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Using computational modeling to transform nursing data into actionable information

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Abstract

Transforming organizational research data into actionable information nurses can use to improve patient outcomes remains a challenge. Available data are numerous, at multiple levels of analysis, and snapshots in time, which makes application difficult in a dynamically changing healthcare system. One potential solution is computational modeling. We describe our use of OrgAhead, a theoretically based computational modeling program developed at Carnegie Mellon University, to transform data into actionable nursing information. We calibrated the model by using data from 16 actual patient care units to adjust model parameters until performance of simulated units ordered in the same way as observed performance of the actual units 80% of the time. In future research, we will use OrgAhead to generate hypotheses about changes nurses might make to improve patient outcomes, help nurses use these hypotheses to identify and implement changes on their units, and then measure the impact of those changes on patient outcomes.

Keywords: Computational modeling; Patient outcomes; Patient safety outcomes; Data; Information; Actionable information; Organizational change

1. Introduction

Transforming organizational research data into timely, actionable information nurses can use to identify cost-effective changes on their units that are likely to improve patient safety and quality outcomes is challenging for several reasons. First, organizational research data are generally collected as snapshots in time, which makes their application in a complex, dynamically changing healthcare system difficult and perhaps even risky. Second, the data tend to be numerous and at multiple levels of analysis. Traditional analytic methods are inadequate to handle the multitude of variables and fail to capture the dynamics of the organization as it adapts 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. One possible solution is computational modeling.

Computational modeling is a set of tools that allows users to create a virtual model of a particular system, such as a hospital or patient care unit, and study its behavior under various conditions [1]. Two different approaches to computational modeling currently exist. The first attempts to include as many variables as possible in the model, assuming that the additional variables increase the model's accuracy. The second creates a virtual model that provides a functional description of the system and omits details (e.g., physical characteristics of the unit) deemed unnecessary for this level of analysis. We have chosen the second alternative because it allows us to explore the relationships judged most crucial while keeping the model reasonably simple.

The usefulness of computational models for building theory about organizational behavior and adaptation has been recognized for some time (see [2,3] for reviews).

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In healthcare, computational modeling has been used to model a variety of clinical problems, such as protein structure [4], mass transfer and its link to atherosclerosis [5], cognition and higher brain function [6], stability in neurons [7], and human movement [8]. In addition, computational modeling has been used in healthcare operations research to help managers schedule appointments more efficiently [9–11], modify workflow [12,13], project resource needs [14], and anticipate the financial and patient outcomes of programmatic changes [15–17]. However, to date computational modeling has had only limited application in nursing, although it has been used to create cost reimbursement models [18] and to reduce clinic waiting times [19].

We are currently using OrgAhead, a computational modeling program, to transform our recently collected research data into actionable information. OrgAhead is a theoretically based organizational modeling program developed at Carnegie Mellon University. We calibrated (tuned) the basic OrgAhead model using actual data collected from 14 patient care units as part of a research project evaluating the impact of workplace characteristics on patient outcomes. The result was 16 "virtual" units that were functionally similar to their real counterparts both in key characteristics (culture, size, patient population, and turbulence, for example) and their patient safety outcomes (medication error and fall rates). In our future research, we will use the "hypothesis generating" power of computational modeling to design unit-specific strategies likely to improve patient care outcomes.

In this paper, we provide a brief overview of computational modeling and the data collection procedures for our larger patient safety research project. We then describe our use of OrgAhead and report the results of our initial model validation studies.

2. Background

In the past decade, computational modeling has become increasingly popular as an alternative way to study complex organizational dynamics because the strengths of computational modeling can compensate for weaknesses found in more traditional research methods. For example, because they must rely on static snapshots of organizations at specific points in time, traditional experimental or correlation research methodologies are ill suited for capturing the dynamic, potentially nonlinear changes that evolve as organizations respond to environmental demands. Individual snapshots may accurately depict the organization's behavior at that 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 the ability to study the trajectories of dynamic organizational processes as they unfold over time [1].

