Using OrgAhead, a computational modeling program, to improve patient care unit safety and quality outcomes

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Summary As part of ongoing research to investigate the impact of patient characteristics, organization characteristics and patient unit characteristics on safety and quality outcomes, we used 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 32 units in 12 hospitals in Arizona. Validation studies demonstrated acceptable levels of correspondence between actual and virtual patient units. In this paper, we report how we used 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 was 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 that could be implemented by actual units to improve safety and quality outcomes. Nurse managers have responded enthusiastically to the additional decision support for quality improvement.

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1. Introduction

The quality of care in U.S. hospitals continues to be in question. Medical errors persist at an alarming rate, despite extensive publicity and considerable research. The cost of these errors, to patients, the healthcare system, and society is extremely high. It has become increasingly clear that medical errors have no simple, single cause, but are much more likely to be the results of systems failures that involve many individuals, many contributing factors,
and encompass multiple levels of the health care system.

Given this, it seems reasonable to assume that patient characteristics, organization characteristics and patient care unit characteristics might interact to affect patient safety and quality outcomes. But just what is the nature of this interaction? 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 Impact Study researchers collected data from 37 patient care units in 12 hospitals in Arizona. The conceptual model used for the research was based on the quality health outcomes model [1] developed by the American Academy of Nursing Expert Panel on Quality and refined by Brewer and colleagues [2]. The model contains four major constructs: context, intervention, client, and outcomes (Fig. 1).

Hospitals that participated in the research included teaching and non-teaching hospitals, as well as public and privately funded hospitals ranging in size from 60 to over 400 beds. Adult medical or surgical care units were used. Data were collected in two waves: patient care units from half of 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. Only units that achieved a 40% staff response rate were retained in the study. Five patient care units were dropped from the study after failing to achieve this criterion, leaving 32 units for the analysis. In all 1179 patients and 867 staff were surveyed.

Following data cleaning, the psychometric properties of each survey scale were assessed at both individual and group levels. Internal consistency reliability was determined for each instrument. Construct validity was assessed through factor analysis at the individual level. Standard group level assessment techniques were used for evaluating reliability and validity. Intraclass correlations, between group significance tests and percent of aggregated interitem correlation coefficients were used for reliability assessment where appropriate. Validity was examined using a measure of within-group agreement.

Two types of modeling were used for data analysis. Causal modeling was used to examine the impact of patient risk characteristics, organizational characteristics and unit characteristics on patient safety and quality outcomes. Computational modeling was utilized to generate hypotheses about the kinds of changes that might be made to improve patient outcomes. In this paper, we focus solely on computational modeling. We first describe our approach and then report our results.

2. Computational modeling using OrgAhead

Hulin and Ilgen have described computational modeling as a “set of loosely interrelated research tools” that have been developed to investigate how complex systems, including the individuals who comprise those systems, function [3]. Computational models are used to ask “what if” questions that cannot be answered by traditional empirical methods. The usefulness of computational modeling for building theory about organizational behavior and adaptation has been recognized for some time [4,5]. Recently, computational modeling has become increasingly appealing as a method for studying complex organizational dynamics. Rather than focus on snapshots, as traditional methods do, computational modeling lets researchers study the paths of dynamic processes as they unfold in the organization over time [3]. In healthcare operations research, computational modeling has been used in a variety of ways, such as appointment scheduling, predicting staffing needs and facility size, workflow analysis, resource needs, and anticipating financial and patient outcomes of program modifications [6–11]. Although computational modeling has had limited use to date in nursing, it has been used to develop cost reimbursement models and reduce clinical waiting times [12,13].

Using computational modeling, researchers can create virtual organizations that correspond func-
tionally to actual organizations and then test, in the virtual environment, the impact of various organizational changes on safety and quality outcomes. Virtual models can offer organizations and their subunits the ability to construct and test hypotheses, i.e., "what if" scenarios. Computational modeling also enables researchers to model complex systems, incorporate multiple levels of analysis (e.g., organization, unit, individual), and study the impact of organizational changes over time. Finally, computational modeling allows researchers to explore how contextual factors interact to constrain the impact of organizational changes on patient outcomes.

