Assessing the Relationship between Care Processes and Clinical Decision Support for Order Entry

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Structured Abstract

Purpose: Quality improvement in care management often involves standardizing care processes using order sets. We hypothesized that the reduction of care variation through the use of order sets improves clinical outcomes.
Scope: We performed a retrospective cohort study of hospitalized patients from 2018 to 2019 at three hospitals in New York. A total of 188,802 patients' data were extracted for the study analysis.
Methods: Study data included computerized physician order entry (CPOE), clinical, and demographic data extracted from electronic health records (EHR). We examined the relationships between clinician use of order sets, patient-level order variation, and patient outcomes while adjusting for acuity, patient demographics and comorbidity burden. Order variation was defined by a metric named longest common subsequence (LCS) that considers the type, frequency, and general trend in the sequences of orders. In conjunction, we also conducted a clinician survey to seek clinician perception of order sets for pain management.
Results: Significant findings were identified among septic patients. Septic patients with a high proportion of order set orders had significantly shorter length of stay (LOS) and lower inpatient mortality compared to those with low proportion. Patients with high proportion of order-set orders also experienced a shorter time to first antibiotics order in the emergency department. Thus, order set usage was associated with less order variation and better outcomes among patients hospitalized for sepsis. Clinician surveys revealed that the intention to use order sets for pain management was associated with performance of existing order sets, influence by leadership and peers, and EHR training and function integration.
Key Words: Order Set, Care Variation, Electronic Health Records

Purpose

Adherence to best practices vary across hospitals due to a myriad of barriers, including hospital resources, emergency department (ED) crowding, and patient characteristics.(1-6) These varying patient care settings affect clinical decision making as reflected in safe and efficient order entries. In response, hospitals have widely designed and implemented clinical decision support (CDS) tools in electronic health record (EHR) systems to improve clinical management through order entry.(7-10) Order sets, a type of CDS in computerized physician order entry (CPOE) that suggests orders as bundles and clinical pathways, are commonly used to standardize care and recommend best practices such as reducing the time to first antibiotics treatment.(11, 12) The positive effects of order sets on patient outcomes has been demonstrated through prior research.(7, 8, 10, 13) For example, Afessa et al. studied a paper protocolized sepsis order set and care process, and found that order set use improved compliance but not mortality.(14) Thiel et al., Micek et al., and Fargo et al. identified positive effects of EHR order sets on improved treatment related to fluid administration and antibiotic therapy, as well as improved patient outcomes including reduced organ failure and mortality.(7, 8, 13)

The positive impact of order sets reflects the mediating effect of order sets on the standardization of care and outcomes.(12) In this study, we proposed that the previously observed relationship between order sets and patient outcomes is in part mediated by reduced variability in order entry.(15) In other words, the use of order sets is associated with improved clinical outcomes, and the relationship may be in part mediated by the reductions in order variation through order set as a form of CDS. We aimed to discover the mechanism by which the use of order sets improves clinical outcomes.

Scope

We examined the trend in order placement across clinical departments at three sites of a large hospital system in New York, New York-Presbyterian (NYP) Hospital. Our overarching hypothesis for this project is that order set use is associated with improved quality of care (i.e., fewer unexplained variations in care). However, clinician-level barriers are limiting uptake of this proven CDS modality. Specifically, we hypothesize that patients receiving care through a higher percentage of orders from order sets for any type and purpose will have less order variability and better clinical outcomes than patients whose care resulted from a lower percentage of orders from order sets, even after controlling for sociodemographic and clinical factors that may contribute to order set variation. To test this hypothesis, we analyzed EHR CPOE data of orders entered to reconstruct the care process of patients admitted at three hospitals. Each patient, from arrival to disposition, receives a series of orders from treating clinicians that form a sequence of orders. These sequences can be evaluated for similarity and dissimilarity using established methods in sequential pattern mining.(15-17) Thus, among controlled patient populations, we can estimate the order variation in care by measuring the similarity and dissimilarity in the orders placed by treating clinicians. In this retrospective cohort study, our primary objective was to estimate the relationships between clinician use of order sets, patient-level order variation, and patient outcomes (mortality and length of stay), while adjusting for patient demographics and comorbidity burden. In addition, we conducted a survey to a wide population of clinicians at the study sites. We hypothesized that a lack of demonstrated benefit of order sets and a lack of supporting conditions may limit order sets' acceptability and intention to use by clinicians. To test our hypothesis, we used the Unified Theory of Acceptance and Use of Technology (UTAUT) framework.(18)

Collectively, we conducted three investigations in the study. First, we assessed the relationship between order set use and care variation while controlling for principal diagnoses, patient complexity, and campus location. Second, we analyzed whether more frequent use of order sets was associated with better care outcomes while controlling for principal diagnoses, patient complexity, and campus location. Third, we conducted a survey with Internal Medicine, Surgery, and Emergency Medicine clinicians in three campuses associated with NYP Hospital.(19)

Methods

Retrospective Analyses

Study Design

We conducted a retrospective cohort study using EHR data for patients admitted to the internal medicine service for all levels of care of the hospital through the ED in 2018 and 2019 from three hospitals in a large US hospital system (NYP Hospital). The three hospitals are distinct in their patient populations and neighboring communities, clinical workflows, and provider characteristics. Two of the hospitals are teaching hospitals from two distinct academic medical centers affiliated with the health system, and one hospital is an affiliated community hospital. We focused on order set use for three areas: sepsis, heart failure, and urinary traction infection (UTI). These areas were selected for the availability of institutionally created order sets as well as the common need for multiple diagnostic events in treating patients.

Selection of Participants

Patients who left against medical advice or walked out before medical evaluation were excluded from the study. Patients who expired in the ED were excluded due to the rarity and likely different presentation of sepsis, but patients who expired after being admitted to the hospital were included. Physicians chose an average of 5.4 order sets according to previous studies of inpatient clinical order patterns' prediction.(20) Thus among the remaining patients, those whose number of orders were three standard deviations above the mean and those who had fewer than five orders were removed as outlier patients whose care patterns were likely different or unique.