Traditional research methods are frequently inadequate for the kinds of cross-level analyses needed to describe organizations [20]. For example, it is well known that organizational knowledge resides, not only at the organization level, but also at the individual level. Less is known about how these levels of knowledge interact, in part because of the measurement difficulties inherent in working at multiple levels simultaneously. By using computational modeling, researchers are better able to explore these kinds of interactions. For example, computational modeling research has shown that interactions that occur among individuals can have nonlinear effects on organizational characteristics, such as the generation of social sanctions, cues and norms [21], as well as on information diffusion [22]. Each of these may play a role in the organization's ability to achieve desired patient safety and quality outcomes.

Improvement in patient safety or quality outcomes may occur through two mechanisms: an organization can learn to do the same thing better (e.g., by locating similar kinds of patient populations on the same units) or it may actually do something different altogether (e.g., change the medication administration system) [23,24]. Computational modeling research has shown that, under some conditions, changes in organizational structure can actually reduce the effect of individual learning and turnover on organizational performance outcomes [25]. For example, an organization may decide to restructure, which requires employees to learn new skills (e.g., multiskilled employees) and diminishes the value of their previous specialized knowledge, which may, at least initially, lead to worse patient outcomes and the need for further reorganization.

Computational modeling is based on a variety of theories (e.g., communication, learning, social, and organizational). In OrgAhead, the major theories used are organizational learning and design, communication, and organizational behavior. These theories are operationalized in OrgAhead as a set of algorithms (i.e., if. . .then statements). For example, one of the rules states that if nurses have more control over their own practice, then fewer standard operating procedures such as protocols will be used. Another rule states that, if there is more turbulence (e.g., admissions, transfers, discharges, physician orders, etc.) on a unit, then task complexity will be increased. Network nodes and connections are initially given inputs selected from variables with distributions that reflect realistic values for a particular characteristic of the modeled construct (e.g., the number of various levels of personnel, such as RNs and LPNs, or staff autonomy).

Organizational behavior is modeled iteratively over time. The state of the organization at Time 1 serves as the input for the state at Time 2, which becomes the input for the state at Time 3, etc. As the organization adapts or learns, changes in its behavior are stored in the database, allowing the researcher to monitor changes in strategic or operational decisions, such as who reports to whom or when a manager or staff member is hired or fired, while monitoring targeted performance measures (e.g., accuracy). Ultimately, to validate the model the researcher compares actual observed data with the modeling output.

Computational modeling applications vary a great deal. They may be continuous or discrete, static or dynamic, stochastic or deterministic. OrgAhead is a discrete event simulator that allows either static or dynamic modeling. For our calibration (model tuning) trials, we used the static version because the actual patient outcome data were taken at a single point in time. To generate hypotheses about potential change strategies, we will use the dynamic version.

Computational modeling tools are each designed to model a particular aspect of organizations, for example, communication or learning. OrgAhead is designed to simulate the organization's ability to redesign itself, adapt to environmental constraints, or learn. In OrgAhead, researchers can run virtual experiments to answer questions such as:

- What is the impact of organizational size on performance?
- What organizational structures (e.g., centralized or decentralized) are most adaptive, given particular environmental constraints?
- How does the way information is transmitted within the organization affect the organization's ability to meet its desired goals?

Once we have demonstrated that OrgAhead can adequately model the current performance of our patient care units, then we will use it to answer questions about the workplace changes nurses can make on units to improve their quality and patient safety outcomes. Although OrgAhead has been, and continues to be, used in a variety of organizational and military settings, this is its first application in healthcare.

3. 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 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 from the first wave of data collection (16 units in 5 hospitals) that were shown to have a significant impact on patient outcomes as a basis for computational modeling.

The conceptual framework for our research is the Systems Research Organizing (SRO) Model [26]. The framework contains four constructs: patient characteristics, organizational characteristics, unit characteristics, and patient outcomes (Fig. 1). All constructs are assumed to interact with each other. We believe that the best target for a nursing intervention will be at the patient care unit level because patient and organization characteristics are likely to be less amenable to change by nurse managers. However, we recognize that the kinds of patients on a patient care unit (e.g., their complexity and acuity) and the organization's culture and other characteristics may have profound effects on any planned unit-level change.