We used OrgAhead, a computational modeling program, to create virtual units that functionally matched our actual units and then evaluated the performance of the virtual units under various conditions. 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. 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 in which individual members of the organization are modeled as goal oriented, cognitively capable, socially situated virtual "agents." [14] OrgAhead has been used previously to study organizational processes in various military and non-military settings (e.g., crisis response and team design for joint task forces); but this is its first application in healthcare [15–17].

OrgAhead assumes that staff members have limited data on which to make a clinical decision. This is operationalized as each individual agent (nurse, unit clerk, or patient care technician) having access to only a limited number of data elements, the number of elements being determined by their training. 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 (or, more precisely, data about a patient). In OrgAhead, patients are modeled as 9-bit binary choice classification tasks, an approach used extensively in team and organizational performance research. Specifically, each virtual "patient" assigned to the patient care unit is presented as an array or vector of 1's and 0's (e.g., 100101101). The precise numbers selected for each array are randomly selected using a Monte Carlo simulation and have no semantic meaning per se (i.e., neither the numbers nor their position map onto any particular patient characteristics), but abstractly can be understood as the total set of data available about a particular patient. The health care team's challenge is to determine if there are more 1s or 0s in the string. This is analogous to deciding whether each patient seen is getting better ("yes") or worse ("no"), given a limited amount of data. Each staff member on the virtual unit sees only a portion (from 1 to 4 characters) of the string and must make a decision based on those data, given their previous experience. Assuming that RNs have more data than the other staff, we arbitrarily assigned RNs 4 data elements, LPNs/PCTS 2 and unit clerks 3. In practice, this meant giving each RN access to four agents' (another RN, an LPN or PCT, or a unit clerk) decisions about the patient's status, each LPN access to two agents' decisions, etc. The RNs provide the final and single "organizational" answer. Predefined decision rules on the array store the actual answer. For example, a simple decision rule is that if there are more 1s than 0s then the answer is 1. A correct response is one that matches the actual answer, i.e., the team's final answer and the stored answer are identical. If this answer matches the real answer for the task vector, then all members of the team receive positive feedback (i.e., "good job!") and are likely to repeat that response when they see the same data. If the team's answer is incorrect, the negative feedback members receive makes them less likely to respond in the same way when they see the same data.

The main performance measures in OrgAhead are accuracy, which is defined as the percentage of patients (tasks) for which the team provided the correct answer, and completion ratio, which is defined as the degree to which agents (and the organization) have the resources required to make accurate patient decisions. Resources can be either personnel or information (i.e., access to more patient data). Further details are available online at http://www.casos.ece.cmu.edu/projects/OrgAhead/and in [18].

In sum, computational modeling provides researchers a new set of tools with which to investigate the functionality of complex organizations and answer questions that cannot be addressed with traditional methods. OrgAhead is one such com-
3. Methodology

Our computational modeling process included five distinct steps: first, variables in our research model were matched to the variables in OrgAhead. Next, we determined the range for each independent variable in OrgAhead. In the third step, values were set for all other variables used in OrgAhead. Fourth, we validated the model with actual data. Finally, experiments were run to generate hypotheses about the kinds of changes that might be made to improve patient outcomes. Each step is described in greater detail in the text that follows.

3.1. Match variables in OrgAhead to constructs in the research model (e.g., unit size, task complexity or autonomy)

In OrgAhead, the primary performance measures are accuracy and completion ratio. Accuracy, in OrgAhead, is defined as the percentage of the organization’s answers that are correct. Completion ratio is defined as the degree to which agents (and the organization) have the resources (information and personnel) required. Safety outcomes in the research model were mapped to accuracy; quality outcomes and one component of patient satisfaction were mapped to completion ratio. During the mapping process, we found no variables in OrgAhead that matched patient risk and complexity variables and turbulence in our research model. This required the creation of a new OrgAhead variable, “task complexity”. Task complexity (TC) incorporated patient characteristics (i.e., number of comorbidities, age, and insurance) that, in our data, were predictors of patient safety outcomes and as-

![Fig. 2 Measured variables and use in causal and computational modeling.](image-url)
Hierarchical structure for each.


differentiate the units, since we used a similar hierarchical modeling. These are the variables that differ-
entiate the units, since we used a similar hierarchical structure for each.