Data Sources

Figure 1. Patient inclusion figure

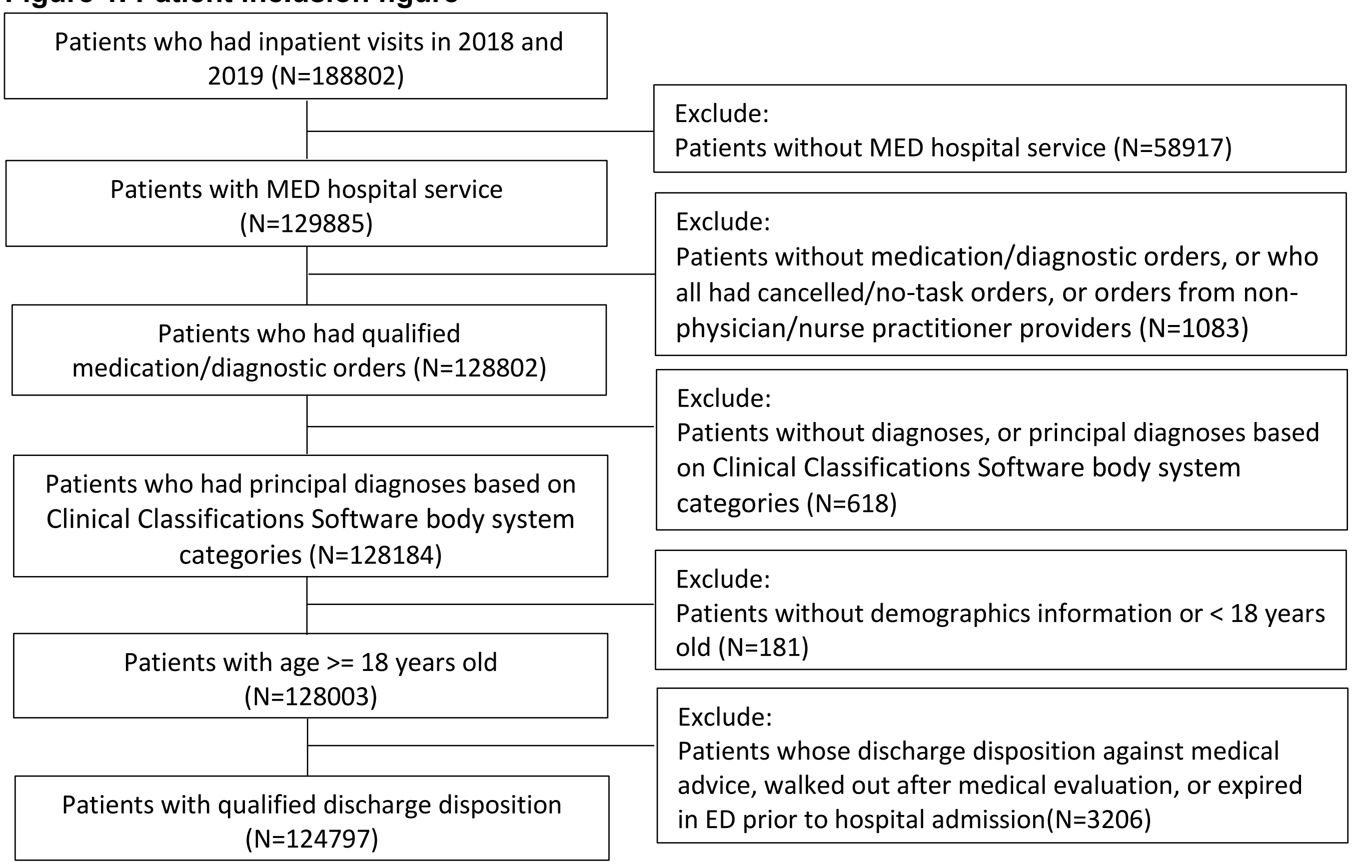


Figure 1 displays the inclusion and exclusion criteria of the study. Study data were derived from the EHR, including patient demographics (date of birth, gender, race, preferred language, hospital, ED presentation time, hospital admission time, hospital discharge time, and discharge disposition). The study data focused on diagnostic and medication orders placed by resident physicians, fellow physicians, attending physicians, physician assistants, and nurse practitioners. Within each encounter, we extracted order name, order set name, order status (completed or cancelled), order category (Laboratory, Radiology, Cardiology, Transfer/Admit, Neurophysiology, Nursing, Speech and Hearing), time of order placement, clinician role, and clinician department. Medication orders were grouped by Multum MediSource Lexicon. We extracted data regarding diagnoses including ICD-10 code and diagnosis type (principal or secondary). In addition, All Patients Refined Diagnosis Related Groups (APR DRG) and Severity of Illness (SOI)(21) data were extracted for each visit.

Orders that were cancelled were excluded from analysis. We define an order sequence as a sequence of orders for a patient from ED presentation until hospital discharge, including orders for assessment, diagnosis, and treatment. Multiple orders placed in the same minute are considered to be placed at once for the purposes of this analysis, as there is unlikely to be a clinical difference based on the sequence they were submitted in the order. Orders can be placed by multiple clinicians in the care team based on a group decision; thus, we did not attribute each order to a specific clinician role in the study data.

Analysis

The patient outcomes were length of stay (LOS) and in-hospital mortality. Our analysis focused on quantifying the variations in the order sequences among patients, assuming that orders needed for diagnosis and treatment should be similar among patients with similar clinical needs. Clinical needs are controlled by having the same principal diagnosis, APR DRG, and similar comorbidity level. In order to measure the variation in order sequences, we applied a machine learning-based process mining algorithm which derives sequences of ordering events.(22) This algorithm has previously been applied to measure variations in the management of chronic kidney disease,(22) diagnosis of undifferentiated abdominal pain,(23) and tracking adverse events after left ventricular assist device (LVAD) implants.(24) Instead of following the trajectory of single order over time, this algorithm captures the interaction of multiple orders over time, thereby allowing us to study order variation more comprehensively.