Hospitals that participated in the research included teaching and non-teaching hospitals, as well as public and privately funded hospitals that 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 6 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. Patients about to be discharged were introduced to one of our research assistants by unit staff. Patients were invited to participate in the study by completing a questionnaire that included three separate scales (General Symptom Distress Scale; Self Care: Condition Management; and How Well Cared For Were You?) either before leaving the hospital or via telephone within their first 72 h at home. Unit staff (nurses, physicians, and other team members) completed a single survey comprised of several scales (Job Satisfaction, Relational Coordination, Self Regulation, Control over Nursing Practice, Accessibility, Hospital Culture, and Perceived Environmental Uncertainty) during months 3 and 4 of data collection. Nurse managers completed a monthly survey and a second, one-time survey that assessed unit and hospital characteristics. Targeted quality (e.g., medication errors, falls) and financial data (e.g., census, insurance data, average length of stay; ICD-9s) were submitted monthly by information services and quality management staff.

All data were entered into an SPSS file, where they were cleaned to ensure data entry accuracy. Ten per cent

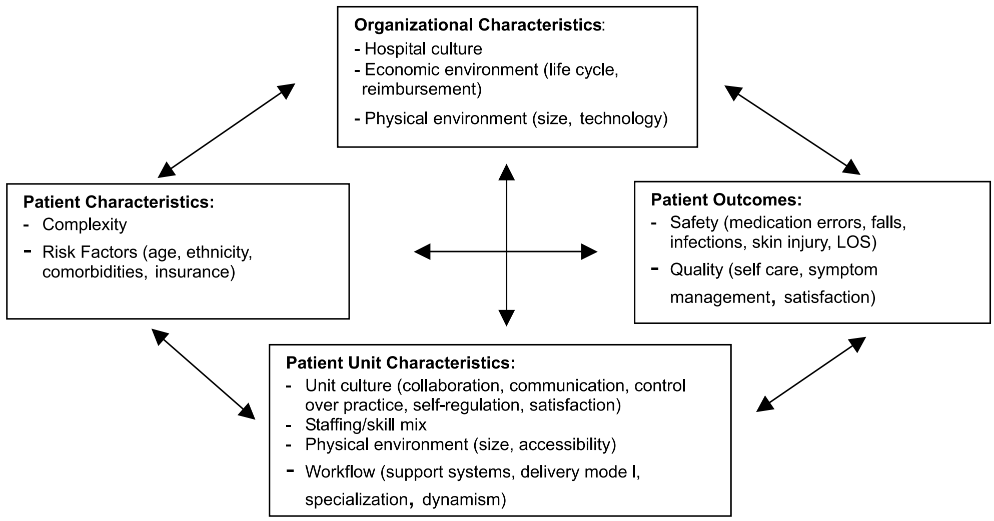

Fig. 1. The conceptual (SRO) model. Also shown are the concepts and variables (in parentheses) used to operationalize each of the four constructs in the model.

of the data was checked for accuracy. A 5% error rate was set as the acceptable limit and was achieved on all checks. Missing data were estimated using multiple imputation techniques. Because many data elements were derived from survey instruments, the psychometric properties of each scale were assessed at individual and group levels. Many of the measures were collected from individuals, but were aggregated to the group level for analysis purposes; hence the need for determining psychometric properties at both levels. Internal consistency, reliability, and construct validity were assessed through exploratory factor analysis at the individual level. Standard group level assessment techniques of intraclass correlation coefficient, between group significance, and percent of aggregated inter-item correlation coefficients >.40 were performed. Altogether, during the first wave of data collection, data were collected from 482 patients, 411 nursing staff and interdisciplinary team members, and 16 nursing unit managers on 16 medical–surgical units in four hospitals.

Following an initial descriptive analysis of the data (e.g., means, medians, standard deviations, and range), data reduction was accomplished using correlation, factor analysis, and linear regression. This resulted in the elimination of a number of variables that did not factor successfully and the addition of several new composite variables: nursing culture, team culture, staffing, workload, and turbulence per patient day.. Causal modeling with unit-level data was used to evaluate each of the relationships in the SRO model. The variables shown to be significant in the revised data set were then used as the basis for our computational modeling [27–29].

The goal of the computational modeling portion of the research is to "reuse" the data we collected to create virtual patient care units that have the key characteristics of the observed units and then to use the modeling tool to generate specific design strategies that, if implemented, can be expected to improve the patient safety outcomes on each unit. These strategies will be shared with nursing staff, together with the expected amount of improvement per change initiative, so that nursing leaders can implement the solution they feel will be the most cost effective for them. Experience has taught us that one solution rarely fits all because of the variation in patient care unit cultures, technology, patient populations, and leadership. Therefore, we expect that individualized solutions will be more actionable, and therefore more effective, than a "generic" solution.

