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Using Computational Modeling to Improve Patient Care Unit Safety and Quality Outcomes

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Abstract

As part of ongoing research to investigate the impact of patient characteristics, organization characteristics and patient unit characteristics on safety and quality outcomes, we are using a computational modeling program, OrgAhead, to model patient care units' achievement of patient safety (medication errors and falls) and quality outcomes. We tuned OrgAhead using data we collected from 16 units in 5 hospitals. Subsequent validation studies demonstrated acceptable levels of correspondence between actual and virtual patient units. In this paper, we report on our initial efforts to use OrgAhead to develop testable hypotheses about the kinds of innovations that nurse managers might realistically implement on their patient care units to improve quality and safety outcomes. Our focus is on unit-level innovations that are likely to be easier for managers to implement. For all but the highest performing unit (for which we encountered a ceiling effect), we were able to generate practical strategies that improved performance of the virtual units by 6-8 percentage points. Nurse Managers have responded enthusiastically to the additional decision support for quality improvement.

Keywords:

Computational modeling, nursing informatics, quality improvement, decision support, safety outcomes

Introduction

How do patient characteristics, organization characteristics and patient care unit characteristics interact to affect patient safety and quality outcomes? What innovations can nurse managers make on their units that are most likely to improve quality and safety outcomes? To answer these questions, over the past two years we collected data from 35 patient care units in 12 hospitals in Arizona. We analyzed the data using traditional methods (e.g., linear regression and causal modeling) and are now using the variables that were shown in our analyses to have a significant impact on patient outcomes as a basis for computational modeling.

The usefulness of computational models for building theory about organizational behavior and adaptation is well known in the organizational literature (see [1, 2] for reviews). In healthcare, computational modeling has been used in healthcare operations research to help managers schedule appointments more efficiently [3-5], modify workflow [6, 7], project resource needs [8] and anticipate the financial and patient outcomes of programmatic changes [9-11]. Until now, computational modeling has seen little use in nursing research, although it has been used to create cost reimbursement models [12] and to reduce clinic waiting times [13].

Computational modeling can enable researchers to evaluate the effects of changing various workplace characteristics on safety and quality outcomes in a virtual environment, thus giving managers an estimate of the kinds of impact innovations will have in the actual environment before they implement the changes. Our focus is primarily on the kinds of unit-level innovations that nurse managers can control, rather than organization or community-level innovations. For our initial studies, we created 16 virtual units which corresponded with the 16 actual units from the five hospitals in the first wave of data collection for our study. Validation studies demonstrated acceptable levels of correspondence between the real and virtual units. [14] In this paper, we report on our initial efforts to use computational modeling to develop testable hypotheses about the kinds of innovations that nurse managers might realistically implement on their specific patient care units to improve quality and safety outcomes.

Materials and Methods

Using OrgAhead

OrgAhead is a theoretically-based organizational modeling program developed by Dr. Kathleen Carley and her colleagues at Carnegie Mellon University, and is grounded in the vast body of empirical and theoretical research on organizational learning and design. OrgAhead has been used previously to study organizational processes in various military and non-military settings, but this is its first application in healthcare.

In contrast to computational models that assume that capturing real-life complexity can be done simply by adding more variables, OrgAhead focuses on modeling the essence of the real situation, using an organizational science approach and an agent-based methodology. This approach enables researchers to study the emergent interaction patterns of individual unit staff in dynamic patient care situations. The model also allows researchers to look both at successful and unsuccessful performance, which eliminates the potential bias of looking at only successful outcomes. [15]

OrgAhead assumes that staff members have limited information on which to make a decision. This is operationalized as each individual agent having access to only a limited subset of information, the size of the information subset being determined by their training. In our virtual units, RNs "see" four pieces of information, LPNs and patient care technicians (PCTs) see two, and Unit Clerks (UCs) see three. OrgAhead assumes that organizational decision making is distributed among a number of members. Thus, decisions made by PCTs and Unit Clerks are passed up to the RNs, who make the final patient care decisions. For more details, see [16].