3.2. Select independent variables and define the range of values they can take

In some cases, continuous variables in our data had to be rescaled or converted to dichotomous vari-
ables for use in OrgAhead’s binary choice model. For example, for each virtual patient care unit a training period was determined. During the training period, the unit gradually “learns” to improve its performance in the binary choice task. 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]. These results were then dichotomized into high or low val-
ues. For modeling purposes, units with higher edu-
cation were arbitrarily assigned a training period of 500 binary choice tasks before their “life cy-
cles” began, and units with lower education val-
ues were assigned 200. Selecting the independent variables and values for those parameters, as well as the dependent measure (e.g., accuracy) defines a virtual experiment. For the initial studies, we varied task complexity, standard operating proce-
dures (or SOP), and training period. Task complexity scores for actual units were rescaled into a range of odd values from 7 to 17, as required in OrgAhead. In the original version of OrgAhead, standard oper-
ating procedures (SOP), the variable that corre-
sponds to our nursing culture measure, was simply an on–off switch. However, that proved to be too insensitive so SOP was modified to be a continuous variable.

3.3. Set non-core variables for each patient care unit, based on actual data

These include variables such as the levels of hier-
archy to be described and the number of staff at each level. OrgAhead allows up to four lev-
els of hierarchy. We created a three-level quasi-
hierarchy with RNs at the top, LPNs and PCTs in the middle, and unit clerks at the bottom. We com-
bined LPNs and PCTs because not all units had both.

Numbers of staff at each level were obtained di-
rectly from the research data for actual units. Two matrices must be created in OrgAhead, a com-
munication matrix and a resource utilization ma-
trix. The communication matrix defines who re-
ceives information from whom. The size of each matrix depends on the number of staff modeled.

As the size of these matrices increases, it becomes more difficult to execute the application success-
fully on a standard computer. Our solution was to rescale the staffing on each unit to one-third actual.

3.4. Calibrate (validate) the model

Our initial calibration procedures entailed com-
paring the observed total reported medication er-
rors and falls (with and without injury) for the 16 units in the first wave of data collection with their corresponding accuracy measures in OrgAhead (Efken et al., 2003). Our goal was to achieve a correlation of 0.80. The correlation coefficient be-
tween the rank orders of accuracy (virtual units) and total errors (actual units) exceeded our tar-
get, r = 0.83. We also correlated actual values for accuracy and total errors and found this correla-
tion acceptable, r = −0.62. We then compared the values of observed measures for quality indicators for 16 units with completion time measures in Org-
Ahead. For the 16 units, the highest correlation was between a composite quality variable (mean of complex self care and symptom management scores) and completion rate (r = 0.66); so, for mod-
eling purposes, initially completion ratio equated to complex self care and symptom management.

We repeated the process with the second wave of units and with all the units combined. Results of the validation testing for all units for which we had complete data are shown in Table 1. Corre-
lations for all units (N = 31) were somewhat lower than for the original 16 units. Comparing the rank order for actual and virtual units resulted in a cor-
relation of 0.61; for actual values of accuracy and total errors, the correlation was −0.51. When out-
liers in both waves were deleted from the sam-
pel (N = 27), correlations improved to 0.83 for the rank orders of actual and virtual units. For the total sample, completion ratio correlated better with a combination of complex self care, symptom management and patient satisfaction with caring so we used the mean of these values as the cor-
relate for completion ratio in subsequent model-
ing.
3.5. Hypothesis generation

We then used OrgAhead to generate hypotheses about strategies managers could use to improve patient safety and quality outcomes on their units. To identify the kinds of changes that would improve accuracy (patient safety outcomes) and completion ratio (quality outcomes), we increased or decreased variables and observed the outcomes. Changing individual variables had little effect on outcomes so combinations of variables were changed in subsequent iterations. For example, we systematically made changes in task complexity and workload and evaluated the impact on accuracy (safety) and completion ratio (quality). We then explored how changes in the various components of task complexity (percent patients over 75-years-old, number of comorbidities, percent self pay patients, RN workload, and turbulence) contributed to task complexity, particularly focusing on finding the maximum decrease in task complexity possible, given the actual units’ current values in each of the components. We also broke down turbulence into each of its components (perceived environmental uncertainty, distance traveled to give care, etc.; accessibility to supplies, medications, etc.; responsiveness of support staff) to see what kinds of innovations might have the most impact on turbulence. We followed a similar procedure to evaluate the impact of the nursing culture (standard operating procedures) and education/experience (training) variables on safety and quality outcomes (accuracy and completion ratio), respectively.