4. OrgAhead: a computational modeling tool

4.1. Description

OrgAhead is a theoretically based computational modeling program for examining organizational performance that was developed by Dr. Kathleen Carley and her team at Carnegie Mellon University. For our purposes, computational modeling has two unique advantages: it allows us to analyze complex, adaptive systems (patient care units) and it facilitates theory building and hypothesis generation [30]. We are using OrgAhead, a computational modeling program, to transform the results of our research into actionable information for the patient care units. In contrast to computational models that assume that by simply adding more variables, the complexity of the real life situation will be captured, OrgAhead focuses on modeling the essence of the real situation, using an organizational science approach and an agent-based methodology. The latter allows us to examine the emergent interaction patterns of individual unit staff in dynamic patient care situations. The model also allows us to look both at successful and unsuccessful performance, which eliminates the potential bias of looking at only successful outcomes [30]. Additional details about the program are available online at http://www.casos.ece.cmu.edu/projects/OrgAhead/.

OrgAhead is grounded in the vast body of empirical and theoretical research on organizational learning and design. For example, the model assumes that managers have bounded rationality (i.e., that they have limited information on which to make a decision). This is operationalized as each individual having access to a limited subset of information, the size of the information subset being determined by their education. In our instantiation of the model, RNs "see" four pieces of information, LPNs and patient care technicians (PCTs) see two, and Unit Clerks see three. Further, the model assumes that organizational decision making is distributed among a number of members. That is, decisions made by agents at lower levels of the hierarchy are passed up to the supervisors at higher levels for a "final" decision. The model also assumes that different design choices will be effective under different conditions. Most theories treat matching the change to the environment fairly statically, without considering how the organization learns to change to a new design based on either current performance or past experience. In OrgAhead, the linkages between strategy, design, and performance can be explored dynamically. The simulated organization can change its structure based on perceived environmental changes or desired outcomes, and individual employees can learn and therefore improve their performance over time [23]. 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.

The organization and individual employees operate in a "task" environment wherein a "task" equals a patient. In OrgAhead, patients are modeled as nine-bit binary choice classification tasks, a device used extensively in team and organizational performance research. Specifically, the organization's task is to determine, for each "patient," whether a given binary string is of Type A or B. Think of this as making a correct diagnosis or treatment decision, given only two options. Each member of the organization makes a decision (Type A or B) based on the information available to them, and then passes that information up to a superior. The top-level manager (in our case, the registered nurse) makes the final decision (Fig. 2). For more details, see [23].

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 four-layered structure with registered nurses (RNs) at the top level, licensed practical

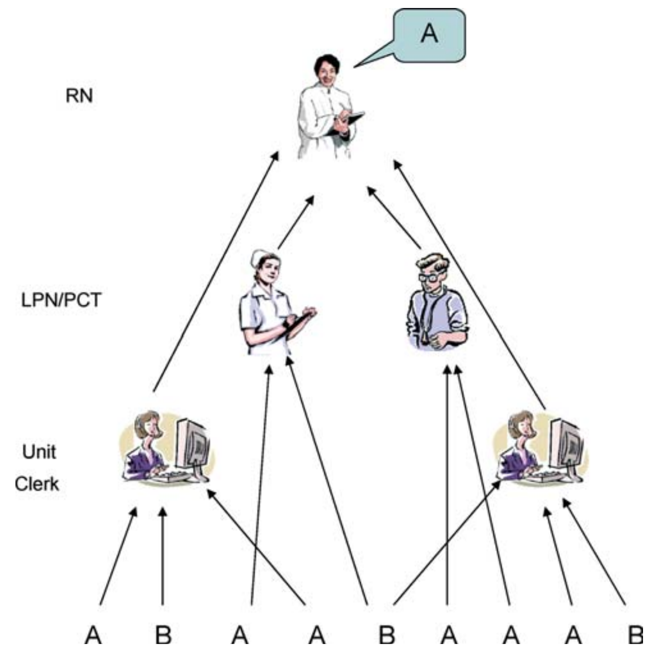

Fig. 2. Solving the nine-bit binary choice classification task. Each task corresponds to a patient. Various bits of information about the patient are seen by each staff member, and individual "decisions" are passed along up to the RN who makes the ultimate decision about whether there are more A's or B's in the string (i.e., what is the status of the patient?).