Order sequences were constructed in the data as follows. For simplicity, we use N to define the number of unique orders observed in the population, and m as the number of orders in each order entry session. At each order placement session, there is a possibility for each patient to receive one, or up to N orders. Thus, each time point forms an N-dimensional vector. In the vector, we set the value to 1 for the presence of an order and 0 for absence. When m orders are placed at one time, m dimensions are set to 1 in the N-dimension vector. Thus, for each patient, we can form a single order sequence which consists of multiple N-dimension vectors sorted by the time of order entry, reflecting the care process from arrival to disposition. This setup of the data can accommodate multiple orders being placed at the same time. The variations among patients' order sequences are measured by computing the longest common subsequence (LCS) distance. LCS is the longest subsequence that two sequences have in common while preserving the order of occurrence.(17) LCS is a reasonable metric for measuring order variation, as it considers the individual sequence length as well as a general trend in the sequence. As a distance measure between a pair of sequences, it is defined as the sum of the two sequences minus twice their LCS, or $dLCS = |seq\ 1| + |seq\ 2| - 2LCS$. Smaller values of LCS distance ($dLCS$) indicate higher similarity between two order sequences. Within a cohort of patients, we can measure the average $dLCS$ between each pair of order sequences. Thus, a smaller average dLCS indicates less order variation within a cohort of patients in this study. *P* patients can have up to *P* distinct order sequences, but similar patients would be expected to have similar sequences. Due to the high number of unique orders, the computation of LCS targeted commonly placed orders that were a union of orders related to the treatment.

Since the level of care is expected to differ according to individual clinical conditions, in order to adjust for the expected level of variation by clinical needs to the best level possible, we computed comorbidity burden as measured by the Charlson Comorbidity Index (CCI)(25), categorizing patients into 3 CCI groups: low (CCI= 0), medium (CCI= 1-2), and high (CCI>=3). CCI was computed based on all diagnosis codes extracted from the EHR during individual patient encounters. We then computed LCS within each CCI group of patients as intra-group variation. Within each CCI group, we categorized patients by the level of order set orders in their total orders. Order set use level is defined by stratifying patients into quartiles according to patients' proportions of orders placed from order sets out of all orders received from the encounter. Specifically, we compared patients who were in the fourth quartile (highest order set proportion) against those who were in the first quartile (lowest order set proportion). Within each group, the intra-group LCS distances between each pair of patients' order sequences were computed.

Statistical tests were conducted according to data types (numeric and categorical) and distributions (normal and non-normal). For bivariate analyses, we used Wilcoxon rank sum test or Welch t-tests to test the differences in LCS distance, LOS, and time to first antibiotics. We used Fisher's exact test for the differences in mortality between the low and high order set patients for each group. Statistical modeling was used to evaluate the relationship between order set use and LOS, and between order set and mortality. The models considered patients' age, preferred language (English vs. non-English), sex, CCI, race, and hospital location.

Prospective Analysis

Study Design

We used a cross-sectional, online survey in English that was accessible via a secure website. It generally took 5 to 10 minutes to complete. Provider characteristics included department affiliation, clinical role, levels of experience (attending physician, resident, and nurse practitioner), and gender. Under UTAUT, we extracted effort expectancy (perceived ease of use), performance expectancy (perceived value of using order sets in terms of easing workload and providing CDS), social influence, and facilitating conditions (level of IT training and literacy provided by the institution (26, 27) and past experience in designing or modifying order sets), and behavioral intention. Lastly, we surveyed on desired functions in the order set particularly related to pain management. Response options were multiple choices and 7-point Likert scales.

Selection of Participants

We recruited clinicians including physicians, physician assistants, and nurse practitioners. There were two inclusion criteria. First, the participant had to be eligible to use order sets to order or prescribe, and second, the eligible participant had to have used, or tried to use, order sets to place an order at least once within a 1-year period before the survey. Participants were recruited from emergency medicine, internal medicine, surgery, and other divisions in medicine. Recruitment venues included the listservs of departmental residents and faculty/staff. Participants received a $10 gift card as an incentive.

Data Sources

Anonymous survey responses were collected using Qualtrics (Provo, UT) for analysis. Table 1 displays the questions and response rate.

Table 1. Summary of answers to question related to UTAUT

Construct	Question	N (%) answered agree/yes *
EE1	Q8: The current EHR is easy to use.	105 (90.5%)
EE2	Q10: It requires less work to use order sets compared to free-standing orders in the current EHR.	64 (55.2%)
PE1	Q9: The current order sets in the EHR make order placement easier.	103 (88.8%)
PE2	Q15: Current order sets help me practice safe pain management.	32 (27.6%)
SI1	Q20: My institution encourages me to use order sets.	93 (80.2%)
SI2	Q21: My current peers use order sets regularly for clinical decision support or convenience.	88 (75.9%)
FC1	Q7: Did you receive sufficient electronic health record (EHR) training at your current institution?	110 (94.8%)
FC2	Q11: I know how to suggest changes to order sets at my current institution.	47 (40.5%)
FC3	Q14: Order sets for pain management are well integrated with other functions in the EHR at my current institution.	25 (21.6%)
BI	Q16: Would you be interested in having an order set for pain management?	103 (88.8%)
BI	Q17: Would you be interested in having an order set, with decision support, for alternative pain management to opioids?	105 (90.5%)
Other	Q12: I want reminders within the EHR for me to practice safe pain management.	74 (63.8%)
Other	Q13: Do you have access to a pain management order set in your EHR?	18 (15.5%)

Analysis

For each construct, to test the difference of provider characteristics and UTAUT constructs between participants with high and low construct score groups, we defined those with scores higher than 4 as high construct score group and others as the low construct score group. To compare the scores of different constructs for different groups of participants, we conducted Wilcoxon rank sum tests for continuous variables and chi-square or Fisher's exact tests for categorical variables at an alpha of 0.05. Further, we converted answers to behavioral intention (BI) questions to be a binary outcome variable. We tested the difference in provider characteristics and the four constructs between outcome groups, with Wilcoxon rank sum tests for continuous variables and Chi-square or Fisher's exact tests for categorical variables at a significant level of 0.05. Lastly, we built a logistic regression model to analyze the relationship between clinical roles and UTAUT constructs.