We were able to improve virtual units’ accuracy, on average, by about 3.5 points. Only values of task complexity were used that were realistically achievable based on the actual unit’s current values for turbulence, distance traveled, etc. We estimate that this would correspond to decreasing reported

<table>
<thead>
<tr>
<th>Unit/rank order</th>
<th>Task complexity</th>
<th>Environmental task complexity components</th>
<th>SOP (nursing culture) Accuracy (%)</th>
<th>CR</th>
</tr>
</thead>
<tbody>
<tr>
<td>A 7, 9</td>
<td>10 (7–17)</td>
<td>1.45 (1–4)</td>
<td>0.50 (mod)</td>
<td>80</td>
</tr>
<tr>
<td>B 25, 27</td>
<td>10 (7–17)</td>
<td>1.90 (1–4)</td>
<td>0.51 (mod)</td>
<td>77</td>
</tr>
<tr>
<td>C 20, 12</td>
<td>10 (7–17)</td>
<td>2.21 (1–4)</td>
<td>0.56 (mod)</td>
<td>78</td>
</tr>
<tr>
<td>D 2, 2</td>
<td>14 (7–17)</td>
<td>1.50 (1–4)</td>
<td>0.67 (mod)</td>
<td>82</td>
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<tr>
<td>E 21, 26</td>
<td>17 (7–17)</td>
<td>3.87 (1–4)</td>
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</tr>
<tr>
<td>F 14, 11</td>
<td>11 (7–17)</td>
<td>3.47 (1–4)</td>
<td>0.51 (mod)</td>
<td>78</td>
</tr>
<tr>
<td>G 17, 14</td>
<td>11 (7–17)</td>
<td>3.57 (1–4)</td>
<td>0.51 (mod)</td>
<td>79</td>
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<tr>
<td>H 11, 5</td>
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<td>I 13, 13</td>
<td>9 (7–17)</td>
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<tr>
<td>J 26, 24</td>
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<td>0.51 (mod)</td>
<td>70</td>
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<tr>
<td>K 23, 20</td>
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<td>1.53 (1–4)</td>
<td>0.67 (mod)</td>
<td>77</td>
</tr>
<tr>
<td>L 4, 8</td>
<td>12 (7–17)</td>
<td>1.35 (1–4)</td>
<td>0.83 (mod)</td>
<td>80</td>
</tr>
<tr>
<td>M 15, 16</td>
<td>11 (7–17)</td>
<td>3.54 (1–4)</td>
<td>0.52 (mod)</td>
<td>79</td>
</tr>
<tr>
<td>N 24, 17</td>
<td>11 (7–17)</td>
<td>4.00 (1–4)</td>
<td>0.52 (mod)</td>
<td>77</td>
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<td>O 12, 13</td>
<td>9 (7–17)</td>
<td>3.65 (1–4)</td>
<td>0.50 (mod)</td>
<td>78</td>
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<tr>
<td>P 1, 1</td>
<td>7 (7–17)</td>
<td>1.15 (1–4)</td>
<td>0.51 (mod)</td>
<td>78</td>
</tr>
<tr>
<td>Q 16, 21</td>
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<td>3.20 (1–4)</td>
<td>0.37 (mod)</td>
<td>79</td>
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<tr>
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<td>10 (7–17)</td>
<td>1.54 (1–4)</td>
<td>0.37 (mod)</td>
<td>82</td>
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<tr>
<td>S 9, 11</td>
<td>14 (7–17)</td>
<td>3.86 (1–4)</td>
<td>0.42 (mod)</td>
<td>80</td>
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<td>11 (7–17)</td>
<td>2.97 (1–4)</td>
<td>0.52 (mod)</td>
<td>78</td>
</tr>
<tr>
<td>U 18, 22</td>
<td>12 (7–17)</td>
<td>2.25 (1–4)</td>
<td>0.38 (mod)</td>
<td>78</td>
</tr>
<tr>
<td>V 3, 3</td>
<td>11 (7–17)</td>
<td>3.20 (1–4)</td>
<td>0.19 (mod)</td>
<td>80</td>
</tr>
<tr>
<td>W 12, 7</td>
<td>12 (7–17)</td>
<td>3.74 (1–4)</td>
<td>0.37 (mod)</td>
<td>79</td>
</tr>
<tr>
<td>X 10, 15</td>
<td>11 (7–17)</td>
<td>2.96 (1–4)</td>
<td>0.41 (mod)</td>
<td>79</td>
</tr>
<tr>
<td>Y 6, 18</td>
<td>12 (7–17)</td>
<td>1.45 (1–4)</td>
<td>0.42 (mod)</td>
<td>80</td>
</tr>
<tr>
<td>Z 1, 7</td>
<td>11 (7–17)</td>
<td>3.20 (1–4)</td>
<td>0.47 (mod)</td>
<td>79</td>
</tr>
<tr>
<td>AA 22, 19</td>
<td>12 (7–17)</td>
<td>3.30 (1–4)</td>
<td>0.46 (mod)</td>
<td>77</td>
</tr>
</tbody>
</table>