OrgAhead also assumes that different organizational design choices will be effective under different conditions (e.g., the level of environmental turbulence or available staffing). Because the focus of our research is on identifying interventions that nurse managers can realistically implement on their units, our "organization" is actually the patient care unit.

In OrgAhead, the organization (patient care unit) and individual employees operate in a "task" environment in which a "task" corresponds to a patient. Patients are modeled as nine-bit binary choice classification tasks, a common device in team and organizational performance research. The staff's task is to determine, for each "patient" encountered, whether a given binary string is of Type A or B. This is akin to making a correct diagnosis or treatment decision, given only two options. Each staff member on the unit makes a decision (Type A or B) based on the information available, and then passes that information up to a superior. The top-level staff members (in our case, the registered nurses), make the final decision.

We are using two OrgAhead dependent variables, Accuracy and Completion Ratio, as proxies for safety and quality outcome measures for the virtual patient care units. Correlation studies using our actual data showed that Accuracy corresponds to Total Errors (the sum of medication errors and falls) and Completion Ratio is an analog for a composite quality measure comprised of Complex Self Care and Symptom Management. More precisely, Completion Ratio is calculated as the percentage of time the unit met a target level of achievement in which discharged patients were able to carry out specific complex self care tasks (e.g., knowing when changes in their disease states warranted calling a physician or adjusting their treatment regimes) or manage their own symptoms after discharge.

Calibrating OrgAhead

Our first task was to map our research variables onto the variables in OrgAhead. The independent variables we are currently using and their corresponding OrgAhead variables are shown in Table 1. Task Complexity is a complex variable that was added to OrgAhead for our study. Task complexity is comprised of a number of our research variables (weighting for each component was determined by the actual weighting of the variables in our earlier causal modeling).

Table 1: Research independent variables and their corresponding OrgAhead variables

Research Variable	OrgAhead Variable
Percentage of self-pay patients	Task Complexity component
Age (percentage of patients > 75 years)	Task Complexity component
Number of comorbidities	Task Complexity component
Workload (calculated as average number of patient days / RN FTEs)	Task Complexity component
Turbulence per patient day (calculated as distance staff travel while giving care + responsiveness of support systems + accessibility / patients per day	Task Complexity component
Control over nursing practice (autonomy) at each level of the nursing hierarchy	SOP (use of standard operating procedures) at each level of the nursing hierarchy
Training (calculated as years of education + years in hospital + 2 * years on unit)	Training period
Staffing (number of RNs, LPNs, PCTs, and Unit Clerks)	Number of staff at each level in hierarchy
Experiential competency	Memory (rolling window of cases that are used by the organization as basis for making current decision)

We then had to replicate the actual staffing patterns for each patient care unit in OrgAhead. This resulted in 4 levels: RN, LPN, PCT/Nurse Aide, and Unit Clerk. One unit had no LPNs, so it had only 3 levels.

Calibration (tuning) of the basic OrgAhead model using actual data collected from 16 patient care units resulted in 16 "virtual" units that were functionally similar to their real counterparts both in key characteristics (culture, size, patient population, and turbulence, for example) and patient safety (medication error and fall rates) and quality outcomes. When the rank orders of Accuracy (virtual units) and Total Errors (actual units) were compared for all 16 units, the correlation coefficient exceeded our target for acceptable correspondence of .80 (r = .83). Correlation at the value level (using actual numeric values for Accuracy and Total Errors rather than rank order) was also acceptable (r = -.62). For completion ratio, ranking units by percentage of achievement resulted in a number of "ties" at various values so we could not use order level validation, and instead adopted the value measure only. The correlation of the composite quality measure we had created with Completion Ratio was acceptable (r = .66).

