.15	0.01, 0.30	0.0634	0.12	0.01, 0.23	0.0367
38~42	0.13	-0.03, 0.29	0.1074	-0.01	-0.12, 0.1-	0.8764
43~52	0.01	-0.13, 0.16	0.8461	0.01	-0.09, 0.11	0.8851
53~59	0.02	-0.14, 0.18	0.7978	0.00	-0.11, 0.12	0.9338
Average encounters per day						
< 4	0.50	0.34, 0.66	<0.0001	0.51	0.40, 0.62	<0.0001
≥4 and ≤ 8	0.34	0.22, 0.46	<0.0001	0.22	0.14, 0.30	<0.0001
≥8 and ≤12	0.12	0.00, 0.23	0.0453	0.12	0.03, 0.20	0.0053
Medical school: top 5	0.09	0.00, 0.18	0.0391	0.07	0.01, 0.13	0.0335
Residency hospital: top 5	−0.07	−0.16, 0.03	0.1567	0.03	−0.04, 0.10	0.3753
Medicaid: not accepted	0.07	−0.03, 0.17	0.1762	0.06	−0.01, 0.13	0.1099
House staff and <33-year old	−1.01	−1.57, −0.44	0.0005	−0.44	−0.84, −0.04	0.0295
House staff and 33~37-year old	−1.12	−1.69, −0.54	0.0001	−0.32	−0.84, −0.04	0.1219

House staff and 38~42-year old	−1.20	−1.82, −0.58	0.0001	−0.23	−0.67, 0.20	0.2896
House staff and 43~52-year old	−1.15	−1.80, −0.51	0.0005	−-0.43	−0.88, 0.02	0.0623
House staff and 53~59-year old	−1.23	−2.00, −0.46	0.0018	−0.30	−0.84, 0.24	0.2755

DISCUSSION

Providers in the U.S. are rapidly converting to electronic health records as the result of the meaningful use financial incentives, and it is hoped that some of the key safety benefits will be obtained from CDS around medication safety.[24] However, little is known about how provider characteristics affect override rates. It is important to note that many overrides are clinically appropriate, and it is incumbent upon systems to show alerts that are clinically meaningful. In the system we studied, major efforts have been made to display alerts that are clinically important. In this study, we found that the responses to alerts differed between physicians and NPs. The following six characteristics were associated with override rate among physicians: physician type, age, number of daily encounters, medical school ranking, residency hospital ranking, and acceptance of Medicaid, with the first four of these being the strongest predictors.

Few studies have explored the relationship between physician characteristics and alert override. Weingart et al.[4] evaluated drug-allergy and drug-interaction alerts and found that physicians were less likely than hospital staff to override an alerted medication (odds ratio=0.26, 95% CI 0.08~0.84). The authors suggested that their findings could be explained by novice house staff being more receptive to new information and to the introduction of technology into their practice than other more trained staff.

With respect to the prescribing behavior of physicians, another study[25] explored the physician characteristics associated with off-label prescribing in primary care. The effects of physician gender, years since graduation, and evidence-based orientation on off-label prescribing were assessed. The authors found that an evidence-based orientation was the only factor that contributed to a low rate of prescribing off-label drugs. Other studies have summarized the provider-related factors impacting on computerized CDS system uptake using literature reviews or expert interviews and addressed the possible role of past experience of a system, attitude toward and belief in health information technology, and personal preference.[6, 17] Riedmann et al.[17] hypothesized that a senior physician with many years of working experience would probably receive fewer alerts than a resident, which would result in lower override rates. However, our data shows that staff physicians had low override rates but larger numbers of encounters, as well as larger numbers of prescriptions and alerts than did house staff.

Several studies have explored the relationship between physician characteristics and quality of care and physician performance. One study[26] examined the relationship between physician characteristics and performance scores using quality measures from RAND's Quality Assessment Tools generated by 1.13 million patients, and found that three physician characteristics were independently associated with significantly higher overall performance: female gender, board certification, and US graduation. In another study[27] in which relative physician clinical performance rankings were investigated within a large academic primary care network, physician characteristics of gender, practice site, period since graduation, and patient panel size were assessed, among which gender and practice site were associated with significantly different physician clinical performance; a greater proportion of female physicians were in the top tertile and fewer top tertile physicians practiced in community health centers.

Related to physicians' perceptions of CDS integrated into a CPOE, Rosenbloom et al. [28] surveyed the attitudes of house staff and medical student users regarding CDS at an academic medical center. They found that two thirds of respondents either agreed or strongly agreed that a CPOE improves the quality of care that they provide, and over half mentioned that the decision support usually helped them to provide quality patient care and to enhance their medical training. However, the tools most favored were those designed to enhance workflow efficiency such as rounding reports and specific order sets. In addition, the years of training of the houses staff had no effect in this context.