a Numbers correspond to the rank orders (for accuracy) of virtual and actual units, respectively.
b Numbers in parentheses indicate the scale on which the value is based. For turbulence, a composite variable which ranges from negative to positive scores, values are simply categorized as low, moderate, or high.
Table 2 Improvements in accuracy and completion ratio ($N = 27$)

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial</td>
<td>74.95</td>
<td>83.40</td>
<td>79.16</td>
</tr>
<tr>
<td>Best</td>
<td>78.19</td>
<td>86.39</td>
<td>82.91</td>
</tr>
<tr>
<td>Completion ratio</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial</td>
<td>0.18</td>
<td>0.48</td>
<td>0.30</td>
</tr>
<tr>
<td>Best</td>
<td>0.20</td>
<td>0.50</td>
<td>0.34</td>
</tr>
</tbody>
</table>

Initial values were taken from actual units and used to initialize the simulation.

Errors by 3.5 per 1000 patient days. Given the low number of reported errors, this is a significant improvement.

The average improvement we could make in virtual units’ completion ratio was 0.04. This seems small, but an increase of 0.02 in completion ratio corresponds to an approximate 14% increase in quality achievement for discharged patients (as measured by their survey scores) so this is potentially very significant (Table 2).

As shown in Table 3, we were generally able to realistically reduce task complexity by only a little over one point unless we also reduced nursing workload. One of the reasons for this is that we held patient days constant, assuming that nurse managers have little control over that factor. To reduce task complexity further therefore required reducing RN workload.

Table 4 shows the average initial values of SOP used in the simulations and the values that resulted in the highest accuracy scores for each job level. The simulations suggest that safety outcomes can be improved by decreasing SOP for RNs by 0.20, increasing SOP for PCTs and LPNs slightly (0.05) and increasing SOP for clerks by 0.22. Because OrgAhead’s SOP variable is inversely related to our research variable of nursing culture (control over nursing practice), that means giving RNs more control over their practice and unit clerks more protocols.

Individual units showed considerable variability. Unit A ranked seventh among the virtual units in accuracy (81%) and ninth among the actual units in patient safety outcomes (medication errors and falls). Unit A’s initial task complexity (based on the results of the actual unit) was fairly low (10 on a scale of 7–17). The two major components of task complexity, workload and turbulence had low and moderate values, respectively. Holding workload constant and reducing the amount of turbulence did not have a substantial effect on accuracy or completion ratio. However, decreasing both workload and turbulence decreased task complexity, improving accuracy from 81 to 85% and completion ratio from 0.33 to 0.41. Increasing standard operating procedures for unit clerks and reducing them for RNs increased accuracy further from 85 to 86% (changing standard operating procedures did not change completion ratio since they are not related in OrgAhead). In our meeting with managers

Table 3 Average improvements in task complexity and workload for the simulated units

<table>
<thead>
<tr>
<th>Task complexity/workload</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial task complexity</td>
<td>7</td>
<td>17</td>
<td>11.58</td>
</tr>
<tr>
<td>Best task complexity</td>
<td>7</td>
<td>16</td>
<td>10.12</td>
</tr>
<tr>
<td>Initial workload</td>
<td>1</td>
<td>4</td>
<td>2.44</td>
</tr>
<tr>
<td>Best workload</td>
<td>1</td>
<td>3</td>
<td>1.42</td>
</tr>
</tbody>
</table>

