Using Computational Modeling to Study the Impact of Workplace Characteristics on Patient Safety Outcomes

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Introduction

Linking patient outcomes to nursing structures and processes in today's complex, dynamic healthcare system is a difficult task for the researcher. Traditional methods of analysis fail to capture the dynamics of an organization adapting to changes in the environment and the inevitable nonlinear, stochastic cross-level interactions (e.g., among organization characteristics, patient care unit characteristics, and individual staff characteristics) typical of a complex, dynamic system. Computational modeling provides a potential solution to the researcher's dilemma.

Computational modeling has become increasingly popular as an alternative approach to the study of complex organizational dynamics because its strengths can compensate for weaknesses found in more traditional research methods. [1] For example, traditional experimental or correlation research methodologies are ill suited for capturing the dynamic, potentially nonlinear changes that evolve as organizations respond to environmental demands because they must rely on static snapshots of organizations at specific points in time. Individual snapshots may accurately depict the organization's behavior at that particular point in time; but the researcher has no good way to determine at what intervals (weekly, monthly, daily, etc.) to collect observations so that they can ultimately be assembled to re-create the original trajectory with its underlying dynamics. Without knowing the various rates at which interacting processes are unfolding, researchers are likely to miss observations at critical points in time, especially if the processes are nonlinear. For that reason, snapshots (observations) of the same organization taken at different times can lead to very different, perhaps erroneous, conclusions. By contrast, computational modeling gives the researcher a way to study the trajectories of dynamic organizational processes as they unfold over time. [2]

Although it has been used in clinical research (e.g., [3]), until now computational modeling has had little application to healthcare or nursing organizations. We are using computational modeling to explore how patient characteristics and organizational characteristics interact with patient unit characteristics to affect patient safety outcomes.

We developed our initial computational model by using a combination of existing organizational theory and actual data from a previous research study. We are currently tuning the initial model using actual data collected from 16 patient care units in four hospitals. Ultimately, we will refine the model further, using data from additional units from different hospitals. In this paper, we describe our application of *Orgahead*, a computational modeling program developed at Carnegie-Mellon University, and demonstrate its utility.

Modeling the Impact of Workplace Characteristics on Patient Safety Outcomes

How do patient characteristics, organization characteristics and patient care unit characteristics interact to affect quality, safety, and cost outcomes? What changes can nurse managers make on their units that will optimize outcomes for their patients? To answer these questions, we are collecting data from 35 patient care units in 12 hospitals in Arizona, analyzing the data using traditional methods, and then using the results as a basis for computational modeling.

The conceptual framework for our research is the Systems Research Organizing (SRO) Model.[4] The framework includes four constructs: patient characteristics, organizational characteristics, unit characteristics, and patient outcomes (Fig. 1). All constructs are assumed to interact with each other. We assume that the best target for a nursing intervention will be at the patient care unit because patient and organization characteristics are likely to be less amenable to change by nurse managers. However, the complexity and acuity of patients, organizational culture and other characteristics will certainly affect any change targeted at the patient care unit level.

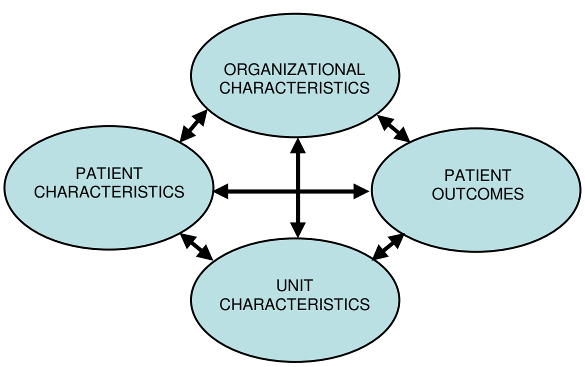

Figure 1. **The SRO Model**

Hospitals that participated in the research included teaching and non-teaching hospitals, as well as public and privately funded hospitals and ranged in size from 60 to over 400 beds. We used only adult medical or surgical units to control for variability due to specialty units. Data were collected in two "waves;" patient care units from half the hospitals were assigned to each wave. Each wave of data collection required six months to complete. Data related to each of the model components were collected through surveys of patients, staff, managers, quality improvement departments, and information services. All data were entered into an SPSS file, where they were cleaned and their validity and reliability evaluated. Following a descriptive analysis of the data, data reduction was accomplished using correlation, factor analysis and linear regression. This resulted in the addition of several new composite variables and the dropping of others. The revised data set was then used as a basis for computational modeling.

