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Reducing Unintentional Duplicate Orders using Passive Inline Just-in-Time Decision Support

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ABSTRACT

Background: EHRs allow teams of clinicians to simultaneously care for patients but an unintended consequence could result in duplicate ordering of tests and medications. We implemented a simple reminder for busy teams of clinicians in our emergency department by placing a red highlight around the checkbox of a computer-based order if previously ordered.

Methodology: We performed an interrupted time series to analyze all patient visits 1 year before and 1 year after the intervention. Significance testing was performed using a negative binomial regression with Newey-West standard errors, correcting for patient level variables and environmental variables that might be associated with duplicate orders. The primary outcome measure was the number of unintentional duplicate orders.

Results: After the intervention, the number of duplicate orders for laboratory orders decreased with an incidence rate ratio 0.63 (0.53-0.74) and for radiology orders decreased with an incidence rate ratio of 0.61 (0.45-0.83).

Conclusion: Passive visual queues provide that provide just-in-time decision support are effective, not disruptive of workflow, and my decrease alert fatigue in busy clinical environments.

1. BACKGROUND AND SIGNIFICANCE

EHRs play a vital role in patient safety by improving communication, providing access to information, assisting with calculations, monitoring, and providing decision support.[1] EHRs routinely support patient safety by checking for drug allergies, drug-drug interactions, appropriate drug dosages, and duplicate orders.[2] Oftentimes, this support comes in the form of interruptive alerts that help prevent a user from doing the wrong thing. However, there is another approach. Larry Weed had a vision that EHRs could both guide and teach. Passive just-in-time reminders could also be used to help guide users to the right thing, rather than preventing them from doing the wrong thing. The level of interruption to clinician workflows, whether guiding, preventing, or both, should be tailored to the severity and immediacy of the harm being prevented.

Electronic health records (EHRs) enable teams of clinicians to simultaneously access patient information and collaborate in care. Computerized physician order entry (CPOE) allow physicians to prescribe medications electronically, with the goal of eliminating hand-written orders creating a safer prescribing system [3]. However, CPOEs themselves may have unintended consequences. [4,5] For example, healthcare providers might be more likely to overlook existing orders and duplicate work.[6,7] Duplicate orders may be the intention of a provider looking to measure a lab value or radiology study serially. However, duplicate orders may also be markers of poor communication between two providers caring for the same patient, or may be an order placed on the wrong patient, a so-called “near miss”. [8]

The time sensitive nature of Emergency Department (ED) visits, combined with the need for parallel workflows and team-based care makes the ED setting particularly vulnerable to unintended duplicate orders. [9,10] When duplicate orders are recognized prior to being carried out, they lead to increased work to reconcile the discrepancies, but if not caught in time, they might lead to patient harm, unnecessary testing, and increased cost.

Common strategies to reduce duplicate orders include additional training for users, downstream workflow mitigation (such as screening by pharmacy, laboratory, or radiology), or interruptive alerts. [11] Though interruptive alerts can be effective, they generally occur after the provider has completed the ordering process, which can result in increased click-count, cognitive dissonance, frustration, and alert fatigue. [12,13] Interruptive alerts can also disrupt current thought processes, which may lead to other errors. [14] Furthermore, alert fatigue can cause users to disregard important alerts that would have prevented patient harm. [15–18] Ideally, the cue would be provided just-in-time, before the user makes their selection, thus preventing all of the above negative effects. Reducing the unintentional negative effects of EHR's is important as EHR's are becoming increasingly linked to physician dissatisfaction and burnout.[19–22]

The goal of this investigation is to show the effect of a passive inline just-in-time decision support on reducing unintentional duplicate orders in the emergency department. This approach need not be mutually exclusive from interruptive alerts. For example, we implement both strategies for drug allergy alerts and drug-drug interactions.

2. METHODS AND METHODS

2.1 Study Design

We performed an interrupted time series to analyze all patient visits 1 year before and 1 year after each intervention. The intervention was part of a quality improvement project to reduce unintentional duplicate orders in the ED.

2.2 Setting and Selection of Participants

The study was performed in a 55,000 visits/year Level I trauma center and tertiary, academic, adults-only, teaching hospital. All consecutive ED patient visits 1 year before and 1 year after each intervention were included in the study. No visits were excluded. The EHR used was custom developed at the institution.

2.3 Intervention

As part of a quality improvement project, we implemented a user interface within our CPOE system in the ED that provides passive inline just-in-time duplicate order decision support while the user is in the process of placing an order. If an order had previously been placed during that ED visit, we cue the user by showing a red highlight around the checkbox of that order. (*Figure 1*) The intervention was performed as a phased implementation starting with laboratory orders (8/13/13), followed by medication orders (2/3/14), and lastly radiology orders (12/12/14).