Generating hypotheses

Having created the 16 virtual patient care units and validated that OrgAhead was able to match their actual performance, we began to use OrgAhead to generate hypotheses about strategies managers could use to improve patient safety and quality outcomes on their units. To accomplish this required making changes in the various independent variables that went into our initial modeling (e.g., Task Complexity, Workload, Turbulence, Standard Operating Procedures, Training, and Memory. Starting with the unit's initial values (based on actual data), we then attempted to change those values to improve accuracy and completion ratio (the analogs for safety and quality outcomes). To demonstrate the approach, we present the results for three different patient care units. We are using these three units as pilot units to test our methodology before implementing a larger experiment using the remaining units. In that study, patient care units will select one or more of our hypothesized innovations to implement. We will then evaluate the results, again comparing real to virtual units.

Results

Unit A

Unit A is one of our smallest patient care units. Of the 16 units, this unit ranked last in terms of patient safety outcomes (for the actual units) and 12th for the virtual units. Unit A's actual data revealed a moderate level of task complexity (10 on a scale of 5-17), a fairly low workload index (1.89 on a scale of 1-5), and very low turbulence (-14). Because perceived environmental turbulence scores are scaled from negative to positive values; a negative value does not mean negative or the absence of turbulence, but it does reflect low turbulence. Training (which is calculated based on staff's months of experience in the hospital and on the patient care unit plus years of education) was 343 months, or 28.5 years (the mean for the units was 309 months, or 25.7 years. Memory was set at the default value of 100 (which reflects the number of cases individual agents "recall" to make the next decision).

Because task complexity is a very powerful predictor in our model, we looked at its effects first. Task complexity is comprised of five components (distance traveled by staff while providing care, perceived environmental uncertainty, accessibility to ancillary services, turbulence, and responsiveness of ancillary services) divided by the average number of patients per day. To change task complexity requires changing one or more of the components. While it is unlikely that managers can control their census (patient days), they may be able to change the other factors. We therefore concentrated on changing the values of the more easily changed variables and observing the effects. Table 2 shows the effects on accuracy and completion ratio (our analogs for safety and quality outcomes) for various values of task complexity (TC), training and memory (T/M), and standard operating procedures (the inverse of autonomy).

Because perceived environmental turbulence was low for this unit, the only factors contributing to Task Complexity that managers could improve are distance traveled and responsiveness of support services. For that reason, we were only able to realistically reduce Task Complexity by one point (from 10 to 9). This still results in a significant improvement in performance.

Unit B

Unit B, a large patient care unit, ranked 12th in terms of accuracy among the 16 units and 13th for the corresponding virtual unit. Table 3 shows the effect on accuracy and completion ratio of changing various parameters. For improvement in performance, managers would need to decrease RN workload and improve access to and responsiveness of support services.

*Table 2: Effects of changing variables on accuracy and completion ratio (safety and quality outcomes, respectively) of Unit A. * = Initial values for actual patient care unit.*

TC	T/M	Standard Operating Procedures			% Accuracy	Completion Ratio
		RN	LN/PCT	UC		
10*	343/100	.53	.38	.52	77.96	.475
9	743/700	.90	.10	.70	86.01	.500
8	743/700	.50	.10	.50	86.38	.531
7	743/700	.90	.10	.70	88.16	.607

*Table 3: Effects of changing variables on accuracy and completion ratio (safety and quality outcomes, respectively) of Unit B. * = Initial values for actual patient care unit.*

TC	T/M	Standard Operating Procedures			% Accuracy	Completion Ratio
		RN	LN/PCT	UC		
9*	197/100	.40	.54	.51	77.85	.370
9	197/100	.10	.40	.70	80.55	.370
8	186.199	.10	.40	.70	82.90	.417
8	897/800	.10	.60	.70	84.41	.417

Unit C

Unit C was our top-ranked unit in terms of safety and quality outcomes—both for virtual and actual units. This created a ceiling effect that prevented us from improving its performance. Instead we explored conditions that, if initiated, would degrade its performance (Table 4). Unit C had very low turbulence (7), but Table 4 shows the degradation in performance that could be anticipated if perceived environmental turbulence increased. We were able to improve the unit's performance only by drastically, and perhaps unrealistically increasing the values of training and memory, as well as increasing autonomy for various roles. When we presented the data to the manager group, they were quite content with having data to help them know what changes not to make. They specifically identified areas within task complexity (particularly distance nurses have to walk to deliver care) that they wanted to improve.