Contrary to what we expected, we found that physicians with a lower number of encounters were more likely to override alerts. This finding can be interpreted based on its relationships with the types of physician and age variables that were significant in the regression model. House staff were more likely to override prescriptions and alerts, and they were more like to be younger and to have a lower average number of encounters per day than were faculty staff. Another possible interpretation is that physicians with lower encounter rates have more time to consider warnings, while those with higher rates might be more likely to cut corners. One study[29] that examined the behavior of 187 physicians regarding drug-duplication alerts for outpatients in Taiwan retrospectively showed that workload significantly affected the ordering behavior of the physicians. Those authors quantified workload based on the number of orders and encounters per 3-hour clinic session, one-third of which involved over 50 orders, implying a relatively full appointment schedule. The average numbers of encounter per day in our study setting were less than five and less than ten for house staff and staff physicians, respectively.

We were surprised that a high medical school ranking was associated with higher override rates. Potential explanations include possibilities that the education regarding medication provided in these schools is ineffective, or that graduates of these schools are overconfident. Our results in this regard are similar to those of previous research showing a partial association between medical school ranking and quality of care: a higher performance on quality measures was found among attendants at lower ranked or unranked schools compared to those at top 10 schools in the areas of acute care and female specific care, while there were no differences in chronic care and preventive care.[26] A systematic review by Moxey et al.[6] revealed that CDS use was perceived by some to enhance knowledge, while others reported that using CDS was " admitting a personal inadequacy." There was evidence of a strong belief that clinicians were already practicing in an evidence-based fashion, and there was a perception that introducing CDS systems threatened professional autonomy. Tierney et al.[30] reviewed the literature on the effects of using EHR on medical learners, and found strong mistrust and concerns that CDS functions in EHR and CPOE system can result in an unacceptably high volume of clinically insignificant alerts and may negatively affect the development of critical thinking and clinical decision-making skills. This negative attitude may affect young graduates and trainees.

We found different patterns between physicians and NPs in override rates. For nurse practitioners, there were no associations between the number of prescriptions and alerts or alerts and override ratio, even though there were negative correlations between the number of prescriptions and override ratio. There are two potential explanations for these findings: (i) the 95% CIs of the number of prescriptions and alerts were relatively wide in the NP group, which could have been due to either the smallness of the sample or actual wide variations being present, which negated the possible significance of any association or (ii) NPs may have more practical experience than physicians when they enter into expanded roles.

Next steps in this work will include profiling providers assessing the likelihood that they will override clinically important warnings. If groups like this can be identified, we plan to intervene with them to understand their rationale for overriding and to try and decrease the likelihood that they will override when it is clinically inappropriate.

Our study had several limitations. The provider characteristics that we were able to access were demographics and educational and clinical background, which were available in the hospital systems. Although we complemented these with publicly available data on individual physicians, there were many missing values, which thus led to exclusion in this analysis, such as race and practice site. In addition, information on over half of the providers, including physicians, who had moved away from Massachusetts were not available (many former house staff), again resulting in the exclusion of many subjects. However, our sample size was sufficiently large to ensure adequate statistical power in the regression analysis. It would have been interesting to have additional data from providers such as their willingness to accept risk, or tolerate uncertainty. Another potential limitation was the absence of patient level data for the patients treated by physicians, which might affect the patterns we found. However, we think it is unlikely that patient characteristic issues would explain our findings. We also could not assess the role of alert characteristics in these multivariate models. As we described in the introduction, many potential relevant factors are mentioned in the variability of providers' responses including alert type, severity, relevance etc. The focus of the present study was to assess provider-level variation in terms of how prescribers responded to alerts, or what provider attributes affect override rates. The appropriateness of over-riding does vary by alert category and severity level. Our study was limited to Partners Healthcare System serving hospitals in Massachusetts, which have a high density of academic medical centers and higher overall quality of care than the national average. It is possible that in this setting of high clinical quality, the effect of physician characteristics may be less important than it would be in a setting characterized by a higher overall variation in physician characteristics. Although the warnings that are displayed have been carefully vetted, many are no doubt still inappropriate, and many overrides are thus clinically justified. It is thus uncertain what an optimal override rate should be.