Results

Retrospective Analysis

Principal Findings

This study analyzed the order set use at three urban hospitals with distinct provider groups and patient populations. Among sepsis patients, we found that patients with a higher percentage of orders placed from any order sets, while adjusting for comorbidity burden, have shorter LOS and less mortality. This analysis also found that order set use is associated with smaller order variation related to the sepsis care processes, and shorter time to first antibiotics, potentially explaining study findings. Order sets analyzed include not only sepsis-specific order sets but all order sets, thus suggesting the value of order sets generally for sepsis care.

Outcomes

Of the study-eligible patients, there were 9663, 6063, 3283 sepsis, heart failure, and UTI patients, respectively, in the analysis across the three hospital campuses. There were 4,831 sepsis patients in the lowest and highest quartiles of order set use by their treating clinicians. As shown in Table 2, 3, 4, patients' sex and age did not differ significantly across hospitals. The racial composition of the populations varied, with each of the three hospitals (labelled as A, B, C) having most White, Asian, and Black patients for sepsis and UTI population, respectively. For heart failure patients, hospital B had the highest proportion of Asian and white patients, while hospital A had the highest proportion of black patients.

Table 2. Demographics and clinical profiles for sepsis population

Hospital	**Overall**	**Hospital A**	**Hospital B**	**Hospital C**
N	9663	2211	4595	2857
Female (%)	4919 (50.9)	1077 (48.7)	2377 (51.7)	1465 (51.3)
Age (mean (SD))	71.08 (17.57)	72.11 (17.60)	71.92 (17.05)	68.93 (18.18)
Race (%)				
Asian	1823 (18.9)	461 (20.9)	1295 (28.2)	67 (2.4)
Black	1216 (12.6)	236 (10.7)	540 (11.8)	440 (15.4)
Other	1477 (15.3)	314 (14.2)	1088 (23.7)	75 (2.6)
Unknown	1706 (17.7)	135 (6.1)	44 (1.0)	1527 (53.5)
White	3441 (35.6)	1065 (48.2)	1628 (35.4)	748 (26.2)

Table 3. Demographics and clinical profiles for heart failure population

Hospital	**Overall**	**Hospital A**	**Hospital B**	**Hospital C**
N	6063	1660	1789	2614
Female (%)	3031 (50.0)	829 (50.0)	885 (49.5)	1317 (50.4)
Age (mean (SD))	74.14 (14.59)	73.63 (15.21)	77.10 (13.56)	72.44 (14.56)
Race (%)				
Asian	635 (10.5)	209 (12.6)	375 (21.0)	51 (2.0)
Black	1197 (19.7)	435 (26.2)	278 (15.5)	484 (18.5)
Other	686 (11.3)	285 (17.2)	360 (20.1)	41 (1.6)
Unknown	1592 (26.3)	98 (6.0)	15 (0.8)	1479 (56.6)
White	1953 (32.2)	633 (38.1)	761 (42.5)	559 (21.4)

Table 4. Demographics and clinical profiles for UTI population

Hospital	**Overall**	**Hospital A**	**Hospital B**	**Hospital C**
N	3283	1137	1023	1123
Female (%)	2256 (68.7)	779 (68.5)	720 (70.4)	757 (67.4)
Age (mean (SD))	72.97 (18.83)	71.77 (20.19)	76.26 (16.70)	71.19 (18.86)
Race (%)				
Asian	353 (10.8)	140 (12.3)	195 (19.1)	18 (1.6)
Black	398 (12.1)	154 (13.5)	86 (8.4)	158 (14.1)
Other	445 (13.6)	200 (17.6)	219 (21.4)	26 (2.3)
Unknown	731 (22.3)	66 (5.8)	11 (1.1)	654 (58.2)
White	1356 (41.3)	577 (50.8)	512 (50.1)	267 (23.8)

The results from a structural equation model to evaluate the relationship between order set use and mortality are listed in Tables 5 to 7. We controlled for patients' age, a binary indicator of whether the patient is English speaking, sex, CCI, race, and hospital. Findings on order set use was significant among only sepsis patients. As shown in Table 5, the results suggest that just a 1% increase use of order set orders is associated with 0.34% decrease in odds of mortality for sepsis population, while adjusting for patient characteristics and hospital location. The results indicate that a 1% increase use of order sets is associated with a 0.02% decrease in the odds of mortality for heart failure patients and a 0.01% decrease in the odds of mortality for UTI patients, after adjusting for patient characteristics and hospital location.

Table 5. Structural equation modeling results on mortality for sepsis population

Outcome	Variable	Coefficient	P-value	95% CI	
Mortality					
	% OS orders	-0.00338 (odds ratio =0.9966)	<0.001	-0.00399	-0.00276
%OS orders					
	Age	0.055	<0.001	0.043	0.067
	English as preferred language	-0.696	0.002	-1.142	-0.251
	Sex (Female)	-0.957	<0.001	-1.342	-0.572
	Charlson Index	-0.800	<0.001	-0.926	-0.674
	Race (White)				
	Asian	1.132	<0.001	0.516	1.749
	Black	0.595	0.069	-0.046	1.235
	Other	0.836	0.009	0.206	1.465
	Unknown	0.669	0.051	-0.004	1.341
	Hospital (C)				
	B	3.475	<0.001	-4.015	-2.752
	A	-3.383	<0.001	2.881	4.069

Table 6. Structural equation modeling results on mortality for heart failure population