Table 4 Initial and optimal (for improving accuracy) values of SOP by job title

<table>
<thead>
<tr>
<th>Job level</th>
<th>Standard operating procedures (SOP)</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>RN</td>
<td>Initial/optimal</td>
<td>0.19</td>
<td>0.73</td>
<td>0.45</td>
</tr>
<tr>
<td>PCT/LPN</td>
<td>For optimal accuracy</td>
<td>0.10</td>
<td>1.0</td>
<td>0.25</td>
</tr>
<tr>
<td>UC</td>
<td>Initial</td>
<td>0.10</td>
<td>0.80</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>For optimal accuracy</td>
<td>0.10</td>
<td>0.83</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>For optimal accuracy</td>
<td>0.20</td>
<td>0.90</td>
<td>0.68</td>
</tr>
</tbody>
</table>

Lower values of standard operating procedures (SOP) correspond to higher values of nursing culture (control over nursing practice, communication, and job satisfaction).
of unit A, we emphasized decreasing workload and turbulence, along with changes in nursing culture as the most likely changes to improve patient safety and quality outcomes.

Unit E ranked 21st among the virtual units in accuracy (76%) and 26th of the actual units in patient safety outcomes (medication errors and falls). Unit E’s initial task complexity was extremely high (17 on a scale of 7–17). On unit E, workload was fairly low (1.07), but staff perceived environmental turbulence as very high (8.57). We were only able to decrease task complexity through decreasing turbulence by 1 point, and that improved accuracy to 77.8% and completion ratio to 0.19. Although there was room for improvement in the various components of turbulence, on unit E the number of patients per day was extremely high (94.4); and that essentially cancelled the effect of improvements in the other factors. Increasing the standard operating procedures for unit clerks and reducing it for RNs increased accuracy from 77.8 to 80%, an overall increase in accuracy of 4%. In our meeting with managers of unit E we emphasized the effect of the very large unit (two units had previously been combined), as well as various components of turbulence, along with changing nursing culture as the most likely changes to improve patient safety and quality outcomes significantly.

When we reported the predictions generated by computational modeling to managers and selected staff on each of the units; their responses to the additional information were overwhelmingly positive. Managers found the information useful for suggesting possible unit changes, as well as comparing their actual results with those of the model in those cases where they had already made improvements. The only negative was the length of time (up to 2 years) that had elapsed between when the data were collected and when we reported to them due to the need for descriptive and causal modeling prior to computational modeling; as a result, several of the units were quite different (e.g., different managers, size, location, staffing) from when the research data were originally collected.

4. Limitations

This research used a fairly small (N = 32) sample of patient care units in only one state in the U.S. Only medical/surgical units were used, but even these showed considerable variability. To run the application on a laptop computer required that we use only one-third of the staff on the unit in the model. This may have had little impact on the essentially static modeling that we reported here, but did affect subsequent dynamic modeling.

It is not clear that a hierarchy with registered nurses at the top, patient care technicians and licensed practical nurses in the middle, and unit clerks at the bottom is the best way to model patient care units. We did not use nurse managers as part of the unit because, in several cases, the same manager was in charge of more than one unit. Unit clerks have a unique role, and are not as directly involved in patient decisions and may need to be included in the model in a different way.

5. Conclusion

As part of research investigating the impact of patient characteristics, organization characteristics and patient unit characteristics on safety and quality outcomes, we used a computational modeling program, OrgAhead, to model patient care units’ achievement of patient safety (medication errors and falls) and quality outcomes. We calibrated OrgAhead using data we collected from 32 units in 12 hospitals in Arizona. After validation studies demonstrated acceptable levels of correspondence between actual and virtual patient units, we then used OrgAhead to generate hypotheses about the kinds of innovations nurse managers might initiate to improve safety and quality outcomes on their units. On average, we were able to increase accuracy on units by 3.5 points, which approximates a decrease of 3.5 errors, and completion ratio by 0.04, which approximates a 14% increase in quality achievement.

Our results suggest that computational modeling can be a valuable new tool in the researcher’s arsenal when dealing with complex, multi-level problems. For the nurse manager, computational modeling offers 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, computational modeling may be very valuable indeed.

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