2.4 Duplicate Order Algorithm

An order was determined to be a duplicate if two identical orders were placed, and then one was subsequently cancelled. For the purposes of this algorithm, a laboratory order is uniquely identified by an internal laboratory code, which is then mapped to a LOINC code. Medication orders are uniquely identified by the combination of an internal medication code, route, and dose. For example, two orders for morphine 5 mg IV once would be considered a duplicate

order, while an order for morphine 5 mg IV once and morphine 2 mg IV once would not be considered a duplicate. Each internal medication code is then mapped to a medication entry in First Data Bank. Radiology orders are uniquely identified by a Simon-Leeming code.[24]

2.5 Methods of Measurement

Data was collected for each patient visit and then aggregated into 8 hours bins, corresponding to the 8 hour shifts worked by clinicians (7a-3p, 3p-11p, 11p-7a). For each bin, the mean patient age was calculated, as well as the percent of female patients, percent of patients with an emergency severity index (ESI) greater than or equal to 3, percent of patients with English as a primary language, percent discharged, and percent admitted. We also collected environmental variables to describe the state of the emergency department when the patient first arrived in the ED. These environmental variables included the current number of patients in the department, number of patients in observation, number of new patients, number of ICU bed requests, number of telemetry bed requests, number of floor bed requests, and number of boarders. We then calculate the mean for each of these environmental variables for each bin. ESI is on a scale from 1 to 5, with 1 being critically ill patients requiring immediate intervention and 5 being the least acute. Boarders are patients who have been admitted to the hospital, but have not yet received a bed after 2 hours.

2.6 Outcome Measure

The outcome measure was the number of unintentional duplicate orders in each bin for each of the order types: laboratory, medication, and radiology. How an order is determined to be unintentionally duplicated is described in the prior section.

Intentional duplicate orders can be clinically necessary. For example, a patient in hemorrhagic shock will often receive serial hematocrits to monitor their condition, a type of intentional duplicate order. In this paper, we intend the term duplicate order to mean unintentional, unless otherwise stated.

2.7 Data Analysis

Data was analyzed using an interrupted time series analysis. Since we performed a phased implementation, we shifted the days so that the intervention occurred on the same day for each order type. Orders were aggregated into 8 hour bins described in the section Methods of Measurement.

The following negative binomial regression was used for significance testing for each of the order types (laboratory, medications, and radiology):

$$log(\mu_t) = \beta_0 + \beta_1 Post_t + \beta_2(Post_t * T_t) + \beta_3 T_t + \beta_4 X_t + \delta_t + \gamma_d + \theta_m + \varepsilon_t$$

where μ_t represents the expected number of duplicate orders of its type. The total number of orders, less duplicates, were included as an offset term. $Post_t$ is an indicator variable that equals 1 after the intervention date for that order type and 0 before. T_t is the number of shifts at time *t* since the beginning of the sample for that order type, where the sample begins 1 year prior to the intervention date. X_t is a vector of controls at time *t* at the shift-level, including average patient age, gender composition of patients, whether patients were native English speakers, percent of patients with an emergency severity index 3 or greater, percent of patients discharged home, number of observation patients, number of new patients, number of ICU beds requested, number of telemetry beds requested, and number of boarders. δ_t, γ_d, and θ_m are shift fixed effects, day-of-week fixed effects, and month-of-sample fixed effects, that control for

how duplicate orders may follow a cyclical pattern throughout the day, week, and year, respectively. ε_t are Newey-West standard errors, which are robust to autocorrelation and heteroskedasticity.

The coefficients of interest are β_1 and β_2. β_1 estimates the immediate effect, or the level change, of the intervention on duplicate orders while β_2 estimates the change in trend of duplicate orders after the intervention. β_3 estimates the pre-intervention trend of duplicate orders, thus, $(\beta_2 + \beta_3 - 1)$ represents the post-intervention trend in duplicate orders. Coefficients are transformed into incidence rate ratios in Table 2.

We also fit a Poisson model which yielded very similar results, but used a negative binomial model for more accurate effect estimates due to the over-dispersion of covariates. Stata/SE 14.2 software was used for statistical analysis.

2.7 Human Subjects Research Statement

A determination was made by our Committee on Clinical Investigation that this did not constitute human subjects research and that no further review was required. (#2019D000239)

3. RESULTS

3.1 Summary Statistics

A total of 730 days were analyzed. Patients were slightly older in the laboratory and medication intervention groups. Patients were also slightly more acute (fewer patients with ESI >=3). There were also slightly fewer patients discharged in the medication intervention group.

For environmental variables, there were slightly more patients in the department. There were slightly fewer patients in observation in the laboratory group, but more in the medication and radiology intervention groups. There were slightly more ICU bed requests and telemetry bed requests. There were also slightly more foor bed requests in the medication and radiology intervention groups. There were slightly less boarders in the laboratory intervention group, but more in the radiology intervention group. Patient demographics and order summary statistics are reported in *Table 1*.