Outcome	Variable	Coefficient	P-value	95% CI	
Mortality					
	% OS orders	-.000222 (odds ratio =0.9998)	0.229	-.000584	0.0001395
%OS orders					
	Age	0.027	0.007	0.0074	0.046
	English as preferred language	-0.443	0.123	-1.006	0.121
	Sex (Female)	-0.622	0.018	-1.139	-0.106
	Charlson Index	-0.387	<0.001	-0.572	-0.202
	Race (White)				
	Asian	0.922	0,056	-0.025	1.869
	Black	0.827	0.035	0.059	1.595
	Other	0.271	0.559	-0.638	1.180
	Unknown	-0.338	0.408	-1.137	0.462
	Hospital (C)				
	B	4.122	<0.001	3.357	4.887
	A	-2.467	<0.001	-3.210	-1.724

Table 7. Structural equation modeling results on mortality for UTI population

Outcome	Variable	Coefficient	P-value	95% CI	
Mortality					
	% OS orders	-0.00014 (odds ratio =0.9999)	0.161	-0.00034	0.00006
%OS orders					
	Age	0.061	<0.001	0.039	0.083
	English as preferred language	-1.395	0.003	-2.310	-0.481
	Sex (Female)	-1.253	0.004	-2.094	-0.411
	Charlson Index	-0.403	0.009	-0.703	-0.103
	Race (White)				
	Asian	1.457	0.047	0.018	2.896
	Black	-0.193	0.773	-1.505	1.119
	Other	0.959	0.147	-0.336	2.254
	Unknown	-0.616	0.348	-1.903	0.671
	Hospital (C)				
	B	2.466	<0.001	1.212	3.719
	A	-1.835	0.002	-3.018	-0.652

Table 8: Order variation and patient mortality

Comorbidity burden	OS use level	N	N inpatient mortality (%)	Order Variation (SD)	Average OS/order ratio (SD)	Average N orders
Low	low	352	12 (3.4)	7.02 (5.20) ***	0.38 (0.06)	110.57 (75.88)
	high	349	6 (1.7)	5.03 (4.16)	0.66 (0.06)	68.84 (37.98)
Medium	low	1138	151 (13.3) ***	8.61 (6.83) ***	0.39 (0.06)	146.32 (91.75)
	high	1137	84 (7.4)	6.29 (4.83)	0.64 (0.06)	91.34 (57.78)
High	low	929	269 (29.0) ***	9.58 (6.09) ***	0.38 (0.05)	179.88 (96.23)
	high	926	145 (15.7)	8.18 (5.94)	0.62 (0.06)	132.17 (86.84)

We did additional analysis among the sepsis patients. Table 8 shows the number of patients, order variation defined by the average LCS distance, the number of inpatient mortalities, the percentage of order set orders, average number of orders by comorbidity burden level. We found that the order variation is smaller among patients who had higher percentage of order set orders. Among patients with medium and high comorbidity burden, patients who had a high proportion of order set orders had a significantly lower mortality than patients who had a low proportion of order set orders.

To better elucidate our findings, we examined the time to antibiotics between the high and low order set groups with the median and interquartile range (IQR) across groups, as shown in Table 9. While not statistically significant, the median hours to first antibiotic order was lower among patients who had high proportion of order set orders across comorbidity burden levels.

Table 9. The time to first antibiotics

Comorbidity burden	OS use level	Median hours to 1st sepsis antibiotic order since ED presentation [IQR]	P-value	Total N and N patients without antibiotics
Low	low	3.23 [1.42, 5.88]	0.113	352 (3)
	high	1.70 [0.72, 3.83]		349 (4)
Medium	low	1.95 [0.70, 4.35]	0.655	1138 (10)
	high	1.18 [0.52, 3.22]		1137 (14)
High	low	1.77 [0.67, 4.22]	0.700	929 (4)
	high	1.23 [0.53, 3.49]		926 (4)

Discussion

This analysis of CPOE data from three urban hospitals associated with a large US hospital system, among cohorts of patients with sepsis found an association between order set use, smaller order variation, and better patient outcomes as defined by LOS and mortality. We did not observe significant findings with UTI and heart failure patients, suggesting that the benefit of order set is dependent on the condition and workflow. The shorter median time to first antibiotics since ED presentation could explain the shorter LOS and lower mortality observed across hospitals. Sepsis is a leading cause of death in hospitalized patients and the implementation of sepsis-specific order sets has been reported to be associated with decreased mortality (7-10,12). This analysis supports prior pre-post studies showing the benefit of sepsis order sets. Moreover, this analysis reveals that greater percentage of orders placed from any order set, not necessarily sepsis-specific order sets, is associated with smaller care variation and patient outcomes. Additionally, this study offers a quantitative measure for the variation in consistency and quality of order placement in the sepsis care processes, demonstrating the association between less variation and better outcomes. Our finding suggests that order variation is computable and an important process metric to target when implementing CPOE interventions for sepsis. The three hospitals, while all in an urban setting, comprise of distinctly different patient populations in terms of race and social determinants of health. The care providers in the hospital also follow different workflows and affiliations. Thus, the results observed from this multi-site study data allow us to potentially generalize them across urban patient and provider populations.

Our study has a few limitations. First, it is possible that patients whose symptoms were more indicative of sepsis were easier to diagnose and treat via order sets. For example, clinicians who were treating patients who had clearer sepsis symptoms may have been more likely to opt for order sets, while patients with more complicated presentations could have warranted more a la carte orders. Our analysis may not have been able to tease out clinical differences that prompted more order set usage. Nevertheless, our analysis included all order sets and not only sepsis-focused, thus alleviating the potential confounding between sepsis symptoms and usage of order sets. Relatedly, in the structural equation models, while we controlled for demographics and comorbidity burden by CCI, the modeling was not able to incorporate other nuances such as acuity. Future studies may use other acute disease burden indicators such as Laboratory-based Acute Physiology Score (LAPS)(28) to better adjust for clinical needs and acute symptoms. In addition, we used the time to first antibiotic use as a proxy for time to first antibiotic use used for the purpose of treating sepsis, selecting only the antibiotics suggested in the CDC Hospital Toolkit for Adult Sepsis Surveillance.(29) The majority of sepsis is present on ED arrival and treated in the ED, and all patients included in our analysis had a diagnosis of sepsis. However, our analysis could still have included antibiotics used to treat other infections before patients developed sepsis. Moreover, while each order can be attributed to a single clinician, the order decision is often made jointly by a care team, limiting the characterization of providers who were more likely to use order sets from those with less tendency. We were not able to examine the effect of individual clinician-level order set usage on patient outcomes as patients often have many clinicians involved in placing orders. Lastly, the EHR used at the time of the study was Allscripts Sunrise. The EHR system configuration and usability may affect clinicians' likelihood of order set use, and future studies should investigate whether findings from this study may replicate in other EHR systems, and in other health systems and non-urban, non-academic environments or resource constrained settings.