CONCLUSIONS

Clinical decision support is expected to deliver many future benefits, but, we still have limited understanding of how provider characteristics affect response patterns. We examined the relationships between override rates and the available prescriber characteristics, with a particular focus on physicians because they represent the largest majority of prescribers. We found that combined six characteristics − physician type, age, number of daily encounters, medical school ranking, residency hospital ranking, and Medicaid acceptance as well as an interaction term of age and physician type explained 30% of the variability in the prescriptions OR and half of the variability in the alerts OR. Such evaluations may help to improve our ability to target alerts in the future.

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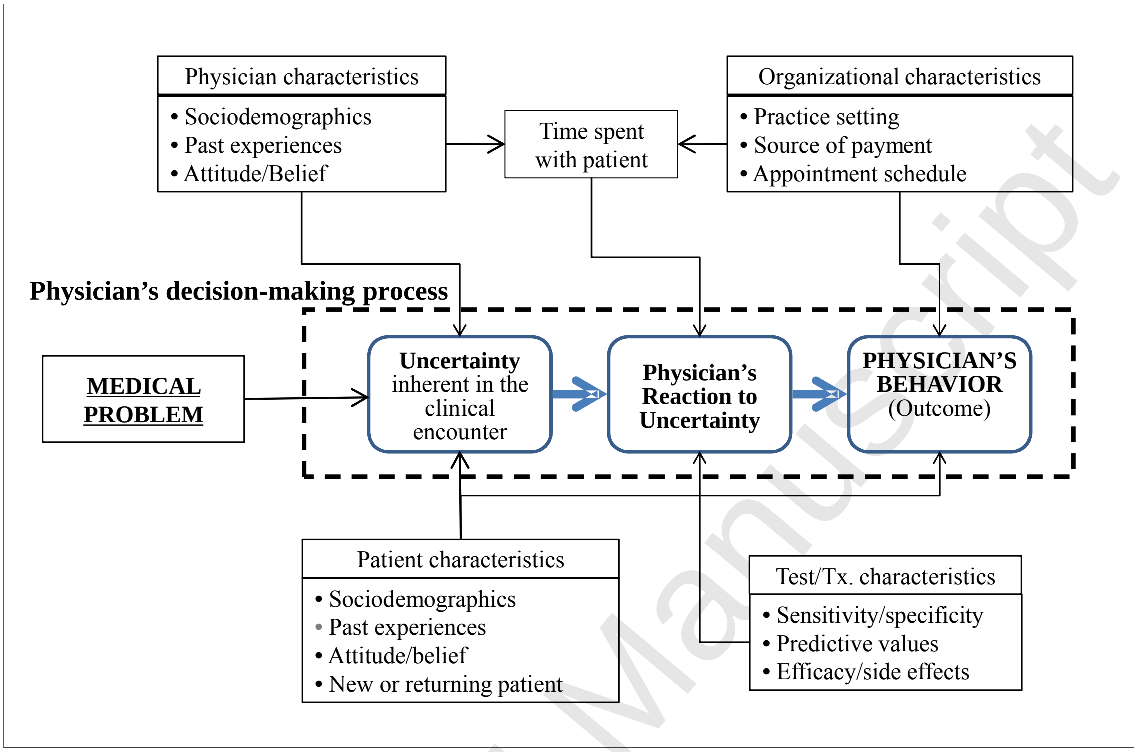

Fig.1 Conceptual model of factors influencing how physicians react to uncertainty [simplified from the original model of Gerrity et al.(18)]. Abbreviation: Tx., treatment.