Validating the results

We are currently sharing each model and set of recommendations for performance improvement to the nurse managers and selected staff of each of the pilot units. Feedback from the first session was extremely positive. Managers were able to validate the recommendations—and were able to identify from the possible interventions those that they would like to try.

*Table 4: Effects of changing variables on accuracy and completion ratio (safety and quality outcomes, respectively) of Unit C. * = Initial values for actual patient care unit.*

TC	T/M	Standard Operating Procedures			% Accuracy	Completion Ratio
		RN	LN/ PCT	UC		
7	235/100	.48	.45	.51	84.55	.471
8	235/100	.48	.45	.51	72.35	.425
10	235/100	.48	.45	.51	77.77	.367
7	235/100	.10	.90	.90	85.74	.471
7	1035/ 1000	.10	.90	.70	85.91	.471

Discussion and Recommendations

Thus far, we have been able to improve performance on the virtual units about 6-8 percentage points (to the mid to high 80s)—with the exception of the highest performing unit, for which we encountered a ceiling effect and could only improve performance by 1%, and alternatively show how to degrade performance (or what not to do!). Whether these 6-8 percentage point changes represent "clinically significant" levels of change remains to be seen. One reason for our not being able to improve performance to 90% or higher is undoubtedly related to the small number of variables we are currently using in the modeling. Given the number of variables that could potentially affect safety and quality outcomes, perhaps it is surprising that we could effect even this much change with this limited subset. Further, we have focused only on those that managers are likely to able to change on their units; therefore factors such as patient census, hospital culture, and patient characteristics are not included.

Feedback from the managers suggested that the modeling results had face validity; they made sense from their perspectives. Managers were able to select particular strategies that were feasible to implement on their units.

For this experiment, we changed values manually, increasing and decreasing each by a percentage. We are currently automating this process so that all possible combinations are tested.

We are limited in the variables we can test by what is currently contained in OrgAhead—and by what we can effectively map from our measured variables onto OrgAhead. To adapt OrgAhead for our use, Dr. Carley and her colleagues added one major independent variable, Task Complexity to the initial OrgAhead program and converted SOP (Standard Operating Procedures) from a toggle (on/off) to a scaled variable, which better reflected the range of control over practice values we obtained. Other changes may be needed to obtain greater modeling accuracy.

The results reported here used data collected in our first "wave" of data collection. We will be refining the model using the complete set of data (from an additional 18 units).

In our future research, we will present a set of hypotheses generated by OrgAhead to a set of experimental patient care units and then work with nurse managers to select those they seem most realistic and valuable to implement. We will then assist them in the implementation process and evaluate the results, comparing the actual results against those predicted by the computational modeling.

Conclusion

To investigate the impact of patient characteristics, organization characteristics and patient unit characteristics on safety and quality outcomes, we are using a theoretically-based computational modeling program, OrgAhead, to model patient care units' achievement of patient safety (medication errors and falls) and quality outcomes. For our initial studies, we created 16 virtual units which corresponded with the 16 actual units from the five hospitals in the first wave of data collection for our study. Subsequent validation studies demonstrated acceptable levels of correspondence between actual and virtual patient units.

We then used OrgAhead to develop hypotheses about strategies that nurse managers might use to improve outcomes on their patient care units. We tested the approach on three pilot units. The model generated different hypotheses for each of the units. We focused primarily on strategies that nurse managers could feasibly implement on their units, rather than more global or organizational strategies.

The results of our pilot tests are very positive. Computational modeling offers the nurse manager a way to test potential innovations in the virtual world before implementing them in the real world. This may be a very cost effective way of testing in advance the probable effects of a given innovation. Given the high rate of failure in organizational redesign and restructuring efforts historically, this may be a very useful decision support tool.

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