3.2 Main Results

After the intervention, there was a significant level change with a decrease in laboratory duplicate orders incidence rate ratio (IRR) 0.63 (0.53-0.74) and radiology duplicate orders IRR 0.61 (0.45-0.83). However, there was an increase in medication duplicate orders IRR 2.64 (1.94-3.60). There was no change in trend for any of the intervention groups. We report these results from the interrupted time series in *Table 2*.

For patient variables, an ESI >= 3 (lower acuity) was also associated with more radiology duplicate orders after the intervention IRR 1.75 (1.05-2.91).

For environmental variables, the number of new patients during that shift was associated with a decrease in duplicate orders in the laboratory and medication intervention groups. The number of patients admitted to the ICU during that shift was associated with a decrease in the number of laboratory duplicate orders, but was associated with an increase in radiology duplicate orders. Patients admitted to the floor during that shift was associated with a decrease in laboratory duplicate orders, while associated with an increase in radiology duplicate orders. Lastly, the

number of patients boarding during that shift was associated with an increase in laboratory duplicate orders.

We also report the top 5 duplicate orders for each order type in *Table 3* to better illustrate the most common unintentional duplicate orders.

4. DISCUSSION

4.1 Just-in-time Passive Decision Support

We have demonstrated a simple, yet effective method of reducing duplicate laboratory and radiology orders that avoids many of the downsides of traditional, interruptive methods. This method was evaluated in a busy clinical setting that relies on effective and efficient team work to care for patients. In our emergency department, a red highlight around an order's checkbox (Figure 1) significantly reduce duplicate orders for both laboratory testing and radiological procedures but not medications.

It takes 9 clicks and the typing of a password to cancel an order in our EHR, which takes 30 seconds to complete. The predicted reduction in unintended duplicate orders saved 17,936 clicks in the year after the intervention, which amounts to 16 hours and 36 minutes of regained productivity. This is regained time that was previously waste and provided no value that can now be spent instead at the bedside taking care of patients. Though 30 seconds may not seem like a large amount of time, sometimes it only takes 30 seconds to connect with a patient, offer a kind gesture, and help patients heal.

In an interrupted time series, the effect size can be thought of as the level change (β_1), especially when there the pre-intervention trend and post-intervention trends are both 1. In our intervention, the effect was unlikely due to chance or secular trends, as the individual interventions on laboratory, medications, and radiology orders were phased in at different times and then time shifted so that the intervention date occurred on the same date.

At baseline, we had relatively few medication duplicate orders compared to laboratory and radiology duplicate orders, which is consistent with ED workflow. Nurses often order laboratory and radiographic studies per clinical protocol, but do not routinely order medications, except in an emergency when a physician gives a nurse a verbal order. A medication duplicate order would normally only occur if two physicians, for example, a resident and attending, both ordered the same medication. Though the effect size is large for medication duplicate orders IRR 2.64 (1.94-3.60), this is likely because the pre-intervention rate of duplicate orders was so small with an absolute increase of only 0.06, from 0.23 to 0.29. Though this is statistically significant, we do not believe this to be clinically significant.

4.2 Comparison to Interruptive Alerts

Starting in 2011, the Cleveland Clinic developed a list of more than 1,200 lab tests that could not be ordered more than once per day without a hard stop phone call to explain why an intentional laboratory duplicate order was medically appropriate.[25] This intervention was successful at reducing duplicate lab orders, with only 3% of interruptive alerts being overridden by a phone call, resulting in a cost avoidance of $183,586 over 2 years accounting for materials and laboratory personnel labor. In their system, the investigators recognized that poor workflows, specifically having to navigate away from the order entry screen to check for pending

orders, was a significant driver of unintentional duplicate orders. They believed relying on laboratory technologists “to detect and eliminate redundant tests would be a gross misappropriation of these valuable human resources.”[25] Though their cost effectiveness analysis captured costs to the laboratory, they failed to capture costs to a key stakeholder, the physician, specifically their time wasted performing what was essentially prior authorization. This prior authorization approach is in stark contrast to our user-centered design approach. We chose to make the right thing easy to do; they chose to make the wrong thing hard to do. Though poor usability can be a powerful deterrent, we believe good usability is a more sustainable approach that respects human autonomy and promotes user satisfaction and physician longevity.

Interruptive alerts can also lead to patient harm. In 2006, a multi-center randomized controlled trial was performed to evaluate an interruptive alert to reduce concomitant orders for warfarin and trimethoprim-sulfamethoxazole.[26] Although, the interruptive alert was successful in reducing this drug pair ordering with an adjusted odds ratio of 0.12 (95% CI 0.045-0.33), it also had the unintended consequence of 4 patients who had delays in treatment. The harm was believed sufficient that the IRB terminated the study early.