Conclusions

Through analyzing order placement patterns in the EHR, we found that order set use was associated with smaller order variation and better hospital outcomes in some patient populations but not others. The findings may be explained by the availability of appropriate order sets for the condition, as well as the nature of the treatment.

Prospective analysis

Principal Findings

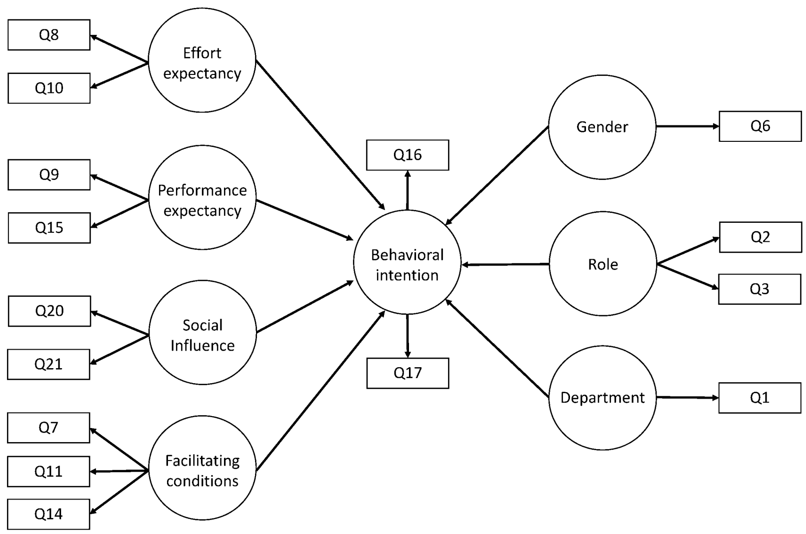
The intention to use order sets for pain management was associated with performance expectancy to existing order sets, social influence by leadership and peers, and facilitating conditions for electronic health record training and function integration. Intention to use did not significantly differ by gender or clinician role. Moderate differences were observed in the perception of the effort of, and facilitating conditions for, order set use across gender and roles of clinicians, particularly emergency medicine and internal medicine departments.

Outcomes

The survey was distributed to at least 630 clinicians through emails containing web links to the survey. A total of 116 surveys were analyzed. The gender distribution between male and female is 54 (46.6%) vs. 62(53.4%) and attending physicians 37 (31.9%) vs non-attending clinicians 79 (68.1%). Participants from Internal Medicine, Emergency Medicine, and other departments accounted for 45.7% (N = 53), 44.0% (N

= 51), and 10.3% (N = 12), respectively. The clinicians had a strong interest in order sets for pain management. A majority (88.8%) was interested in having an order set for pain management; 90.5% were interested in using an order set with clinical decision support functions for alternative pain management to opioids. Nearly 89% agreed that order sets make order placement easier, and over half (55.2%) clinicians agreed that it requires less work to use order sets compared to standalone orders in the current EHR.

Figure 2. UTAUT model applied to the study.



Three out of four major constructs, performance expectancy, social influence, and facilitating conditions, have statistical significant impacts on clinicians adoption intention, which are consistent with previous studies on factors impacting clinicians' technology adoption intention by using UTAUT framework.(30-33) Figure 2 displays the mechanism we identified in this analysis.(19) Our study found that social influence has the strongest impact (Odds ratio = 5.25, p-value = 0.015) on clinicians' intention to use order sets in EHR among the four constructs in our UTAUT model. Social influence has been found to be a strong factor which impacts physicians EHR adoption in extant research via various research methods,(30, 34-37) although the impact level varied across studies. We found that performance expectancy has the second strongest impact on clinicians' intention to use the order sets (odds ratio = 3.32, p-value = 0.013). On the contrary to previous studies, we found that the effort expectancy does not have a statistically significant impact on clinician's intention to use the order sets. We also found trends across gender and clinician types. Contrary to our expectation, facilitating conditions, particularly related to EHR training, were negatively associated with intention to use. Since the question asked about order sets, although we are not able to verify, it is possible that those who are more experienced with the EHR had other preferences such as quick-list or order panels.

Discussion

Findings of the study highlight the importance of performance and the technological culture present in the health system in understanding the barriers to order set use. Under the UTAUT framework, we found that the acceptance of order set use for pain management may be steered by its ability as CDS, peer usage, organizational endorsement, and smooth integration. Ensuring that order set design is configured to improve quality metrics and having organizational leadership support to raise awareness may increase acceptance. Ensuring that clinicians across experience levels receive the same training and environment may provide more support to order set use. Future work may also investigate detailed clinician characteristics to determine acceptance. While we considered broad factors in developing our research questions and questionnaires, future studies could assess respondents' attitudes in terms of their specific user preferences as well as their perceptions on having educational initiatives for the same. Qualitative analysis on open-ended free-text responses could provide additional insights.

Conclusions

This study attempted to identify the barriers of order set adoption for pain management and suggests future directions in designing and implementing CDS systems that can improve order set adoption by clinicians. Study findings imply the importance of order set effectiveness, peer influence, and EHR integration in determining the acceptability of the order sets.