nurses (LPNs)—when present—at the second level, patient care technicians (PCTs) and/or Nurse Aides at the third level, and unit clerks at the bottom level. Each individual "agent" (e.g., RN or PCT) may have one or more subordinates and report to one or more managers. This allows researchers to model teams, hierarchies, matrix structures, etc. No individual can make a patient care decision alone (again assuming bounded rationality and distributed decision making); instead the unit decision is modeled as a majority vote of the individual decisions.

In OrgAhead, individual learning occurs through a standard stochastic learning model for boundedly rational agents (e.g., staff members) [31]. In contrast, organizational learning, or adaptation, occurs as a simulated annealing process, which is an optimization heuristic similar to the hill climbing algorithm. To get an intuitive idea of how annealing and hill climbing work, consider a blind person who wants to climb the highest peak in a range of mountains. By extending a cane, the individual can detect a slope. Adopting a rule to climb up each time a slope is detected will result in the person reaching the top of one of the peaks in the mountain range, but it may not be the highest. To reach the highest peak, it may be necessary to descend from one mountain before climbing up the next.

The annealing model was developed originally as a heuristic for solving complex combinatorial optimization problems [32,33]. 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 various constraints [34]. We assume that annealing also can be used to model the efforts of a nurse manager to find the specific unit characteristics that will maximize patient outcomes with acceptable costs (staffing, for example).

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 over the next 100 tasks (patients). We assume that a patient care unit endeavors to optimize performance (e.g., achieve desired quality and patient safety outcomes) while reducing or maintaining costs. The unit will change how it delivers patient care if it views that change as facilitating desired outcomes—and sometimes may even make a change that initially looks unfavorable, a more risky decision, if it is viewed as likely to succeed in the long term. OrgAhead's annealing logic simulates degrees of organizational risk taking. In the annealing model, temperature corresponds to the organization's current level of risk aversion. Temperature drops every 100 tasks (patients) so that the probability of accepting a proposed "bad" change strategy gradually decreases [35].

Organizational adaptation, as depicted in OrgAhead, has two components: executive decisions about particular restructuring goals and strategies and individual employees' experiential learning [31]. Executive decisions are commonly assumed to be "satisficing," rather than optimizing. Research has shown that executives do not consider all possible strategies; instead the first one that seems likely to move the organization toward the goal is selected [36,37]. Similarly, RNs cannot and do not consider every possible intervention when addressing a patient problem, but select the first one that seems likely to work, given their previous experience and current constraints.

4.2. Using OrgAhead

Our use of OrgAhead required four distinct steps:

Step 1. *Identify the core variables* in OrgAhead that correspond to the constructs in the conceptual model (e.g., unit size, task complexity or autonomy). On the surface, some variables in OrgAhead (e.g., agent, CEO, or augmenting the probability of an RN being hired when there is a vacancy on the unit) appeared quite unlike those in our data. Some of the mappings initially seemed counterintuitive, for example, mapping culture onto the "probability of adding a manager's task." However, there is a rationale for this mapping. In our implementation of OrgAhead, a manager equals an RN, so this feature determines which nurse would be assigned to a new patient, for example. Based on the literature, we assumed that hospital culture is a key determinant of whether a new patient is assigned to a nurse based on skill level or workload. From our data, we determined whether the prevailing patient care unit culture was predominantly affiliative or rational. When the culture on the patient care unit was more affiliative (family-like), we expected that a patient assignment would more likely be made on the basis of maintaining harmony on the unit, rather than on the basis of matching skills available to skills required.