4.3 Intervention User Interface Design

We took a user-centered approach to user interface design and followed the best practices of clinical decision support to minimize interruptions unless they are clinically necessary.[27] We placed the decision support for duplicate orders just-in-time, which is at exactly the time the decision to order was being made, rather than an interruptive alert, which is after a decision has already been made. We furthermore placed our decision support inline, so that the decision support was in the same area of focus as the intended action. A common alternative to

providing just-in-time decision support would be to display a list of current orders for a patient on the order entry screen. A user would first need to commit these orders to short term memory and then apply them to the order entry screen. As patients can have tens of orders, this can quickly overwhelm a user's working memory, leading to unintended cognitive errors.

Rather than leverage the user's computational ability to do duplicate order checking, allergy checking, or drug-drug interaction checking, we use a computer's computational ability. Unlike a human, a computer's computational ability is highly reliable, fast, and does not fatigue. We provide this computational capacity in real-time at the time of screen draw with sub-second response times. Though in the past, computational resources were limited and such computations can not be performed in real-time and needed to be precalculated, advances in computational capacity has eliminated this concern.

4.4 Additional Use Cases

We also use these same techniques for duplicate order reminders in our order sets, transforming the order set itself into a visual checklist, as shown in *Figure 3*. These visual checklists engage the visual and spatial reasoning portions of the brain, offloading the language centers. These same techniques can also be used to guide users when using a clinical decision rules, as shown in Figure 4, suggesting the correct responses based on automated information retrieval. In the same way, such methods can also be used to integrate predictive machine learning algorithms into clinical workflows by guiding users to the correct response along with some explanation from the algorithm to show its work. Since a human is still in the loop, this method would be tolerant to less than perfect performance metrics as newer machine learning models are being created.

Though for this application we employed passive inline JIT decision support alone, this approach need not be mutually exclusive with interruptive alerts. For example, we have also implemented common drug decision support in in CPOE and prescribing modules for allergies, pregnancy, and drug-drug interactions using both approaches. Allergy decision support for CPOE and prescribing modules is very amenable to this approach, as some patients can have multiple drug allergies, shown in *Figure 5*. Though EHRs commonly provide JIT decision support by enumerating a patient's allergies on the order screen, users must still commit these allergies to working memory, and then apply them by drug class to each potential order. This workflow creates multiple failure modes: the committing of allergies to working memory, the grouping of allergies to drug classes, and finally the cross-referencing of drug classes to orders. Our inline decision support offloads this cognitive process from the user, freeing their attention to focus on other clinical tasks.

4.5 Limitations

Although randomized controlled trials remain the gold-standard for assessing the effect of interventions, it is not always possible in informatics-based interventions in the ED. Since there are multiple clinicians who care for an ED patient, and each of those clinicians care for different sets of patients, it would be difficult to randomize at the level of the patient or user without significant contamination. Cluster randomized trials, clustered by day or week might have worked, but users would likely have found it confusing to have duplicate order decision support on sometimes, and off at other times. For example, users may mistakenly interpret the absence of a duplicate order warning as the absence of a duplicate order, when in fact they were randomized to the control group, increasing duplicate orders in the control group and the chances of a type 1 error. Therefore, we chose a phased implementation quasi-experimental study design to help control for underlying temporal trends. We also performed an interrupted

time series analysis to further evaluate the longitudinal effects of interventions.[28] We also corrected for every patient level variable or environmental variable collected in our EHR that might be associated with duplicate orders.

Our outcome measure only captured duplicate orders that were subsequently cancelled, using the act of cancellation as a surrogate for user intent. There were also unintentional duplicate orders that were never cancelled and subsequently carried out. Unfortunately, it was not possible to retrospectively differentiate between non-cancelled unintentional duplicate orders and intentional duplicate orders, as we could not reliably ascertain intent without the act of cancellation. As part of our quality improvement process, our ancillary services were more vigilant after the intervention in identifying unintentional duplicate orders. This should have increased the number of duplicate orders captured in our outcome measure, which would have biased us towards the null.

As with any intervention, there may be unintended consequences. Some users may have been biased to not order a test or medication that was medically necessary. Unfortunately, there was no EHR artifact to capture this unintended consequence. Furthermore, these unintended consequences may vary by level of training and would be an interesting direction of future research.

Our intervention and outcome measure only addressed exact duplicate orders. Semantic duplicate orders such as therapeutic duplication are also important and remain as future work. For example, a patient who is ordered acetaminophen/oxycodone should receive passive JIT decision support no only for acetaminophen/oxycodone, but also for its constituent ingredients:

acetaminophen and oxycodone. Similarly, a lab order for a CBC/DIF should also provide passive JIT decision support for a CBC. Existing knowledge bases could be leveraged to help provider therapeutic duplication decision support, however, in practice, would likely still require some manual curation to reduce false positives.

Our study was also performed at an urban, academic, adults-only teaching hospital with a custom EHR. The effectiveness of this intervention may differ in other care settings with different baseline unintentional duplicate orders and mitigation workflows.