The goal of the computational modeling portion of the research is to determine whether we can, using the data we have collected, emulate each patient care unit and then identify strategies that modelling suggests will improve their patient outcomes. To accomplish this, we are using a computational modeling tool called *Orgahead*.

Orgahead

Orgahead is a theoretically based computational modeling program for examining organizational performance. Each aspect of the model is based on existing theory. Because the focus of our research is on identifying interventions that nurse managers can implement on their units, our "organization" is actually the patient care unit. Both the organization and individual employees operate in a "task" environment where a "task" equals a patient.

In *Orgahead*, patients are modeled as 9-bit binary choice tasks. That is, for each "patient," the organization has to determine whether A or B is the correct solution (think of this as making a correct diagnosis, given only two options). Each member of the virtual organization makes a decision (A or B), based on the information available, and then passes that information up to a superior. The final decision is made by the top-level manager (in our case, by the RN).

The patient care unit is modeled as two interlocking networks: an authority structure (who reports to whom?) and a resource management structure (who has access to which resources?). For our initial experiments, we modeled each as a 4-layered structure with RNs at the top level, licensed practical nurses (LPNs) at the second level (when present), patient care technicians (PCTs) and/or Nurse Aides at the third level, and unit clerks at the bottom level.

In *Orgahead*, individual learning occurs through a standard stochastic learning model for agents (nursing staff) who behave rationally, but have access to limited information. [5] Organizational learning, or adaptation, occurs as a simulated annealing process, which is an optimization heuristic similar to the hill climbing algorithm. Simulated annealing is a computational analog of the physical process of annealing (heating and cooling) a solid, in which the goal of the process is to find the atomic configuration that minimizes energy costs. In organizations, this is analogous to a design problem in which the organization is trying to optimize its performance under a variety of external and internal constraints.[6]

During each *Orgahead* simulation, organizational changes (e.g., hiring or firing an individual) are occasionally "proposed" as a random function of the program. The organization has the capability to "look ahead" (the "ahead" part of *Orgahead*) to evaluate the impact of the proposed change. The organization will accept all changes that are evaluated as improving performance and may accept a change that will actually decrease performance initially (a more risky decision), but may improve performance in the long term. Whether an organization will actually accept risky changes is a function of the simulated annealing heuristic.

Using Orgahead

Using *Orgahead* requires five steps:

1. Identify the core variables in *Orgahead* that correspond to the constructs in the conceptual model (e.g., unit size, dynamism, or culture). To model our units required adding a new *Orgahead* variable, "task complexity" (TC), a workload measure that incorporates patient characteristics (i.e., number of comorbidities, age, and insurance) and patient unit characteristics (i.e., dynamism, patient mix, patient turnover, and environmental turbulence) that our data suggested were predictive of patient safety outcomes).

2. Explore the parameter space. This requires defining the range of values that specific variables can take. In some cases, continuous variables in our data set had to be rescaled or converted to dichotomous *Orgahead* variables. Selecting the parameters that will be allowed to vary (the independent variables) and values for those parameters, as well as the dependent measure (e,g, accuracy) defines a virtual experiment.

3. Set non-core variables for each patient care unit, based on actual data. These include variables such as the levels of hierarchy, the number of staff at each level, and the probability of staffing changes at each level.