During the mapping process, it became clear that modeling our patient care units required the addition of a new OrgAhead variable, "task complexity." Task complexity (TC) is a complex variable built by integrating several data elements in our research model related to the patient and patient care unit constructs (Table 1). First, TC incorporates several patient characteristics (i.e., number of comorbidities, age, and insurance) that, in our first wave of data, were predictors of patient safety outcomes. TC also includes patient unit characteristics that were found to be predictive of patient safety outcomes (i.e., workload and turbulence per patient day). Each of these is also assumed to contribute to the complexity of care, and therefore the workload, at the patient care unit level. For example, if patients have more comorbidities, are older and do not have insurance, then they are likely to require more complex care and the demands on caregivers will be more challenging. Similarly, patient care units that have a high degree of change in their environments, care for a wide variety of patients, and have many admissions, transfers, and discharges are likely to place more demands on caregivers, as well.

Step 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 variables. For example, each virtual organization completed a training period before performance was measured. The length of each training period was determined by the reported level of staff education on the unit, calculated as [mean years of education] + [years in hospital] + [2 × years on the patient care unit]. We used the mean score for the 16 units as a threshold for distinguishing high from low values. Units with higher education were assigned a training period of 500 binary choice tasks before their "life cycles" began and units with lower education values were assigned 200.

Table 1
Examples of the mapping from constructs/variables in the research model to OrgAhead variables used in the initial "static" modeling

Construct/concept	Research variable and data source	OrgAhead variable and description
Insurance	Percentage of patients who are self pay (one of three components that sum to task complexity)—obtained from hospital financial data	Task complexity (how many task resources are used). This is the key variable that we manipulate. Self pay status is only one of several components (see below)
Risk for adverse outcomes	Age (% patients >75 years old) (one of three components that sum to task complexity)—obtained from financial data	Task complexity component
Risk for adverse outcomes	Comorbidities (Avg.) (one of three components that sum to task complexity)—obtained from hospital financial data	Task complexity component
Workload	Composite variable calculated as average number of patient days/RN full time equivalents (FTEs)—increases or decreases task complexity—obtained from hospital financial data	Task complexity component
Turbulence per patient day	Composite variable comprised of how often staff leave unit, distance staff travel on unit to deliver care, responsiveness of support systems, dynamism divided by average number of patients per day—increases or decreases task complexity—calculated variable based on data obtained from staff and nurse manager surveys	Task complexity component
Staffing	Education, hours of care, vacancies (used to calculate probability of hiring each level of staff when new staff are hired.)—calculated from data obtained in nurse manager survey	Training period
Autonomy	Control over practice score (based on staff survey response to Control over Practice scale)	SOP (standard operating procedures); (the probability that standard rules or protocols will be used; as control over practice increases, the use of SOP decreases)
Staffing	Number of RNs, PCTs, LPNs, NAs, and Unit Clerks	Number of people in organization & Levels of hierarchy
Experience	Months of experience in hospital and on unit—obtained from staff survey	Training Period (number of time periods simulation runs, as training, before data are collected); This is set at 500 if highly trained staff; 200 if poorly trained
Safety	Reported medication errors, and falls with injury, obtained from hospital quality data	Accuracy (in OrgAhead, this refers to the accuracy of the decision made about the binary choice task (i.e., in each nine-bit string {patient} presented, were there more A's or B's?)
Quality	Percentage of time minimum criterion for complex self care and symptom management achieved; obtained from patient surveys on discharge	Completion rate (describes the degree to which the organization (unit) has sufficient information resources to handle their assigned tasks (patients)

For these analyses, memory cycle, unit structure (people to people and people to resource connections), and information per person were held constant across units. Data sources for the research variables are included, along with descriptions of the OrgAhead variables.

Selecting the parameters that will be allowed to vary (independent variables) and values for those parameters, as well as the dependent measure (e.g., accuracy) defines a virtual experiment. For the initial validation studies, we varied task complexity, autonomy, and training period. Our calculated values for task complexity were rescaled for OrgAhead into a range of odd values between 5 and 17. In the original version of OrgAhead, the variable that corresponds to our autonomy measure (standard operating procedures, or SOP) was simply an on-off switch. However, that proved to be too insensitive so SOP was modified to be a continuous variable, which allows us to use our actual values.

Step 3. *Set non-core variables* for each patient care unit, based on actual data. These include variables such as the levels of hierarchy to be described, the number of staff at each level, and the probability of staffing changes (hiring or firing) at each level. Levels of hierarchy and numbers of staff are obtained directly from the data. The probability of hiring someone in any given month is a calculated variable, based on the number of vacancies and resignations in the previous month. This probability is relevant only for the dynamic experiments.