4.6 Future Directions

Despite our intervention, some duplicate orders still persisted, possibly because there still exists a small time window where two users could place an order simultaneously as described by Schreiber et al, [29] and therefore, neither would receive the intervention. A mechanism to detect this condition and alert users would be a possible next step.

Another possible cause of persistent duplicate orders is that the red highlight may not have been understood by some users. We chose to place the reminder around the checkbox where a user is focused when placing an order, rather than as explanatory text to right of an order, adjacent to a user's focus. A future direction of usability research might be to compare 3 approaches: the red highlight alone, explanatory text alone, or both.

Our implementation was specific to the ED, but should work in any care setting where clinical care teams must collaborate. Other care settings that have clinicians who are geographically dispersed would amplify the effect of such an intervention. Different care settings will require

different thresholds for determining if an order is a duplicate. For example, in the ICU, that threshold might be 4-12 hours. In the hospitalist setting, that threshold may be 24 hours, while in the outpatient setting, it may be 1 week or 1 month. In the ED, having a simple binary representation of whether an order was a duplicate was intuitive and clinically meaningful. However, in the ICU, having multiple stages corresponding with last order time with additional information such as ordered 5 mins ago or ordered 6 hours ago might be important. We will iteratively develop new user interfaces given this increased complexity as we deploy this intervention across these different care settings.

5. CONCLUSION

Passive just-in-time decision support is an effective alternative to interruptive post-order interruptive alerts for reducing duplicate order entry. We believe guiding clinicians to a right action is better than telling the clinician they have made an error. Our approach will help reduce alert fatigue and lessen clinician complaints about EHRs. In our implementation, we were able to reduce laboratory duplicate orders by an incidence rate ratio of 0.63 and radiology duplicate orders by an incidence rate ratio of 0.61.

Table 1: Patient Demographics and Order Summary Statistics

	Laboratory Mean (SD)			**Medications** Mean (SD)			**Radiology** Mean (SD)		
	Before	**After**	**p-value**	**Before**	**After**	**p-value**	**Before**	**After**	**p-value**
Patient Age	**50.32 (4.64)**	**51.01 (4.29)**	**<0.001**	**50.55 (4.58)**	**51.15 (4.38)**	**0.002**	51.09 (4.39)	51.37 (4.05)	0.120
% Female Patients	0.54 (0.08)	0.54 (0.08)	0.604	0.53 (0.08)	0.54 (0.08)	0.273	0.54 (0.08)	0.53 (0.08)	0.213
% Patients with ESI >= 3	**0.62 (0.1)**	**0.61 (0.09)**	**0.010**	**0.62 (0.10)**	**0.60 (0.10)**	**0.000**	**0.61 (0.09)**	**0.59 (0.10)**	**0.000**
% Patients with English as primary language	0.97 (0.03)	0.96 (0.04)	0.295	0.96 (0.03)	0.96 (0.04)	0.168	0.96 (0.04)	0.97 (0.03)	0.062
% Discharged	0.59 (0.09)	0.59 (0.08)	0.455	**0.59 (0.09)**	**0.58 (0.09)**	**0.003**	0.58 (0.09)	0.58 (0.09)	0.105
% Admitted	0.36 (0.09)	0.36 (0.08)	0.554	0.36 (0.08)	0.36 (0.08)	0.583	0.36 (0.08)	0.36 (0.08)	0.464
No. Patients in Department	**39.1 (8.75)**	**40.2 (8.85)**	**0.003**	**38.85 (8.71)**	**42.31 (8.98)**	**0.000**	**41.38 (9.04)**	**45.61 (8.94)**	**0.000**
No. Patients in Observation	**9.47 (3.69)**	**8.80 (3.61)**	**0.000**	**8.98 (3.62)**	**9.4 (3.71)**	**0.006**	**9.24 (3.73)**	**10.46 (3.91)**	**0.000**
No. New Patients	6.86 (2.62)	6.81 (2.57)	0.646	6.77 (2.59)	6.90 (2.56)	0.233	6.86 (2.55)	6.97 (2.56)	0.314
No. ICU Bed Requests	**0.84 (0.61)**	**0.91 (0.67)**	**0.018**	**0.86 (0.63)**	**1.01 (0.74)**	**0.000**	**0.94 (0.69)**	**1.26 (0.87)**	**0.000**
No. Telemetry Bed Requests	**2.3 (1.47)**	**2.67 (1.74)**	**0.000**	**2.40 (1.51)**	**3.12 (2.01)**	**0.000**	**2.82 (1.83)**	**3.8 (2.17)**	**0.000**
No. Floor Bed Requests	3.53 (1.88)	3.64 (1.95)	0.178	**3.41 (1.82)**	**3.96 (2.09)**	**0.000**	**3.81 (2.03)**	**4.71 (2.44)**	**0.000**
No. Boarders	**2.48 (1.88)**	**1.34 (1.67)**	**0.000**	1.79 (1.83)	1.85 (2.07)	0.448	**1.50 (1.79)**	**2.98 (2.64)**	**0.000**
No. of Orders	306.51 (149.31)	308.69 (141.95)	0.725	**140.82 (64.12)**	**155.77 (71.84)**	**0.000**	**56.93 (26.76)**	**60.52 (28.05)**	**0.002**
No. of Unintentional	**4.1 (5.18)**	**2.49 (3.39)**	**0.000**	**0.35 (0.68)**	**0.46 (0.74)**	**0.000**	**0.87 (1.18)**	**0.71 (0.98)**	**0.001**