Significance

Clinical decision support presents healthcare providers with relevant clinical knowledge and patient information to improve health and healthcare delivery(38). Examples of CDS include computerized alerts, diagnostic support, visualized summaries, and many other modalities(39). One of the key areas for CDS is within computerized physician order entry (CPOE). Adopted by over 95% of the US' non-federal acute hospitals,(40) CPOE allows clinicians to place medical orders electronically, and is one of the most important phases in patient care. Since a majority of potential adverse drug events occur as a result of errors during order placement(41), CPOE also is an area that can be targeted to reduce medical errors(41). A classic CDS for order entry in CPOE is an order set. Order sets present multiple orders for a particular clinical purpose as a set, with appropriate default settings, for clinicians to select(42). Despite order sets' common presence in CPOE and expected benefit, evidence on the mechanism of how order sets facilitate better care processes and outcomes in inpatient and emergency room (ER) settings remains limited.(43, 44) Addressing the knowledge gap, this study investigated the mechanisms of order set and care outcomes while controlling for patient characteristics.

Implications

Findings from the study may lead to strategies to improve clinical decision making and evaluate care quality. They may also lay the groundwork for prospective large-scale and interventional studies to strategize safe and efficient care practices through order sets that have sufficient clinician uptake. For example, hospitals may track order set use as part of performance metric to encourage higher usage of well-designed order sets and to evaluate the adherence of best practices. In addition, our findings suggest order sets lead to smaller care variations in certain population such as patients with sepsis. Thus, order sets may be used to ensure consistent and equitable care for patients. Through a survey using pain management as a use case, this study also identified factors to be considered when incorporating order sets. Identified factors represented the importance of performance expectancy, social influence, and facilitating conditions in using order sets. Insights into barriers of order set use are crucial to understand in implementing system-level changes to ensure its efficacy in patient care.

Published Work

Liu Y, Hao H, Sharma MM, Harris Y, Scofi J, Trepp R, et al. Clinician Acceptance of Order Sets for Pain Management: A Survey in Two Urban Hospitals. Appl Clin Inform. 2022;13(2):447-55.

Data-Driven Clinical Decision Support for Computerized Physician Order Entry: Development, Evaluation, and Implementation, AMIA 2020 Annul Symposium, 2020, Virtual

Examining Variations in Computerized Physician Order Entry for Emergency Medicine and Inpatient Management of Heart Failure, AMIA 2021 Informatics Summit, 2021, Virtual

References

1. Madsen TE, Napoli AM. The DISPARITY-II study: delays to antibiotic administration in women with severe sepsis or septic shock. Acad Emerg Med. 2014;21(12):1499-502.
2. Peltan ID, Bledsoe JR, Oniki TA, Sorensen J, Jephson AR, Allen TL, et al. Emergency Department Crowding Is Associated With Delayed Antibiotics for Sepsis. Ann Emerg Med. 2019;73(4):345-55.
3. Lopansri BK, Miller Iii RR, Burke JP, Levy M, Opal S, Rothman RE, et al. Physician agreement on the diagnosis of sepsis in the intensive care unit: estimation of concordance and analysis of underlying factors in a multicenter cohort. J Intensive Care. 2019;7:13.
4. Schultz MJ, Dunser MW, Dondorp AM, Adhikari NKJ, Iyer S, Kwizera A, et al. Current Challenges in the Management of Sepsis in ICUs in Resource-Poor Settings and Suggestions for the Future. In: Dondorp AM, Dunser MW, Schultz MJ, editors. Sepsis Management in Resource-limited Settings. Cham (CH)2019. p. 1-24.
5. Hatfield KM, Dantes RB, Baggs J, Sapiano MRP, Fiore AE, Jernigan JA, et al. Assessing Variability in Hospital-Level Mortality Among U.S. Medicare Beneficiaries With Hospitalizations for Severe Sepsis and Septic Shock. Crit Care Med. 2018;46(11):1753-60.
6. Walkey AJ, Shieh MS, Liu VX, Lindenauer PK. Mortality Measures to Profile Hospital Performance for Patients With Septic Shock. Crit Care Med. 2018;46(8):1247-54.
7. Thiel SW, Asghar MF, Micek ST, Reichley RM, Doherty JA, Kollef MH. Hospital-wide impact of a standardized order set for the management of bacteremic severe sepsis. Critical Care Medicine. 2009;37(3):819-24.
8. Micek ST, Roubinian N, Heuring T, Bode M, Williams J, Harrison C, et al. Before-after study of a standardized hospital order set for the management of septic shock. Crit Care Med. 2006;34(11):2707-13.
9. Amland RC, Hahn-Cover KE. Clinical Decision Support for Early Recognition of Sepsis(.). Am J Med Qual. 2019;34(5):494-501.
10. Ackermann K, Baker J, Green M, Fullick M, Varinli H, Westbrook J, et al. Computerized Clinical Decision Support Systems for the Early Detection of Sepsis Among Adult Inpatients: Scoping Review. J Med Internet Res. 2022;24(2):e31083.
11. Sutton RT, Pincock D, Baumgart DC, Sadowski DC, Fedorak RN, Kroeker KI. An overview of clinical decision support systems: benefits, risks, and strategies for success. npj Digital Medicine. 2020;3(1):17.
12. Rivers EP, Coba V, Rudis M. Standardized order sets for the treatment of severe sepsis and septic shock. Expert review of anti-infective therapy. 2009;7(9):1075-9.
13. Fargo EL, D'Amico F, Pickering A, Fowler K, Campbell R, Baumgartner M. Impact of Electronic Physician Order-Set on Antibiotic Ordering Time in Septic Patients in the Emergency Department. Appl Clin Inform. 2018;9(4):869-74.
14. Afessa B, Mullon J, Badley A, Gajic O. The impact of protocolized sepsis order set on the process of care in patients with severe sepsis/septic shock. Critical Care. 2007;11(4):1-2.
15. Lenert MC, Miller RA, Vorobeychik Y, Walsh CG. A method for analyzing inpatient care variability through physicians' orders. J Biomed Inform. 2019;91:103111.
16. Zhang YY, Padman R, Patel N. Paving the COWpath: Learning and visualizing clinical pathways from electronic health record data. J Biomed Inform. 2015;58:186-97.