Step 4. *Conduct virtual experiments*. Computational modeling allows for developing organizational experiments that would be difficult to control in the real setting. The purpose of our initial experiments was model validation. Because OrgAhead had not been used in healthcare before, it was important to know whether we could really use it effectively to model patient care units.

5. Model validation

5.1. Calibrating the patient safety model

Our initial experiments were aimed at model validation using a calibration technique and patient safety data. We needed to determine how well the Accuracy measure in OrgAhead mapped onto our observed patient safety outcome measures (i.e., Medication Errors and Falls—with and without injury). Because our data were reported, not actual, medication errors and falls, we set our desired level of match at pattern, rather than actual values. Our goal was to calibrate OrgAhead so that the accuracy of simulated units generally (at least 80% of the time) ordered in the same way as observed units.

5.1.1. Design and procedure

Calibration entailed comparing the observed total reported Medication Errors and Falls (with and without injury) for 16 units with their corresponding Accuracy measures in OrgAhead. We carried out "static" (non-annealing) simulations for each of the 16 units with task complexity, autonomy, training period, and number of staff on the unit set on the basis of our observed data. These particular variables were selected because of their statistically significant impact on medication errors or patient falls in our previous causal modeling. In addition, we controlled the structure of the organization. Although the number of people varied according to the actual unit data for number of staff at each level, we kept the amount of information each level (i.e., RNs, LPNs, PCTs, and Unit Clerks) could access the same, and also kept the hierarchical structure the same across units. We then rank ordered the performance of virtual and actual units and compared them using Pearson Product Moment Correlation statistics.

5.1.2. Results and discussion

When the rank orders of Accuracy (virtual units) and Total Errors (actual units) were compared for all 16 units (Table 2), the correlation coefficient exceeded our target, $r = .83$. Correlation at the value level (Accuracy and Total Errors) was reasonably high as well, $r = -.62$. With two small specialty units that were outliers both in terms of size and the task complexity excluded from the sample, the correlations were even stronger. At the pattern level (rank order of virtual and actual performance measures), $r = .86$. At the value level (i.e., Accuracy for virtual units and Total Errors for actual units), $r = -.76$. Overall, our effort to model the 16 patient care units by controlling the variables shown to be statistically significant in the causal modeling exceeded our expectations.

5.2. Calibrating the quality outcomes model

Our second set of experiments utilized a second OrgAhead outcome measure, Completion Rate. We initially had assumed that Completion Rate would correspond to Length of Stay. However, some of our research team found it equally plausible that Completion Rate might reflect the degree to which units successfully met quality criteria (e.g., the percentage of patients that achieved minimal self care outcomes). Our second experiment was conducted to test these competing hypotheses.

5.2.1. Design and procedure

We adopted the same design and procedure that we had adopted to calibrate the safety outcomes model. However, for this analysis, quality measures were converted to percentage of achievement above minimum thresholds. Quality measures used in the study were Simple Self Care (e.g., patients' abilities to get

Table 2
Virtual unit performance accuracy compared with actual unit total errors for 16 patient care units

Unit	Virtual		Actual	
	Accuracy	Rank order	Total errors	Rank order
1	75.85	15	21.02	15
2	74.95	16	12.49	14
3	77.75	11	8.15	12
4	84.55	1	1.79	1
5	81.6	3	2.13	2
6	79.45	7	2.88	3
7	81.3	4	4.73	7
8	77.65	12	26.18	16
9	81	5	4.09	6
10	83.4	2	4.87	8
11	77.65	12	10.83	13
12	78.6	9	5.4	10
13	79.2	8	3.04	4
14	76.45	14	7.22	11
15	78.45	10	4.98	9
16	80.95	6	3.26	5

Table 3
Corresponding values of OrgAhead's completion time measure with actual observed quality outcome variables, and average length of stay for 16 patient care units