Duplicate Orders									
% Duplicate Orders	**.0129 (.0165)**	**0.0081 (.0124)**	**0.000**	**0.0023 (0.0049)**	**0.0029 (0.0053)**	**0.003**	**.0157 (.0238)**	**.0121 (.0197)**	**0.000**

Table 2: Interrupted Time Series Analysis

	Laboratory	Medications	Radiology
	IRR (95% CI)	IRR (95% CI)	IRR (95% CI)
Level Change (β_1)	**0.63 (0.53-0.74)**	**2.64 (1.94-3.60)**	**0.61 (0.45-0.83)**
Change in Trend (β_2)	1.00 (1.00-1.00)	1.00 (1.00-1.00)	1.00 (1.00-1.00)
Pre-Intervention Trend (β_3)	1.00 (1.00-1.00)	1.00 (1.00-1.00)	1.00 (1.00-1.00)
Post-Intervention Trend ($\beta_2 + \beta_3$-1)	1.00 (1.00-1.00)	1.00 (1.00-1.00)	1.00 (1.00-1.00)
Age	1.00 (0.99-1.01)	0.99 (0.98-1.00)	1.00 (0.99-1.01)
Gender (Female)	1.34 (0.71-2.5)	0.70 (0.23-2.13)	0.66 (0.43-1.02)
Emergency Severity Index >= 3	0.96 (0.76-1.23)	0.97 (0.67-1.42)	**1.75 (1.05-2.91)**
Primary Language (English)	1.11 (0.55-2.26)	1.21 (0.55-2.64)	0.42 (0.13-1.34)
No. Patients Discharged Home	3.26 (0.54-19.59)	0.94 (0.55-1.58)	1.70 (0.70-4.11)
No. Patients Admitted	2.99 (0.67-13.30)	1.35 (0.65-2.77)	1.79 (0.89-3.57)
No. Patients in Department	1.00 (0.98-1.03)	1.01 (0.99-1.03)	1.00 (0.99-1.01)
No. Patients in Observation	1.01 (0.99-1.02)	0.99 (0.94-1.03)	1.02 (0.99-1.04)
No. New Patients	**0.96 (0.95-0.98)**	**0.90 (0.87-0.93)**	1.00 (0.95-1.05)
No. Patients Admitted to ICU	**0.94 (0.89-0.99)**	1.05 (0.99-1.11)	**1.05 (1.00-1.10)**
No. Patients Admitted to Telemetry	0.99 (0.95-1.03)	**1.04 (1.01-1.06)**	1.01 (0.99-1.03)
No. Patients Admitted to Floor	**0.97 (0.95-0.98)**	1.01 (0.96-1.05)	**1.03 (1.02-1.05)**
No. Patients Boarding	**1.06 (1.03-1.08)**	1.00 (0.98-1.02)	1.00 (0.99-1.02)

IRR = Incidence Rate Ratios
95% CI = 95% Confidence Intervals
Significance testing was performed using a negative binomial regression with Newey-West standard errors
β_1 estimates the immediate effect, or the level change, of the intervention on duplicate orders while β_2 estimates the change in trend of duplicate orders after the intervention. β_3 estimates the pre-intervention trend of duplicate orders, thus, ($\beta_2 + \beta_3$-1) represents the post-intervention trend in duplicate orders.