17. Elzinga CH. Sequence analysis: Metric representations of categorical time series. Socio- logical Methods and Research. 2008.
18. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS quarterly. 2003:425-78.
19. Liu Y, Hao H, Sharma MM, Harris Y, Scofi J, Trepp R, et al. Clinician Acceptance of Order Sets for Pain Management: A Survey in Two Urban Hospitals. Appl Clin Inform. 2022;13(2):447-55.
20. Chen JH, Goldstein MK, Asch SM, Mackey L, Altman RB. Predicting inpatient clinical order patterns with probabilistic topic models vs conventional order sets. Journal of the American Medical Informatics Association. 2016;24(3):472-80.
21. Horn SD, Horn RA, Sharkey PD. The Severity of Illness Index as a severity adjustment to diagnosis-related groups. Health Care Financ Rev. 1984;Suppl(Suppl):33-45.
22. Zhang Y, Padman R, Patel N. Paving the COWpath: Learning and visualizing clinical pathways from electronic health record data. J Biomed Inform. 2015.
23. Zhang Y, Padman R, Epner P, Bauer V, Solomonides A, Rao G. Identifying Diagnostic Paths for Undifferentiated Abdominal Pain from Electronic Health Record Data. AMIA Jt Summits Transl Sci Proc. 2018;2017:290-9.
24. Movahedi F, Kormos RL, Lohmueller L, Seese L, Kanwar M, Murali S, et al. Sequential pattern mining of longitudinal adverse events after Left Ventricular Assist Device implant. IEEE J Biomed Health Inform. 2019.
25. Charlson ME, Pompei P, Ales KL, MacKenzie CR. A new method of classifying prognostic comorbidity in longitudinal studies: development and validation. J Chronic Dis. 1987;40(5):373-83.
26. Hoonakker PLT, Carayon P, Walker JM. Measurement of CPOE end-user satisfaction among ICU physicians and nurses. Applied Clinical Informatics. 2010;1(3):268-85.
27. Beam KS, Cardoso M, Sweeney M, Binney G, Weingart SN. Examining Perceptions of Computerized Physician Order Entry in a Neonatal Intensive Care Unit. Appl Clin Inform. 2017;8(2):337-47.
28. Escobar GJ, Greene JD, Scheirer P, Gardner MN, Draper D, Kipnis P. Risk-adjusting hospital inpatient mortality using automated inpatient, outpatient, and laboratory databases. Med Care. 2008;46(3):232-9.
29. Control CfD, Prevention. Hospital toolkit for adult sepsis surveillance. Atlanta: US Department of Health and Human Services. 2018.
30. Kijsanayotin B, Pannarunothai S, Speedie SM. Factors influencing health information technology adoption in Thailand's community health centers: Applying the UTAUT model. International journal of medical informatics. 2009;78(6):404-16.
31. Kalavani A, Kazerani M, Shekofteh M. Acceptance of evidence based medicine (EBM) databases by Iranian medical residents using unified theory of acceptance and use of technology (UTAUT). Health Policy and Technology. 2018;7(3):287-92.
32. Hsiao J-L, Chen R-F. Critical factors influencing physicians' intention to use computerized clinical practice guidelines: an integrative model of activity theory and the technology acceptance model. BMC medical informatics and decision making. 2015;16(1):1-15.
33. Liu L, Miguel Cruz A, Rios Rincon A, Buttar V, Ranson Q, Goertzen D. What factors determine therapists' acceptance of new technologies for rehabilitation–a study using the Unified Theory of Acceptance and Use of Technology (UTAUT). Disability and rehabilitation. 2015;37(5):447-55.

34. Hao H, Padman R, Sun B, Telang R. Quantifying the impact of social influence on the information technology implementation process by physicians: A hierarchical Bayesian learning approach. Information Systems Research. 2018;29(1):25-41.
35. Hao H, Padman R, Sun B, Telang R. Modeling social learning on consumers' long-term usage of a mobile technology: a Bayesian estimation of a Bayesian learning model. Electronic Commerce Research. 2019;19(1):1-21.
36. Hao H, Padman R. An empirical study of opinion leader effects on mobile technology implementation by physicians in an American community health system. Health informatics journal. 2018;24(3):323-33.
37. Hao H, Padman R, Telang R, editors. An empirical study of opinion leader effects on mobile information technology adoption in healthcare. AMIA Annual Symposium Proceedings; 2011: American Medical Informatics Association.
38. Middleton B, Sittig DF, Wright A. Clinical Decision Support: a 25 Year Retrospective and a 25 Year Vision. Yearb Med Inform. 2016;Suppl 1:S103-16.
39. Osheroff JA, Teich JM, Middleton B, Steen EB, Wright A, Detmer DE. A roadmap for national action on clinical decision support. Journal of the American Medical Informatics Association : JAMIA. 2007;14(2):141-5.
40. Pedersen CA, Schneider PJ, Scheckelhoff DJ. ASHP national survey of pharmacy practice in hospital settings: Prescribing and transcribing-2016. Am J Health-Syst Ph. 2017;74(17):1336-52.
41. Kaushal R, Shojania KG, Bates DW. Effects of computerized physician order entry and clinical decision support systems on medication safety: a systematic review. Arch Intern Med. 2003;163(12):1409-16.
42. Payne TH, Hoey PJ, Nichol P, Lovis C. Preparation and use of preconstructed orders, order sets, and order menus in a computerized provider order entry system. Journal of the American Medical Informatics Association : JAMIA. 2003;10(4):322-9.
43. Asaro PV, Sheldahl AL, Char DM. Physician perspective on computerized order-sets with embedded guideline information in a commercial emergency department information system. AMIA Annual Symposium proceedings / AMIA Symposium AMIA Symposium. 2005:6-10.
44. Ozdas A, Speroff T, Waitman LR, Ozbolt J, Butler J, Miller RA. Integrating "best of care" protocols into clinicians' workflow via care provider order entry: impact on quality-of-care indicators for acute myocardial infarction. Journal of the American Medical Informatics Association : JAMIA. 2006;13(2):188-96.