Patient care unit	Completion time	Simple self care	Complex self care	Symptom management	Length of stay
51	0.176	0.68	0.66	0.64	3.39
53	0.321	0.61	0.61	0.67	8.33
54	0.269	0.48	0.44	0.5	3.22
55	0.471	0.77	0.71	0.84	2.3
61	0.22	0.69	0.69	0.66	3.43
62	0.282	0.52	0.59	0.75	3.9
63	0.318	0.29	0.59	0.56	4.22
64	0.475	0.69	0.85	0.92	8.22
65	0.325	0.75	0.63	0.52	3.58
66	0.476	0.75	1	1	6.43
91	0.37	0.67	0.62	0.65	3.21
101	0.282	0.75	0.55	0.65	4.56
102	0.275	0.55	0.65	0.71	4.77
103	0.299	0.7	0.6	0.8	5.27
104	0.299	0.67	0.53	0.39	5.33
105	0.326	0.59	0.59	0.71	4.05

help, take medications, and follow their treatment plan on discharge), Complex Self Care (e.g., patients' abilities to manage their conditions and adapt their treatment plans), and Symptom Management (e.g., how well patients are able to manage their symptoms on discharge). The thresholds used for these measures were recently validated in a national study using a Delphi technique [38].

5.2.2. Results and discussion

Ranking units by percentage of achievement resulted in a number of "ties" at various values; for that reason, order level validation could not be used. Therefore, we compared the values of observed measures for quality indicators for 16 units with their corresponding completion time measures in OrgAhead. The results are summarized in Table 3. The correlation between Average Length of Stay and Completion Rate, which we initially expected to be high, was not ($r = .34$). The correlations between Completion Rate and Complex Self Care ($r = .64$) and between Completion Rate and Symptom Management ($r = .62$) were judged as adequate for modeling purposes, but the correlation between Completion Rate and Simple Self Care ($r = .29$) was not. When a composite quality variable was created by calculating the mean of the Complex Self Care and Symptom Management scores, the correlation of that value with Completion Rate was slightly higher ($r = .66$). Assuming that these correlations remain consistent when we retest with the second wave of data, we will map Completion Rate to the composite quality value.

6. Conclusion

We are using OrgAhead, a computational modeling program, to transform data collected for a large research project into actionable information. In validation studies, we demonstrated that we can create virtual units that match the performance of the actual units in our first wave of data collection. Two OrgAhead outcome variables, Accuracy and Completion Rate, were shown through a correlation study to correspond to Total Errors and a composite quality measure comprised of Complex Self Care and Symptom Management, respectively.

6.1. Limitations

The number of parameters that must be experimentally set in OrgAhead to model a specific unit is quite high, particularly for the dynamic simulations. This means that the number of independent variables in a seemingly simple experiment can quickly get too high for statistical analysis. For our preliminary validation studies, we found it useful to use the static model and control some variables so that the effects of others were clearer.

OrgAhead has several parameters that are actually switches; that is, they are either "on" or "off." Initially, standard operating procedure (SOP) was one of those parameters. Because it had such a dramatic effect on organizational performance, it was modified to be a continuous variable so that it mapped more appropriately to our data. So far, this is the only switch that we have changed; however, it is possible that others may need to be altered in the same way.

Not all the data we collected for the research project are available routinely in the hospital, although the financial and quality data are. However, it is not uncommon for hospitals to conduct staff surveys—and patient surveys are common in most organizations. We continue to be limited by the availability of nurse-sensitive outcome data. For example, we are using "reported" medication errors, not observed or actual medication errors; because those data do not exist in the hospitals we are studying. This lack of precise measures of outcome data is likely to make it more difficult to model accurately a patient care unit's performance.

6.2. Implications and directions for further research

Computational modeling is a theoretically motivated analysis methodology that, although not developed specifically for healthcare, has the potential—when variables are correctly mapped—to afford researchers a promising new way to analyze the complexities of the healthcare system and develop predictive models that patient care managers can use to help in their decision making. We have successfully mapped variables collected in a healthcare domain onto OrgAhead. We have provided initial validation for the model by replicating the pattern of performance of 16 patient care units in the first wave of data collection.

Once the results from the second wave of data collection are available, we will refine the model further. We then will use the dynamic version of OrgAhead to generate hypotheses about change strategies that have a high probability of improving outcomes on four pilot units and determine the face validity of the generated change strategies with nurses on the pilot units. Assuming adequate face validity is obtained, we will generate potential change strategies for the remaining units and work with nurse managers to assess the cost effectiveness of each for their purposes. In subsequent research, we expect to work with selected units to implement the selected change initiatives and evaluate their impact on patient safety and quality outcomes.

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