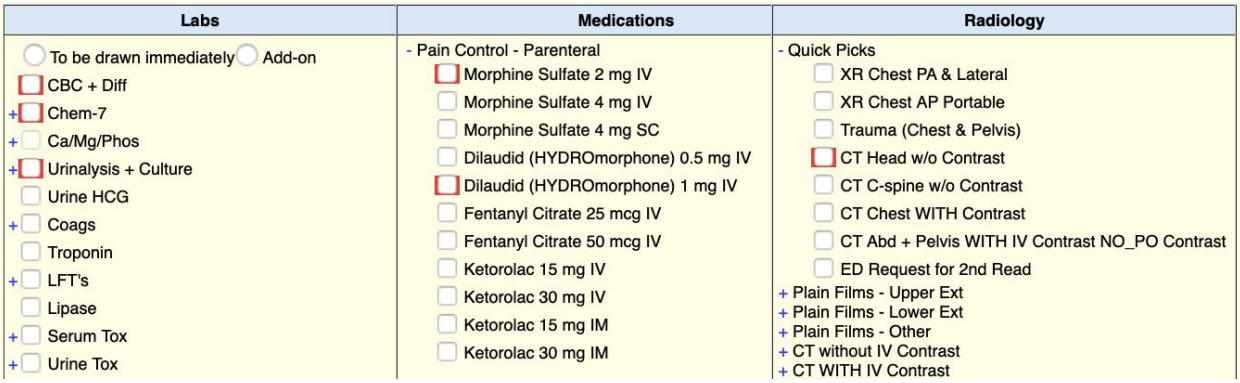
Table 3: Top 5 Unintentional Duplicate Orders

	Laboratory Duplicate Orders			
	BEFORE		**AFTER**	
	Rank	Count (%)*	Rank	Count (%) *
Chem-7	1	726 (16%)	1	361 (13%)
CBC/DIF	2	615 (13%)	2	269 (10%)
Coags	3	239 (5%)	4	171 (6%)
Urinalysis	4	197 (4%)	11	76 (3%)
Lactate	5	194 (4%)	6	124 (5%)
	. . .		. . .	
	Total	**4560**	**Total**	**2729**
	Medication Duplicate Orders			
	BEFORE		**AFTER**	
	Rank	Count (%)*	Rank	Count (%) *
Hydromorphone (IV)	1	53 (14%)	1	58 (12%)
Diazepam (PO)	2	33 (9%)	2	42 (8%)
Morphine (IV)	3	26 (7%)	3	29 (6%)
Lorazepam (IV)	4	11 (3%)	9	11 (2%)
Aspirin (PO)	5	8 (2%)	33	3 (1%)
	. . .		. . .	
	Total	**380**	**Total**	**503**
	Radiology Duplicate Orders			
	BEFORE		**AFTER**	

	Rank	Count (%)*	Rank	Count (%) *
Chest X-Ray (PA & Lat)	1	149 (15%)	2	101 (13%)
CT Head w/o Contrast	2	118 (12%)	3	86 (11%)
CT Abdomen & Pelvis w/ Contrast	3	113 (12%)	1	117 (15%)
CT C-Spine w/o Contrast	4	45 (5%)	7	26 (3%)
Chest X-Ray (Portable)	5	43 (4%)	4	34 (4%)
	. . .		. . .	
	Total	**962**	**Total**	**791**

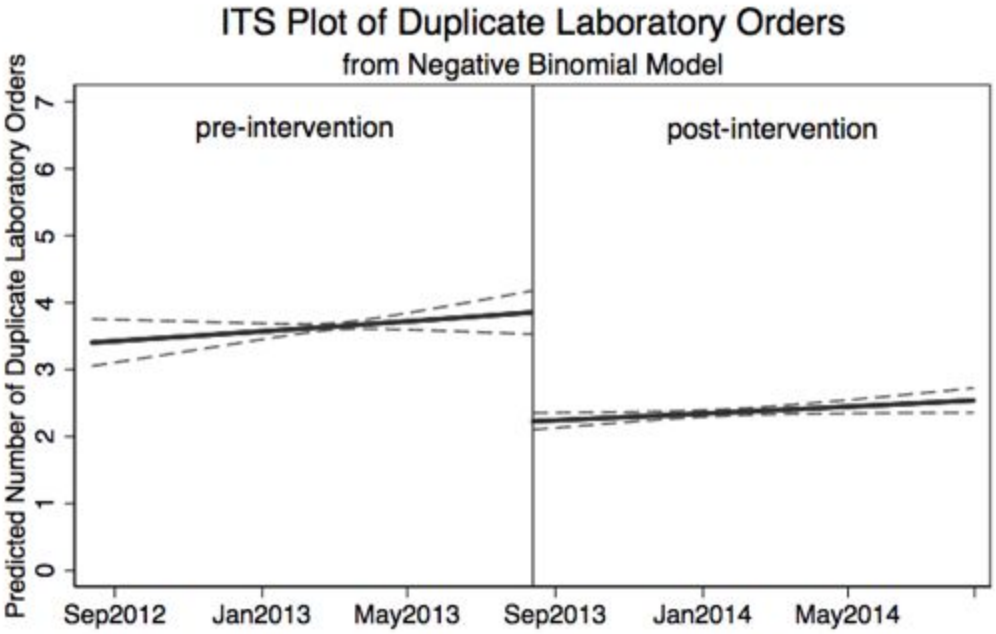
* Count (%) should only be compared vertically, not horizontally, as count (%) are not normalized for differences in the number of patients and total orders in each period. Please use the ranks to compare horizontally. Please refer to *Table 1* and *Table 2* for normalized results to compare between periods.