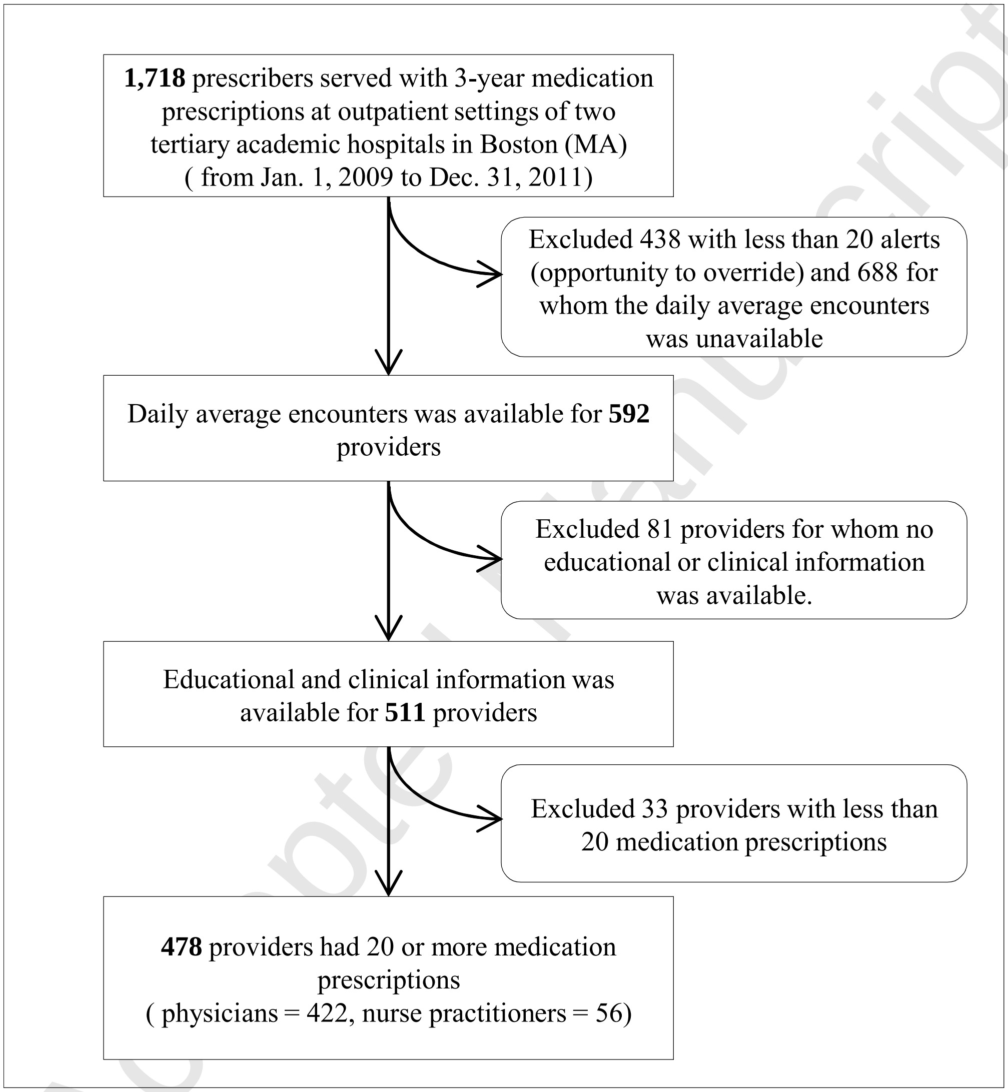

Fig.2 Selection flow for subjects included in the study

Summary Table

- What is already known about this topic?

1. Despite the promise of computerized medication-related clinical decision support (CDS) systems, there is wide variability in their use and in the responses to provider recommendations generated by these systems.
2. Previous studies have identified key steps that organizations should take to ensure the successful implementation and maintenance of a CDS system.
3. Literature also have suggested prescriber type, knowledge and training, preferences, physicians' believes on health information technology, and workload as being associated with the decision to override alerts.
4. However, there have been few explorations of provider-level variation in terms of how prescribers respond to alerts, or what provider attributes affect override rates.

- What does this study add to our knowledge?

1. The providers' override rates were high even at academic medical centers with higher overall quality of care than the national average of US.
2. Six physician characteristics were significantly related to the override rates; physician type, age, number of encounters, medical school ranking, residency hospital ranking, and acceptance of Medicaid
3. House staff were more likely to override than staff physicians, physicians with fewer daily encounters were more likely to override than others, and graduates of the top 5 medical schools were more likely to override than the others.

4. Consideration of six specific physician characteristics may help inform interventions to improve prescriber decision-making.

Contributions of Authors

Manuscript Title The Effect of Provider Characteristics on the Responses to Medication-Related Decision Support Alerts

D.B. initiated the project, designed data collection tools, implemented the study, monitored data collection for the whole trial, analyzed the data, and drafted and revised the paper. C.I. and D.B. designed data collection tools, monitored data collection for the whole trial, wrote the statistical analysis plan, cleaned and analyzed the data, and drafted and revised the paper. They are guarantors. S.S., K.N., D.S., N.M., and J.F. implemented the data collection tools, validate the data, and drafted and revised the paper. P.D. analyzed the data and drafted and revised the paper. S.S. and K.N. wrote the statistical analysis plan, monitored data collection for the whole study, and revised the draft paper. All members of authors reviewed and revised the draft paper.

Research Highlights

Title: The Effect of Provider Characteristics on the Responses to Medication-Related Decision Support Alerts

5. Provider characteristics have effects on how providers respond to medication alerts.
6. Six physician characteristics were significantly related to the override rates.
7. The combined six characteristics explained 30% of the prescription overrides variability.
8. The combined six characteristics explained half of the alert overrides variability.
9. Consideration of specific physician characteristics may help to improve prescriber decision-making.