4. Run virtual experiments. As part of the experiment, each virtual organization is given a training period corresponding to staff education and experience on each unit. These results are then dichotomized into high or low values. For example, a unit with higher education might be assigned a training period of 500 binary choice tasks before its "life cycle" began and the unit with lower education values assigned 200. Each organization is simulated for a number of iterations corresponding to its 6-month total patient days. Organizational performance is calculated as the mean of the last 50 patients (tasks). We repeat this 40 times for each organization then calculate mean accuracy scores for each unit because of the stochastic elements in the model.

5. Statistically analyze results. As in traditional analyses, it is necessary to run standard statistical tests on the results to determine what differences in performance (e.g., accuracy) are statistically significant.

Demonstrations

To show more clearly how computational modeling works, we provide two simple demonstrations. We have found such demonstrations a necessary precursor to full-fledged experiments.

Demonstration 1. Our first demonstration investigated the effect of the new variable we had created, task complexity, on accuracy, efficiency, and completion rate of one virtual unit created by using parameters from data we collected for one actual unit. The completion measure refers to the degree to which nursing staff, and by extension the patient care unit, have the resources required for their assigned tasks. For us, completion rate is a proxy for length of stay (LOS).

Design. For this demonstration we ran the simulation for an abbreviated training period of 20 and simulation time of 50, for 5 values of TC (5, 7, 9, 11, and 15).

Results and discussion. The results are shown in Table 1 As task complexity increased, accuracy over the last 50 tasks (i.e., patients) was fairly stable, while efficiency, which is defined in *Orgahead* as the percentage of accurate choices for the total number of tasks (i.e., patients), gradually increased. The lack of increase in accuracy is likely due to the short simulation time we used for the demonstration. Completion rate was stable at the two lower TC values, and then fell dramatically. This is consistent with the increasing deficit in needed resources for staff as patient complexity increases. This might be interpreted as consistent with length of stay increasing for more complex patients.

TC	Accuracy	Efficiency	Completion Rate
5	10%	61%	.62
7	11%	61%	.62
9	10%	61%	.49
11	10%	65%	.42
13	11%	71%	.37
15	9%	73%	.33
17	10%	80%	.27

Table 1. *Accuracy, efficiency and completion rates of one simulated patient care unit for five levels of task complexity*

Demonstration 2. In Demonstration 2, we compared two virtual units that differed in staff experience. Because the nursing staff of Unit A were considerably more experienced than those on Unit B, we expected that Unit A would demonstrate higher accuracy and lower LOSs.

Design. We compared the two units for one intermediate level of task complexity (TC =11). To simulate the more experienced staff, we used a training period of 50 and simulation time of 80 (compared to the training period of 20 and simulation time of

50 used for the unit with the less experienced staff).

Results and discussion. The results are shown in Table 2. For the same level of task complexity (TC =11), the unit with more experienced staff had a higher accuracy and but a lower completion rate).

Unit	Staff Experience	Accuracy	Completion Rate
A	High	43%	.09
B	Low	10%	.42

Table 2. *Accuracy and completion rates for two units differing in staff experience*.

Conclusion

Computational modeling is yet another tool to add to the informaticist's arsenal, and may be an essential tool if that informaticist wishes to study the impact of information systems in complex socio-technical organizations, such as healthcare. The simple demonstrations we have described can only begin to suggest its potential.

We are currently tuning the model, using the first set of collected data—and that will take some time to complete. Then we will test it against the data collected from the second set of units and further refine the computational model so that we can provide nurse managers with recommendations for improving the outcomes on their units.

One of the limitations of computational modeling is that no single program can answer every question the researcher might have. Different modeling tools must be used to answer different questions—and the results somehow integrated. A second limitation is that, although the computational modeling program can accommodate many variables, the experimental model that must be used to test statistical significance cannot. Therefore, it is necessary to control some variables in the same way that we would in a traditional experiment. This necessitates a step-wise approach.

For the informatics specialist, computational modeling may have yet other benefits. We have not yet looked specifically at the impact of information on patient safety outcomes, but intend to do so, using another program, *Construct,* which is better suited to answer this type of question.

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