Figure 1: Passive inline just-in-time duplicate order decision support (red highlight)



A red highlight is placed around the checkbox if that order had previously been placed during that ED visit

Figure 2: Interrupted Time Series of Unintentional Duplicate Orders



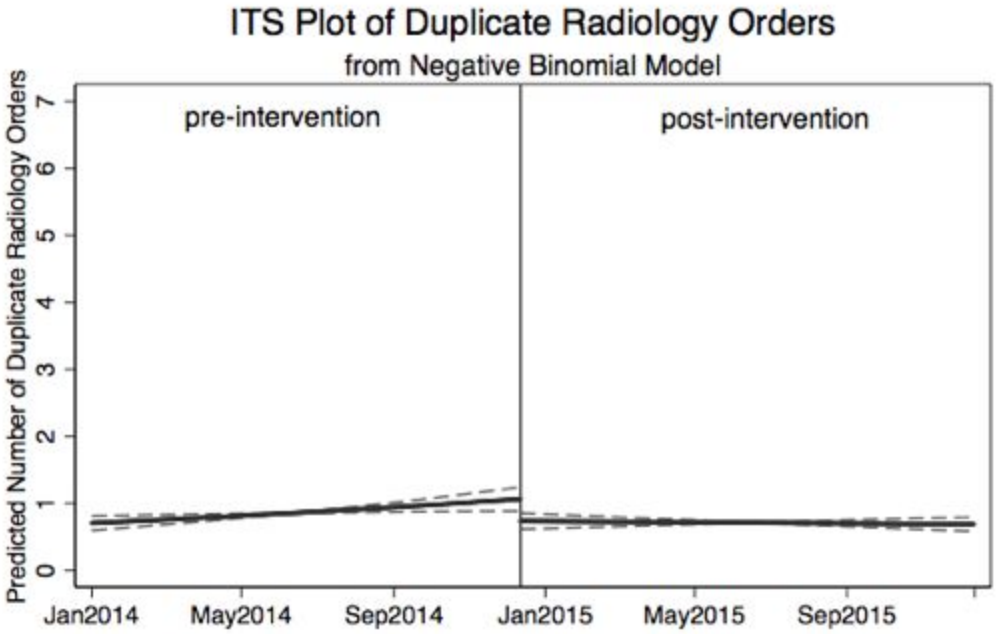


Figure 3: Order Sets as Visual Checklists

- Stroke Order Set

(check all)

To be drawn immediately Add-on

General Order

IVs: Place IV (saline lock); flush per protocol
FSBG
Precautions: Fall Safety
Diet: NPO
EKG (to be performed): Indication: Neuro deficit

Labs

CBC + Diff
+ Chem-7
Troponin
+ Coags
Type & Screen
+ Urinalysis + Culture
+ LFT's
+ Serum Tox
+ Urine Tox

Radiology

CT Head/CTA/CTP (CODE STROKE)

+ Treatment

Contraindication to IV Contrast? Yes No

Order More Order+Sign

Figure 4: Suggestions for Clinical Decision Rules

CHADS2-VASc

clinical risk stratification schemata for predicting stroke and thromboembolism (TE) in patients with atrial fibrillation (AF)

☑ Age 65-74 y	+1 points
☐ Age ≥ 75 y	+2 points
☑ Female	+1 points
☑ Diabetes mellitus	+1 points
☑ Hypertension	+1 points
☐ Congestive heart failure/LV dysfunction	+1 points
☐ Prior Stroke/TIA/TE	+2 points
☐ Vascular disease i	+1 points

Age: 69 y/o
Gender: F
HTN: losartan-hydrochlorothiazide metoprolol tartrate
DM: Januvia glipizide metformin

Total Score 4. (4) 1.9% Rate of thromboembolism in one year -- Recommend warfarin

Figure 5: Allergy Decision Support

- Antibiotics - Parenteral
  - [ ] Azithromycin 500 mg IV *Allergy
  - [ ] CeFAZolin 1 g IV *Allergy
  - [ ] CefePIME 2 g IV *Allergy
  - [ ] CefTRIAXone 1 g IV *Allergy
  - [ ] CefTRIAXone 2 g IV *Allergy
  - [ ] CefTRIAXone 250 mg IM *Allergy
  - [ ] Ciprofloxacin 400 mg IV *Allergy
  - [ ] Clindamycin 600 mg IV
  - [ ] Clindamycin 900 mg IV
  - [ ] Flagyl (MetRONIDAZOLE) 500 mg IV
  - [ ] Levofloxacin 500 mg IV *Allergy
  - [ ] Levofloxacin 750 mg IV *Allergy
  - [ ] Zosyn 4.5 g IV *Allergy
  - [ ] Unasyn 3 g IV *Allergy
  - [ ] Vancomycin 1000 mg IV ONCE
  - [ ] Vancomycin 1500 mg IV ONCE

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